Big data management for periodic wireless sensor networks

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Dedication

This thesis work is foremost dedicated to my husband, Maroun, who has been a constant source of support and encouragement during the challenges and the hardships of this journey. Maroun, your words of encouragement and endorsement for tenacity ring in my ears. I am truly thankful for having you in my life.

I would like to extend my dedication to Dr. Abdallah Makhoul who supported me throughout my journey. I will always appreciate his tireless efforts in scaling up my technical skills, and the countless hours of proofreading he spent.

I dedicate this work as well to my baby girl Skye whom innocent smile gave me the strength to overcome the hardest moments I endured, especially during my last year of this thesis. Baby, you have been my best cheerleader.

A special feeling of gratitude to my mom who supported me in my determination to find and realise my potential. Mom, thank you for your continuous support throughout my life.

Last but most certainly not least, this thesis is dedicated to the loving memory of my father. Dad, Thank you for being there and doing your best with so little you had. You have been my silent inspiration to thrive. Till we meet again, I will always be your little girl.

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Abstract

Big Data Management in Wireless Sensor Networks

Maguy Medlej

The University of Franche Comté, 2014

Supervisors: Jacques Bahi, Abdallah Makhoul

Tides of readings are generated by small sensor nodes which constitute a wireless sensor networks (wsn) providing powerful silos of information that aims to leverage business profitability and enable environmental benefits. The promising results of wsn deployment in medical, commercial, industrial and military applications coupled with the acute need for real time decision making and periodic data collection especially in remote or menacing environments intrigued data consortiums and network communities to invest heavily in this field. Researches focused mainly on the limitations imposed by wsn in terms of energy, computing and communication capacity. This thesis proposes novel big data management techniques for periodic sensor networks embracing the limitations imposed by wsn and the nature of sensor data.

First, we proposed an adaptive sampling approach for periodic data collection. The main idea behind this approach is allowing each sensor node to adapt its sampling rates to the physical changing dynamics. In this way, over-sampling can be minimized and power efficiency of the overall network system can be improved dramatically. We present an efficient adaptive sampling approach based on the dependence of conditional variance of measurements over time. Then, we propose a multiple level activity model that uses behavioral functions modeled by modified Bezier curves to define application classes and allow for sampling adaptive rate.

Then we shift gears to address the periodic data aggregation on the level of sensor node data as a preprocessing phase for an efficient and scalable data mining. For this purpose, we introduced two tree-based bi-level periodic data aggregation

techniques for periodic sensor networks. The first one look on a periodic basis at each data measured at the first tier then, clean it periodically while conserving the number of occurrences of each measure captured. Lastly, data aggregation is performed between groups of nodes on the level of the aggregator while preserving the quality of the information. The second one proposes a new data aggregation approach aiming to identify near duplicate nodes that generate similar sets of collected data in periodic applications. We suggest the prefix filtering approach that avoids computing similarity values for all possible pairs of sets. We define a new filtering technique based on the quality of information.

Last but not least, we propose a new data mining method depending on the existing K-means clustering algorithm to mine the aggregated cleaned data and overcome the high computational cost imposed by data mining techniques as well as sensor networks limitations in terms of energy and power. We developed a new multilevel optimized version of « k-means » based on prefix filtering technique. K-means optimization technique in terms of comparison and number of iterations is applied by exploiting prefix subsets of data. The main idea of this technique is to optimize the clustering of observations generated by sensor networks into groups of related readings without any prior knowledge of the relationships between the prefixes sets.

All the proposed approaches for data management in periodic sensor networks are validated through simulation results based on real data generated by periodic wireless sensor network. These results show the importance of the suggested approach in terms of energy optimization, performance and data quality needed for decision making, analysis and business benefits.

Résumé

Gestion de données volumineuses dans les réseaux de capteurs périodiques

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Université de Franche Comté, 2014

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Durant la dernière décennie, sont apparus les réseaux de capteurs sans fils. Ces réseaux facilitent le suivi et le contrôle à distance de l'environnement physique avec une meilleure précision. Ils peuvent avoir de très diverses applications (environnementales, militaires, médicales, etc). Notons qu'un réseau de capteurs est constitué d'un grand nombre d'unités appelées noeuds capteurs. Chaque noeud est composé principalement d'un ou plusieurs capteurs, d'une unité de traitement et d'un module de communication.

La diversité d'application d'un réseau de capteurs fait que cette nouvelle technologie soit orientée application. Parmi les applications les plus répandues est la sureveillance environementale. Les capteurs environnementaux sont des composants électroniques qui peuvent être utilisés pour mesurer/capter des paramètres de l'environnement comme la température, l'humidité, la pression atmosphérique, la concentration d'un gaz particulier dans l'air, etc. Un réseau de capteurs environnemental permet de très diverses applications comme, le suivi de la qualité des eaux souterraines, la surveillance de la pollution dans une ville, les systèmes d'arrosage, la surveillance des glaciers montagneux, etc.

La collecte des données auprès des réseaux de capteurs environnementaux peut être réalisée à la demande par un dialogue bi-directionnel entre les noeuds et la station de base, ou bien sans demande. Cependant, dans la majorité des cas le modèle

de collecte de données adopté est le modèle d'échantillonnage périodique. Ce modèle est caractérisé par l'acquisition de données par les noeuds capteurs à distance et sa transmission à la station de base d'une manière périodique. Nous appelons réseau de capteur périodique, un réseau de capteur adoptant le modèle d'échantillonnage périodique pour la collecte de données.

Les réseaux de capteurs périodiques, tout comme les réseaux de capteurs traditionnels présentent de nombreuses contraintes, telles que la bande passante, la puissance de calcul, la mémoire disponible ainsi que la consommation d'énergie. Cependant, un défi majeur dans les réseaux périodiques est la gestion de données. En effet, comme chaque noeud est une source de données, et comme il peut être équipé d'un ou de plusieurs capteurs, de nombreurses données seront recueillies. Cependant, l'analyse des flux de données pour obtenir des informations et prendre des décisions appropriées, est l'un des challenges de conception pour les réseaux de capteurs périodiques. La gestion des données n'est pas une tâche facile, en particulier pour les réseaux de capteurs d'énergie limitée et ce qui constiue l'objectif principal de cette thèse.

Dans cette thèse, notre travail principal consiste à réduire la grande masse de données générée par les réseaux de capteurs périodiques tout en conservant son intégrité. Nous avons proposé des modèles de gestion de données volumineuses de la collecte de données à la prise de décision. En effet, nous avons conçu un modèle permettant à chaque noeud d'adapter son taux d'échantillonnage à l'évolution dynamique de l'environnement. Par ce modèle on réduit le sur-échantillonnage et par conséquent on réduit la quantité d'énergie consommée. Une deuxième technique permettant la réduction de taille de données est l'agrégation. En effet, les données produites par les capteurs voisins sont très corrélées spatialement et temporellement. Ceci peut engendrer la réception par l'utilisateur final d'informations redondantes. Réduire la quantité de données redondantes transmises par les noeuds permet de réduire la consommation d'énergie dans le système et prépare les données pour la prise de décision. Ensuite, un modèle de fouille de données est proposé et adapté à notre cas.

Ces travaux sont présentés dans cette thèse en 6 chapitres.

Dans le chapitre II, nous commençons par une présentation générale des réseaux de capteurs périodiques tout en mettant en valeur leurs applications et leur caractérisques. Ensuite, les differents défits de ces réseaux en plus des défis imposés par la gestion des données volumineuse générées par les reseaux de capteurs périodiques sont présentés tels que la collecte, la latence and l'integrité des données.

Un premier objectif a consisté à réduire cette masse de données tout en conservant son intégrité. Pour cela, le problème de la collecte de données dans les réseaux de capteurs périodiques est abordé dans le chapitre III. Nous avons conçu un modèle permettant à chaque nœud d'adapter son taux d'échantillonnage à l'évolution dynamique de l'environnement. Par ce modèle on réduit le sur-échantillonnage et par conséquent on réduit la quantité d'énergie consommée. L'approche est basée sur l'étude de la dépendance de la variance de mesures captées pendant une mëme période voir pendant plusieurs périodes différentes. Ensuite, pour sauvegarder plus de l'énergie, un modèle d'adpatation de vitesse de collecte de données est étudié. Ce modèle est basé sur les courbes de besier en tenant compte des exigences des applications. Pour évaluer ses algorithmes, l'auteur utilise OMNeT++ un simulateur à événements discrets. Les données utilisées dans les simulations sont des données réelles récoltées au laboratoire Intel. Les paramètres pris en compte dans l'analyse sont la variation de la vitesse instantannée de l'échantillonnage ainsi que la consommation d'énergie. Les résultats de simulation montrent l'efficacité de l'approche proposée.

Dans les chapitres 4 et 5, nous étudions une technique pour la réduction de la taille de données massive à travers l'agrégation de données. En effet, les données produites par les capteurs voisins sont très corrélées. Ceci peut engendrer la réception par l'utilisateur final d'informations redondantes. Réduire la quantité de données redondantes transmises par les nœuds permet de réduire la consommation d'énergie et économiser de la mémoire.

Dans le chapitre 4, après une étude bibliographique de l'existant, une étude heuristique de deux étapes est présentée pour l'agrégation de données périodiques. A la première étape, chaque nœud fusionne ses mesures redondantes d'une façon périodique tout en conservant l'intégrité de ces mesures à travers d'un poid calculé pour chacune des mesures collectées. A la deuxième étape, l'agrégateur recevant les mesures provenant de plusieurs nœuds les agrèges d'une façon à éliminer de plus de redondances et à les préparer pour l'application de la fouille de donnée. Cette méthode est validée via une série de simulations pour montrer la réduction de la taille de données redondantes.

Le but du chapitre 5 est d'identifier tous les nœuds voisins qui génèrent des séries de données similaires. Deux couches d'agrégation sont proposées. La première au niveau des nœuds eux-mêmes et la deuxième au niveau des agrégateurs. L'auteur adopte une approche hiérarchique. Elle utilise les fonctions de similarité entre les ensembles de données ainsi qu'elle propose un modèle de filtrage par fréquence pour répondre à cette problématique. Plusieurs optimisations sont proposées pour réduire la complexité des algorithmes ainsi que le temps de calcul de similarité entre les séries de mesures. Comme pour les approches introduites dans les chapitres précédents, l'avantage des algorithmes sont illustrés par simulation via des mesures réelles. La réduction de données redondantes, l'optimisation de la consommation d'énergie et le temps de calcul montrent que l'auteur obtient de bons résultats.

Le chapitre 6 s'intéresse à la fouille de données dans les réseaux de capteurs périodiques. La fouille de données est appliquée après la technique d'aggrégation presentée qu'on considere une phase de pré-traitement et de préparation pour le data mining. Nous nous basons sur un algorithme de classification non supervisé, le K-means qu'on adapte pour fouiller les données aggregées tout en tenant compte des contraintes des reseaux de capteurs et de la puissance de calcul dont le data mining algorithme en a besoin. Pour celà, nous developpons une nouvelle technique hiérarchique qui applique le K-means sur les préfixes des données aggrégées. Cette technique est efficace et fiable en terme d'optimisation du k-means puisqu'elle reduit

le nombre d'iterations dont k-means a besoin ainsi optimise la puissance de calcul et d'energie dans les réseaux de capteurs sans fils. Cette approche est nommée le « Préfix-K-means », et validée par plusieurs tests de simulation montrant son efficacité.

Le chapitre 7 récapitule le travail effectué dans le cadre de cette thèse, et ouvre quelques nouvelles perspectives.

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Chapter I Introduction

The need to monitor wide range of application areas has risen significantly during the past years. To answer such demand, wireless sensor networks have been deployed sporadically all over fields of application. Such deployment has failed to account the erroneous and limited nature of these networks in terms of power and infrastructure. Lured with such deficiency, researchers from all over the world have gained exponential interest in improving wireless sensors network lifetime. The mission of WSN became vast and wide spanning into various industrial, environmental and power arenas. A typical topography of a sensor network is distributed redundantly in thousands over a deployment site. Such redundant volume is required to ensure the cooperative sensors readings reliability. Each sensor node has a separate sensing, processing, storage, and communication unit. The sensing unit is primarily concerned with collecting data from its work environment and the microprocessor processing unit handles the tasks. Memory is used to store temporary data or data generated during processing whereas the communication unit mainly interacts with the environment.

Physical resources constraints have to be taken into considerations in a wireless sensor network: due to the limited bandwidth of wireless links connecting sensor nodes, communication should be carefully tackled in order to avoid variable latency and dropped packets. Sensor nodes are powered by a battery which supplies energy; however its lifespan is tightly limited which makes energy optimization a major consideration that affects the lifetime of a wireless sensor network. Finally, sensors computation power and memory size are other issues that could hinder any data processing algorithm.

The major challenge that faces wireless sensor network implementation is improving the lifetime of the network; in other words managing efficiently the battery

and power consumption. Extensive researches have focused on such task as it is difficult and cost ineffective to recharge the battery [1][2]. Energy is mainly consumed during data transmission from the source node to the sink (gateway). Then, sensor node is not expected to carry huge amount of data or complex computations. As a result, packet transmission is one of the core issues to address in order to reduce energy consumption by mainly reducing the size of the packets transmitted.

Data collection from sensor networks can be on demand or by streaming. The first is done by bi-directional dialogs between the sensor nodes and the base station. A request for data is sent via the sink to the sensor nodes which, in return, sends back the data to the requester via multi hop communications. On the other hand, by using streaming, data flows primarily from the sensor node to the sink. We distinguish the periodic sampling and the event driven data models. In periodic sampling, data is reported from the sensors on periodic basis while in event driven model, an event triggers the generation of data. Intrusion detection, battlefield gas detection are good example of applications answered by the event driven sensor networks whereas the periodic model is the best for applications that needs continuous monitoring like environmental or health monitoring.

This thesis focuses on ”periodic sampling” data model in sensor networks, where the collection of sensor data from a number of remote sensor nodes is done on a periodic basis. This data model is appropriate for applications where certain conditions or processes need to be monitored constantly, such as the temperature in a conditioned space or pressure in a pipeline. This type of network is called periodic wireless sensor network.

I. MAIN CONTRIBUTION

Our work focuses on overcoming the challenges imposed by periodic WSN through data management while preserving the quality of the data. In fact, battery power is a main limitation imposed by a wireless sensor network. As a result, saving resource expensive transmission becomes a must. It is commonly understood that newest current applications require data processing with temporal constraints in their tasks. Moreover, periodic applications require querying processed data and real-time storage adding new challenge to WSN. Data Management on the node level will ensure the usefulness of every reading, thus reducing packet transmission size which consequently optimizes the energy consumption. In such periodic networks, data collection, data aggregation and data mining constitute the main components of data management. The listed phases in periodic sensor data management are the pillars of interest in this thesis which analyzes the existing and suggests efficient and improved algorithms.

A. Data Collection

Data collection from remote terrain and transmission of the information to the sink is a fundamental task in periodic sensor networks. The “periodic sampling” data model is characterized by the acquisition of sensor data from a number of remote sensor nodes which are forwarded to the sink on a periodic basis. The sampling period depends mainly on how fast the condition or process varies and what intrinsic characteristics need to be captured. There are couple of important design considerations associated with the periodic sampling data model.

The network is powered by a short lived battery which makes energy consumption and efficiency a major challenge to look out for. Therefore, in order to keep the networks operating for long time, adaptive sampling approach to periodic data

collection constitutes a fundamental mechanism for energy optimization. The key idea behind this approach is to allow each sensor node to adapt its sampling rates to the physical changing dynamics. In this way, over-sampling can be minimized and power efficiency of the overall network system can be further improved. This thesis proposes an efficient adaptive sampling approach based on the dependence of conditional variance on measurements that varies over time. Then, it proposes a multiple levels activity model that uses behavior functions modeled by modified Bezier curves to define application classes and allow for sampling adaptive rate.

B. Data Aggregation

While developing a new technique that addresses the data collection, huge data volumes generated periodically constitutes an intrinsic consideration in periodic sampling data model. The most critical design issue at this stage is the phase relation among multiple sensor nodes. Redundant data exists at this phase leading to huge packet size which overheads the network and depletes the energy thus reducing the life cycle of the network. Hence, in periodic sensor networks two neighboring nodes operate with identical or similar sampling rates so redundant packets from the two nodes are likely to happen repeatedly. It is essential for sensor networks to be able to detect and clean redundantly transferred data from the nodes to the sink.

This thesis introduces a periodic hierarchical data aggregation model to achieve this goal. Two layer algorithms are introduced: at the node level and at the aggregator level. These algorithms aim to optimize the volume of data transmitted thus saving energy consumption and reducing bandwidth on the network level.

At the first level, a simple process aggregate data on a periodic basis avoiding each sensor node to send its raw data as is to the base station.

At the second level, “data aggregator“ sensor node collects the information from its associated nodes where a new part of the filtering aggregation problem is explored. The algorithm at this level identifies the similarity between data sets generated by neighboring nodes and sent to the same aggregator. The objective is to detect similarities between near sensor nodes, and integrate their captured data into one record while preserving information integrity. In this context two techniques are studied: the first technique suggests an algorithm to be applied on the level of the aggregator node itself taking into consideration the number of occurrence of each measure; the second one suggests a new prefix filtering method to study the sets similarity in sensor networks. Many optimization techniques are also proposed to rightfully exploit the ordering of measurements according to their frequencies and for early termination of sets similarity computing.

C. Data Mining in sensor networks

With the challenging data management phases in periodic sensor networks, the large set of collected and aggregated data constitute ideal candidates for data mining techniques. Numerous data mining applications deal with high-dimensional data, however they impose a high computational cost which is not supported by sensor network. Limitation in terms of available energy for transmission, computational power, memory, and communications bandwidth are the main challenges of the sensor network for data mining applications. The presented data aggregation phase will constitute the preprocessing step to get the perfect data set to be mined in an acceptable timeframe.

Data mining is a perfect tool to analyze data, categorize it and summarize the relationships identified. Our approach will adopt this tool on the level of the aggregator allowing it to send only useful information to the base station. The weight collected from

the first step will constitute the optimization key of a data mining algorithm (FP_Tree). Our approach avoids the scanning procedure by working on a different structure resulting from the output of the data cleaning algorithm applied on the level of the aggregator. Another data mining algorithm has been also customized to respect the constraint imposed by wireless Sensor Networks: K-Means. Our objective is to use the prefix filtering to optimize the data mining algorithms in sensor networks. We applied K-means on the prefix cleaned sets results of our data aggregation algorithm.

II. THESIS STRUCTURE

The rest of this thesis is structured as follows:

The second chapter introduces the periodic sensor network and its main objectives and discuss the technological and data management challenges existing in periodic sensor networks. A number of periodic sensor networks applications are also reviewed via some existing examples.

Chapter III focuses on the adaptive data collection in periodic sensor networks to allow each sensor node to adapt its sampling rates to the physical changing dynamics. An efficient adaptive sampling approach based on the dependency of conditional variance on measurements that varies over time is proposed. Then, a multiple levels activity model that uses behavior functions modeled by modified Bezier curves to define application classes and allow for sampling adaptive rate is suggested.

Chapter IV introduces as a first step the aggregation technique applied on a periodic basis at the first level which is the source node level. At the source node level, we look at specified intervals at each data measured and periodically clean the data taking into consideration the number of occurrences of the measures. A second level of data aggregation is performed between groups of nodes called aggregator. This algorithm will

not tolerate the effect of the information that each data measurement provides by preserving the weight of each measure. The result set will constitute a perfect drill to mine without high CPU activities allowing us to send only the information to the sink.

In chapter V, we shift gears to reducing measures redundancy by identifying near duplicate nodes that generate similar data sets. A tree based bi-level periodic data aggregation approach implemented on the source node and on the aggregator levels has been considered. The problem of finding all pairs of nodes generating similar data sets such that, similarity between each pair of sets is above a threshold t, have been explored. We propose a new frequency filtering approach and several optimizations using sets similarity functions to solve this problem. The obtained results show that our approach offers significant data reduction by eliminating in network redundancy and outperforming existing filtering techniques.

In chapter VI, this thesis tackles the problem of adapting distributed "k-means" clustering, a data mining algorithm, on the prefixes sets in order to cluster observations into groups of related data without any prior knowledge of the relationships between the prefixes sets. The main interest in this chapter was to design an efficient prefix mining algorithm in sensor network, both from a statistical and computational point of view. This chapter addressed the energy problem in sensor network and the problem of mining prefix item sets instead of mining the whole set of data. Simulation results have been compared with other model and techniques.

The Last Chapter concludes this work with some aspects of suggested future research work.

Chapter II Periodic Wireless Sensor Networks

Recent technological developments in the miniaturization of electronics and wireless communication technology have led to the emergence of Wireless Sensor Networks which will greatly enhance environment monitoring and lure techniques for periodic taking measurements of some historically unstudied phenomenon. This is particularly important in remote or menacing environments where many essential processes have rarely been studied due to their inaccessibly. In this chapter, we attempt to introduce a periodic sensor network and its main objectives. We review a number of periodic sensor networks applications via some existing examples. Then we discuss the technological and data management challenges in periodic sensor networks.

I. WHAT IS A PERIODIC SENSOR NETWORK (PSN)?

Wireless sensor networks (WSN) are composed of a large number of low cost sensor nodes deployed over a geographical area for a specific monitoring [31]. Typically, a sensor node is a tiny device that includes three basic components: a sensing subsystem for data acquisition from the physical surrounding environment, a processing subsystem for local data processing and storage, and a wireless communication subsystem for data transmission. In addition, a power source supplies the energy needed by the device to perform the programmed task [32]. Wireless sensor networks have a multitude of applications, ranging from environmental to military domains. These applications include contamination tracking, habitat monitoring, health monitoring, traffic monitoring, building surveillance and monitoring, industrial and manufacturing automation, distributed robotics and enemy tracking in the battlefield [31].

The main common task of a sensor node is monitoring some phenomena and relaying data toward a base station called “Sink”. Two categories of data collection in

sensor networks can be distinguished; on demand or by data streaming. The first category is done by bi-directional dialogs between the sensor nodes and the base station. A request for data is sent from the end user via the sink to the sensor nodes which, in return, send back the data to the user via multi hop communications. On the other side, in data streaming, data flows primarily from the sensor node to the sink. In this category we distinguish event-based reporting of outliers and periodic data collection [33]. In event-based data collection, the sensors are responsible for detecting and reporting events like "A Line in the Sand" intrusion detection system [34]. In periodic data collection the acquisition of sensor data from a number of remote sensor nodes are forwarded to the sink on a periodic basis.

Figure II.1. Possible deployment of periodic wireless sensor networks for precision agriculture.

We define a Periodic Sensor Network (PSN) as a Wireless Sensor Network deployed on the purpose of periodic monitoring where periodic updates are sent to the

sink from the PSN, based on the most recent information sensed from the physical parameter. PSNs are typically arrays of sensor nodes interconnected using a radio communication network which allow their data to reach the sink. They are used for applications where certain conditions or processes need to be monitored constantly, such as the temperature in a conditioned space or pressure in a process pipeline. An example of periodic sensor network is shown in Figure II.1. It depicts a precision agriculture deployment. Hundreds of nodes scattered throughout a field detect temperature, light levels and soil moisture at hundreds of points. Every five minutes, each node takes one data measurement and each one hour communicates its data over a multi-hop communication to the end user for analysis.

II. PERIODIC SENSOR NETWORKS APPLICATIONS

Periodic sensor networks are used in several applications and for many purposes [118]. The simplest of these are weather stations, and more complex examples include seismic monitoring. We can find microclimate monitoring, water quality monitoring, cattle monitoring, and other monitoring applications. In the reminder of this section, we give an overview of existing periodic sensor networks applications.

The Georgia Automated Environmental Monitoring Network is a periodic weather sensor network. The data are collected every 1 second and summarized at 15 minutes intervals and at midnight a daily summary is calculated. The data are processed immediately and disseminated via the Internet [35] and analyzed within a cyber-infrastructure system [36]. Another example is the Snow-pack Telemetry (SNOTEL) project which uses meteor burst communications technology to collect and communicate data in real-time [37]. These SNOTEL are generally located in remote high-mountain watersheds where access is often difficult or restricted. They are designed to operate

unattended and without maintenance for a year and are battery powered with solar cell recharge. The main objective in [46] is to provide reliable, long-term monitoring of rainforest ecosystems. The target was a rainforest area in South-East Queensland (Springbrook, Australia) which had a high priority for monitoring the restoration of biodiversity. The first phase of the project was to develop a better understanding of the challenges in deploying long-term, low-power PSNs in rainforest environments.

The Tropical Atmosphere Ocean Project (TAO) which collects real-time data from 70 moored ocean buoys in the Pacific Ocean to study El Niño processes [38]. The system begun during the 1970s, and today the data is transmitted by satellite to the Internet. However, existing infrastructure can be adapted to support local periodic sensor networks. The CORIE project [39] integrates a real-time periodic sensor network, a data management system and advanced numerical models to understand on the spatial and temporal variability of the Lower Columbia River, USA. This project combines environmental observation with forecasting. On a larger scale from this is the US Geological Survey (USGS) NWIS web water data which has 1.5 million stations across the USA providing real-time and sampled data on line [40]. The purpose of the project in [45] was to monitor the salinity, water table level, and water extraction rate at a number of bores within the Burdekin irrigated sugar cane growing district. This is a coastal region and over extraction of water leads to saltwater intrusion into the aquifer. The area we monitored was approximately 2 - 3 km^2. The PSN had to operate unattended; it was very sparse with very long wireless transmission ranges (with average link length over 800 m). One simplification was that many nodes could be mains powered (since they were co-located with pumps). Another PSN was deployed to measure vertical temperature profile at multiple points on a large water storage that provides most of the drinking water for the city of Brisbane, Australia. The data, from a string of temperature transducers at depths

from 1 to 6 m at 1-m intervals, provide information about water mixing within the lake which can be used to predict the development of algal blooms [50].

The Volcano Tungurahua project [41] used a wireless periodic sensor networks to monitor volcanic activity by specially-constructed microphones to monitor infrasonic (low-frequency acoustic) signals emanating from the volcanic vent during eruptions. The network gathered over 54 h of continuous infrasound data, transmitting signals over a 9 km wireless link back to a base station at the volcano observatory. The GlacsWeb project [42] which uses a wireless sensor network to understand sub-glacial processes using sensor nodes embedded in the glacier and sub-glacial sediment. From August 2004 to August 2005 it collected the equivalent of 859 days of probe data (36,078 sensor readings) on sub glacial water pressure, case stress, temperature, tilt angle and resistivity. From this they were able to reconstruct how sub glacial processes operated over the year in order to understand the relationship between glacier dynamics and climate change. Other periodic sensor networks projects have been developed by the Centre for Embedded Network Sensing at University of California, Los Angeles (UCLA) which has over eight projects (like the Great Duck Island project) in different environments [43]. In these projects, sensor nodes are responsible of measuring generic parameters such as incoming solar radiation, air temperature and humidity, soil temperature and soil moisture. They are mostly installed within a small area (up to 2 km^2), and report back to a central base station either directly or via a relay. The authors in [44] describes how data are collected by one node and shared with others, these nodes can react and change their behavior on the basis of this shared data. They define this behavior as a sensor web.

III. CHALLENGES FOR PERIODIC SENSOR NETWORKS

Extracting periodic data gathered by sensor nodes deployed in different (maybe inaccessible) locations involves some unique challenges. These issues can be common to the traditional wireless sensor networks.

Power consumption: The only power source of a sensor node often consists of a battery with a limited energy budget. In addition, it could be impossible or inconvenient to recharge the battery, because nodes may be deployed in a hostile or unpractical environment. On the other hand, the PSN should have a lifetime long enough to fulfill the application requirements.

Communication: The bandwidth of wireless links connecting sensor nodes is usually limited, and the wireless networks connecting sensors provide only limited quality of service such as variable latency and dropped packets. On the other side, radio communications success is unpredictable in wet and windy locations. For example, radio losses are not negligible in glacier ice and other environments, e.g. leaf cover changes in forest habitats. The ability to alter transceiver power and the use of lower frequency or acoustic fallback systems is commonly used.

Computation: Sensor nodes have limited computation power and memory sizes that restrict the types of data processing algorithms that can be deployed and intermediate results that can be stored on the sensor nodes.

Scalability: Periodic sensor networks deployed large number of sensor nodes in order to monitor some phenomenon. Any node wishing to communicate with other nodes generates more packets than its own data packets. These extra packets are generally called control packets or network overhead. Moreover, the larger the network the more potential there is for interruption in communication links, resulting in the creation of more control packets. In summary, more overhead is unavoidable in a larger scale

periodic sensor network if the communication paths are to be kept intact. Since the available overall bandwidth is limited, an increase of overhead results in the decrease of usable bandwidth for data transmission. As the network continues to grow, only a very small amount of bandwidth will be left for application data transmission.

Remote management: Sensor nodes in isolated locations cannot be visited regularly so remote access is essential. Bugs need fixes, subsystems might need shutting down and schedules changed. For example, the Duck Island project found that their sensors could short circuit their power when wet. Custom communications make remote access more complex because normal logins and routing are not available. More software development and failure scenario testing is required in order to achieve good remote management.

Security: Although security is a necessity in other types of networks, it is much more so in sensor networks due to the resource-constraint, susceptibility to physical capture, and wireless nature. Security issues are important at all levels of periodic and event driven sensor networks from physical to data interference. PSN can cope with the loss of one or more nodes due to failure or damage. Data may need to be protected against deliberate and accidental alteration. However security should not be used to hamper public access to information. A balance between security and information needs to be reached so that all parties can trust the deployed PSN; this will dramatically affect their development and implementation.

Data management: The main difference between the traditional event driven sensor networks and PSN is the huge amount of data collected from the field of monitoring. In the event driven model, the kind of data collection is less demanding in terms of the amount of wireless communication, since local filtering is performed at the sensor nodes, and only events are propagated to the base station. In the next section, we

introduce data management in periodic sensor networks and its challenges from the collection to the decision making.

IV. DATA MANAGEMENT CHALLENGES IN PSN

Massive and heterogeneous data collected from periodic sensor networks brings the data management challenges. The traditional approach of migrating raw data to centralized points for data storage and analysis may incur debilitating communication and high energy costs. In this section, we will discuss different challenges in the data management field for periodic sensor networks.

Data collection: Periodic data collection in periodic sensor networks enables complex analysis of data, which may not be possible with query processing because of the great amount of the collected data. Researchers' strategies are directed to minimize the amount of data retrieved (communicated) by the network without considerable loss in fidelity (accuracy). The main objective of this reduction is first to increase the network lifetime and then to help in analyzing data and making decision. Using compression schemes is one way to reduce the amount of data that needs to be transferred to the base station. Another method is to scale periodic wireless sensor networks to the size of the system/region under study and sample data at frequencies equivalent to physical phenomenon changes. Periodic sensor networks with these properties can provide the appropriate fine-grain information needed for accurate modelling and prediction.

Data delivery latency: Real-time delivery is very important in most applications of periodic sensor networks. Therefore, reducing latency is very important. The periodic data collected from the sensor nodes are expected to be delivered to the end user with a minimum latency. For example, snow monitoring data must be delivered in the order of hours to days, but not weeks. The major challenge for periodic sensor networks lies in the

fact that this latency guarantee need to be met in the presence of hard power constraints and limitations of radio connectivity. The data needs to be delivered via a multi-hop communication using radio transceiver with limited communication range (about 30 meters). This problem warrants an ultra-low-power solution that not only meets the data-delivery latency requirements, but also maximizes the network lifetime simultaneously.

Data integrity and quality: To ensure a good understanding of the monitored phenomenon, it is imperative to assess the quality of the data gathered by periodic sensor networks before presenting them to the users. The first challenge is about ensuring temporal integrity. PSN applications require periodic measurements to be time-stamped to an accuracy of seconds to milliseconds. Thus, assigning accurate timestamps to the collected measurements is a non-negligible issue in PSN. Apart from ensuring temporal integrity, the data gathered by such network contains a lot of missing values and are inherently noisy. Sensor calibration is vital for high quality data collection. Furthermore, it is crucial to apply methods that are robust and can deal with data of such nature. Finally, defining the exact source of sensor data is important when they are analyzed. This data source will need to be preserved without placing too much burden on the users.

Big data volumes management: Periodic sensor networks produce immense amount of data continuously. For example, a 50 node deployment that collects data every minute from 10 different sensing fields will produce over 26 million records over a year period. Knowing that sensor nodes have limited memory and computational resources and cannot save all the collected data. Important for data processing in PSN will be intelligent data reduction at individual sensor nodes through the computation of measures aggregates. In addition to these local computations, we need to be able to process and combine received data from several sensor nodes. This can be done by an effective data aggregation technique. Another major challenge with sensor data is converting raw

sensor values into final usable data and ready to make decisions. This will require concerted efforts to make simple and efficient data mining on periodic collected data with different levels of detail and low latency.

Distributed data management: Sensor nodes collect the data about the environment from different locations and different sources in order to send it to the end user for a variety of analysis. Unfortunately, post analysis of the data extracted from the periodic sensor networks incurs high sensor communication cost for sending the raw data to the base station and at the same time runs the risk of delayed analysis. To overcome this, distributed data management algorithms have been proposed to deal with the data on site. These algorithms utilize the computing power at each node to do some local computations and then exchange messages with its neighbors leading to a consensus regarding a global model. These algorithms reduce the communication cost vastly and extend the whole network lifetime.

V. CONCLUSION

In this chapter, we introduced the periodic sensor network which is the core interest of this thesis. Several applications are in need of periodic sensor network in order to answer crucial objectives like monitoring, preventing or forecasting. As presented, sensor network architectures include some design aspects imposing big challenges when working with them. Energy efficiency is the primary challenge to increase the network lifetime. Therefore, data management techniques are an essential building blocks aiming to reduce energy consumption by reducing the number of transmissions required. This chapter highlights the main challenges of data management in periodic sensor networks that need to be accounted for. The upcoming chapters will tackle in details the data

management in periodic sensor networks by introducing new overcoming suitable approaches.

Chapter III Adaptive Data Collection in periodic sensor networks

Data collection from unreachable terrain and then transmit the information to the sink is a fundamental task in periodic sensor networks. However, in order to keep these networks operating for long time, adaptive sampling approach to periodic data collection constitutes a fundamental mechanism for energy optimization. The key idea behind this approach is to allow each sensor node to adapt its sampling rates to the physical changing dynamics. In this way, over-sampling can be minimized and power efficiency of the overall network system can be further improved. In this chapter, we present an efficient adaptive sampling approach based on the dependence of conditional variance on measurements that varies over time. Then, we propose a multiple levels activity model that uses behavior functions modeled by modified Bezier curves to define application classes and allow for sampling adaptive rate. The proposed method was successfully tested in a real sensor data set.

I. INTRODUCTION

Due to the large amounts of data generated by wireless sensor networks(WSN), collection of sensing data to be forwarded from the sensor nodes to a central base station constitute a major process for WSN. This process is known as Data Collection. Unfortunately, the transmission of large quantities of data is a threat on the lifetime of the sensor network due to the limited energy resources of the sensor nodes. On the other hand most of the applications require all the data generated and doesn't tolerate any loss of detail as to reach the accuracy required. For instance, we can list the structural health monitoring application [3] that requires more than 500 samples per second to efficiently

detect damage. All of this makes the data collection in WSN an interested area of research where transmission of data should be studied carefully.

The "periodic sampling" data collection model is characterized by the acquisition of sensor data from a number of remote sensor nodes then pushing them to the sink on a periodic basis. These periodic models are used for applications where certain conditions or processes need to be monitored constantly, such as the temperature or pressure, etc. As seen in the previous chapter, some examples of these applications include the observation of nesting patterns of storm petrels at Great Duck Island [4], measuring light intensities at various heights in a redwood tree [5] and logging temperature and humidity in the canopy of potato plants for precision agriculture [6]. The sampling period in periodic data collection model depends mainly on how fast the condition or process varies and what intrinsic characteristics need to be captured. As seen in chapter II, there is couple of important design considerations associated with the periodic sampling data model. One of them is the over-sampling. For instance, the dynamics of the monitored condition or process can slow down or speed up; if the sensor node can adapt its sampling rates to the changing dynamics of the condition or process, over-sampling can be minimized and power efficiency of the overall network system can be further improved.

II. RELATED WORK

Predicting the values measured either in source node or sink in a periodic wireless sensor networks is one of the data reduction methods to reduce the amount of data sent by each node. Many researches fall in this area aiming to reduce the communication overhead by selecting a subset of the data produced and reconstructing all the original data with some level of accuracy. Some work [10][21] that guarantees that the data

maintained at the central server is within a certain interval of the actual sensor readings and node, reports their readings to the server in case the value is outside this interval. [29] proposed an energy efficient clustering and prediction protocol which uses mobile sink to route the path efficiently. On the other hand, we should highlight that time and space are two main factors based on which prediction and adaptive sampling can be performed since data is correlated in both time and space.

Hence, adaptive sampling helps to reduce the number of samples by exploiting either spatial, temporal or spatio-temporal correlations between sensed data. [11], [12] rely on the time factor to perform data reduction while [13], [14] count on the space domain. Some few approach count on the temporal and spatial domain [20], [16]. The below elaborates the different prediction model approaches existing for data collection in periodic wireless sensor networks.

A. Time Series Approach

As a record of the target trajectory, a time series of historical target positions is transferred among the sensor nodes with sensing tasks. When the current target position is obtained, the historical target is also available in the active sensor nodes so that target forecasting can be performed.

Reporting approximations of sensor readings at regular time intervals is required in many applications of wireless sensor networks. Hence, Time series prediction techniques have been adopted as an effective technique to reduce the communication effort while preserving the accuracy of the collected data. The target is often predicted by a number of sensor nodes and a Fisher information matrix (FIM) is used to evaluates the target localization error [17]. Measurements of the target are produced by using time series of historical target positions transferred among the sensor nodes with sensing tasks. Time series analysis in WSN implements the target position forecasting through the known target trajectory. [49] processes the time series by empirical mode decomposition introduced in [18] described by ARMA models adaptively. Then, the forecasted results of

each component are combined to forecast the target position. The operation energy consumption of sensor node is optimized using a probability awakening approach noting that an anti-colony optimization (ACO) [19] is introduced to optimize the routing scheme for the next sensing period.

On the other hand, Goel and Imilienski [16] visualize the sensor readings as an optical image which let them adapt the MPEG standard for video compression and generate a prediction model so the readings is sent to the sink only if it differs significantly from the predicted model. The prediction model in this case is only valid for a specific period of time. Deshpande et al. [15] propose a similar model driven approach where the temporal prediction model is learnt from historical data then use to predict the new sensor readings in the current time period. Guestrin et al. [13] use a kernel linear regression to build a model of the data by letting the nodes transmit only the changes on the level of the model coefficients instead of the raw data. In [14], the subsets are used in a round robin fashion by relying on a single subset identified from several nodes subsets to predict the readings of the remaining subsets. In this approach, only one subset is solicited at a time which leads to energy savings.

A temporal correlation of data is used also in [22], where the authors propose an adaptive sampling scheme suitable to snow monitoring for avalanche forecast. Some approaches are based on the prior identification of some parameters like Dual kalman filter that perform linear prediction by sending updates to a central server only when the prediction error exceeds some given threshold. Many kalman filters as the number to remote sources run in parallel at the central server in order to reconstruct the phenomenon observed on the source node and reconstruct the model based on the data received or the computed predictions. A drawback of this approach is its dependency on the model of the observed phenomenon that should be provided by both server and node to the filter. [23] Overcomes this limitation by proposing least mean square (LMS) an adaptive algorithm

that doesn't require nodes to be assisted by a central entity to perform prediction, since no global model parameters need to be defined. However this algorithm consider a loss-free communication links between sink and source and rely only on single sensor reading in the time domain.

All the described approaches required a central entity that collects the sensor readings from neighboring nodes for the extraction of the prediction model. Therefore the sensor nodes are dependent on this central entity to ensure the data reduction which means that all these approach are centralized. To note also that this model may suffer from inaccuracy since it might become outdated.

B. Spatial Approach

Other existing methods are limited to only space correlation and based on grouping nodes into clusters. Spatial data correlation is used in [24], where a back casting scheme is proposed. Mainly, nodes deployed with sufficient density do not have to sample the sensed field in a uniform way. In fact, more nodes have to be active in the regions where the variation of the sensed data quantity is high. In this work a cluster based method is used to group sensors in clusters, each managed by a cluster-head. The authors in [25] define a spatial Correlation based Collaborative MAC protocol (CC-MAC) that regulates sensor node transmissions so as to minimize the number of reporting nodes while achieving the desired level of distortion. In [26] a TA-PDC-MAC protocol is proposed, a traffic adaptive periodic data collection MAC which is designed in a TDMA fashion. This work is designed in the ways that it assigns the time slots for nodes activity due to their sampling rates in a collision avoidance manner. Adaptive Sampling Approach to Data Collection (ASAP) is proposed in [27]. This technique splits the network into clusters. A cluster formation phase is performed to select cluster heads and select which nodes belong to a given cluster. The metrics used to group nodes within the

same cluster include the similarity of sensor readings and the hop count. Then, not all nodes in a cluster are required to sample the environment. Adaptive sampling techniques are very promising, because of their efficiency to optimize energy consumption and the network overload. However, most of the previous proposed solutions are implemented in a centralized manner that requires rather huge computations and communications.

C. Spatio-Temporal Approach

Some works [28], [16], [30] exploit the spatio-temporal correlation among data and predict the measurements from the subset of sensor reading identified for this purpose. The predicted data solve the issue of delivering the whole data to the sink, thus reducing communication.

In this thesis that specifically addresses periodic sensor networks; we propose a non-complex distributed adaptive sampling algorithm that is based on the sensed data variation. Moreover, we take into account the application criticality and propose a model that dynamically defines multiple levels of sampling rate corresponding to how many samples are captured per unit of time. The final goal is to provide the necessary algorithmic support for environmental surveillance applications to express their objectives.

The rest of this chapter is organized as follows. In section II we present our model of adaptive sampling rate based on the variance study. In section III we describe how to integrate the application criticality level in order to adapt the sampling rate. Section IV presents our experimental results based on real data readings. We show that our model performs well and allows to dynamically adapt its sample rate in order to save its energy consumption. Finally we conclude with some few remarks.

III. ADAPTING SAMPLING RATE

A. Variance study

In this section we perform a statistical model allowing to compare means of measures taken by a node in different periods. Based on this comparison a node will adapt its sampling rate. With a period p a sensor node takes several measures of temperature or humidity for example. To illustrate, we consider a sensor node n after J periods. The objective is to compute the variation between periods after every new period to adapt the sampling rate in function of the new variance. The variance between periods may be thought of as a signal of measures differences. Therefore, we use the one way ANOVA model to test whether or not the means of several periods are all equal and if the variance differs from one period to another. We suppose that measures inside each period J are independent, with mean $\overline{y_j}$ and the variances of periods are equal $\sigma_j^2 = \sigma$.

Then the measure's variable can be written as follows:

$$y_{ij} = \overrightarrow{Y_j} + \epsilon_{ji}, j = 1, \dots., J;\ i = 1, \dots, n$$

Where ϵ_{ij} are the residual which are independent and are normally distributed following $N(0; \sigma^2)$.

We denote by:

$$\overline{Y_j} = \frac{1}{n_j}\sum_{i=1}^{n_j} y_{ji},\ \sigma_j^2 = \frac{1}{n_j}\sum_{i=1}^{n_j}(y_{ji} - \overline{Y_j})^2, \overline{Y} = \frac{1}{n}\sum_{i=1}^{n_j}\sum_{j=1}^{J} y_{ji}$$

the mean and the variance in each period and the mean of all the J periods respectively.

The total variation (ST) is the within period variation (SR) and the between period variation (SF). The whole idea behind the analysis of variance is to compare the ratio of between period variance to within period variance. If the variance caused by the

interaction between the measures is much larger when compared to the variance that appears within each period, then it is because the means aren't the same. Let us consider:

$$ST = SR + SF$$

$$\sum_{j=1}^{J}\sum_{i=1}^{n_j}(y_{ji} - \overline{Y})^2 = \sum_{j=1}^{J}\sum_{i=1}^{n_j}(y_{ji} - \overline{Y_j})^2 + \sum_{j=1}^{J} n_j(\overline{Y_j} - \overline{Y})^2 \quad (1)$$

B. Mean's period verification

In this section we present how each sensor after each period compares the means and computes the variance to then adapt its rate. After a period j, each sensor node will test the hypothesis that all the previous period means and the new one are the same or not. Therefore we used the Fisher test, let

$$F = \frac{SF/_{J-1}}{SR/_{N-J}} \quad (2)$$

If the hypothesis is correct then, F will have a Fisher distribution, with F(J - 1; N - J) degrees of freedom.

The hypothesis is rejected if the F calculated from the measurements is greater than the critical value of the F distribution for some desired false-rejection probability (risk α). Let $F_t = F_{1-\alpha}(J-1; N-J)$. The decision is based on F and F_t:

- If $F > F_t$ the hypothesis is rejected with false-rejection probability α, and the variance between periods are significant
- If $F \leq F_t$ the hypothesis is accepted.

C. Illustrative example

Consider the measures and periods as shown in the following table:

Periods (j)	1	2	3	4	5	
	1.51 1.92 1.08 2.04 2.14 1.76 1.17	1.69 0.64 0.90 1.41 1.01 0.84 1.28 1.59	1.56 1.22 1.32 1.39 1.33 1.54 1.04 2.25 1.49	1.30 0.75 1.26 0.69 0.62 0.90 1.20 0.32	0.73 0.80 0.90 1.24 0.82 0.72 0.57 1.18 0.54 1.30	
$\overline{Y_j}$	1.66	1.17	1.46	0.88	0.88	$\overline{Y}$ = 1.189
s_j^2	0.175	0.144	0.115	0.123	0.074	
n_j	7	8	9	8	10	N = 42

Table III.1: Measures Example

For $\alpha = 0.01$ we have $F_t = 3.83$, after the fifth period we find $F = 8.066$ and after the fourth period we find $F = 7.43$.

IV. ADAPTATION TO APPLICATION CRITICALITY

In periodic sensor networks and in order to save energy, it is desirable to be able to adjust the sampling rate according to the applications requirements. If we are in the context of critical applications, sensor nodes should speed up its sample rate faster than sensor nodes in non-critical applications. In our approach we express the application criticality by the r^0 variable which can take values between 0 and a defined 1 representing the low and the high criticality level respectively. Low level criticality indicates that the application does not require a high sampling rate while a high level criticality does. Then,

according to the applications requirements, r^0 could be initialized accordingly into all sensors nodes prior to deployment.

To take into account the application criticality, a naïve approach would consist in fixing the measure sampling rate of all sensor nodes to a given rate. As illustrated in Figure III.1, we show how the sensor nodes capture speed can be regulated proportionally to the dynamic risk level r^0. For instance, a high criticality level pushes sensor nodes to capture at near the maximum sampling rate capability. The idea behind this model is, when the observed F become greater than threshold F_t (= $F_{1-\alpha}$) the sampling rate is balanced to the maximum sampling rate or to the minimum sampling rate in the other cases. However, this simple approach presents some drawbacks:

(i) Setting sensor nodes to work at full capacity provides high number of taken measures which need high bandwidth and leads to run out the sensor batteries and thus reducing the network lifetime

(ii) Although setting the nodes at low capacity saves energy and extends the network lifetime, it provides poor data quality where some important measures will be missed.

(iii) Choosing a moderate sampling rate could balance between capture quality and network lifetime but at the same time sensors cannot be fully exploited if it is necessary and the physical changes are very dynamics.

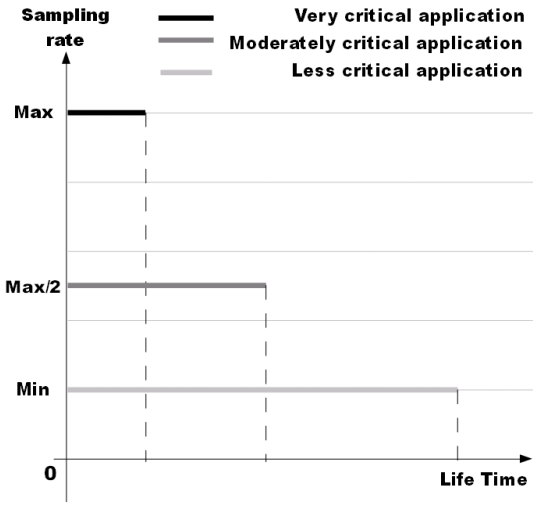


Figure III.1. Naïve approach.

A. Dynamic sampling model

To fully exploit the sensor node capabilities we propose that a node sampling rate depends on the result of the fisher test F as shown in figure III.2. Based on the results and residual of the variance test described above, the idea is that when a node noticed high variance differences, it can increase its sampling rate in order to prevent missing important measures and decrease its sampling rate when the variance are lesser than the threshold. In general, it is desirable to be able to adjust the sampling rate according to the application's requirements. In our approach we express the application criticality by the quantitative variable r^0 which can take values between 0 and 1 representing the low and the high criticality level respectively. Low level criticality indicates that the application does not require a high sampling rate while a high level criticality does. Then, according to the application's requirements, r^0 could be initialized accordingly into all sensors nodes prior to deployment. It is also possible during the network lifetime to dynamically change r^0 , in all sensor nodes or for a given subset only, if some kind of supervision and

control platform is available. In what follows we will define different application classes which will determine a node's sampling rate.

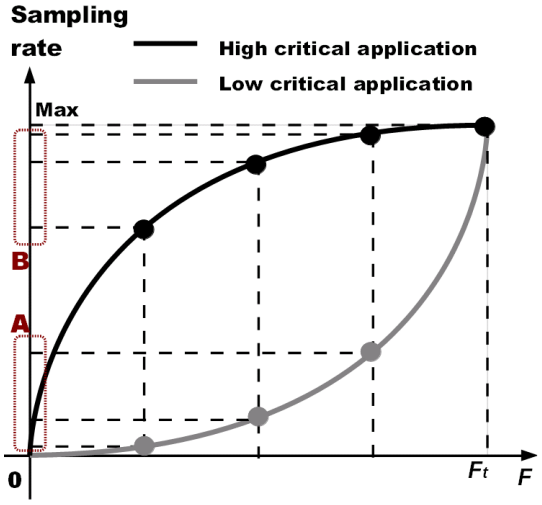


Figure III.2. Dynamic approach.

1) Influence on the F-ratio:

In this section, we discuss why the sampling rate increases when the F-ratio increases. In fact, the greater the difference among the means, the higher is the F and the greater the likelihood of obtaining variance differences. Hence, it is important to note that a large F does not by itself convey why or how the means differ from each other. A high F value can be found when the means for all of the groups differ at least moderately from each other. Alternatively, a high F can be obtained when most of the means are fairly similar but one of the means happen to be far removed from the other means. In this last case, F ratio is influenced by group means, where the variances intra groups are very different. In these two cases, the sensor node must increase its sampling rate to capture all physical changes.

2) Application classes:

We can broadly classify applications into different categories based on their criticality level. In our approach we define two classes of applications: high and low

criticality applications. This criticality level is represented by a mathematical function y = $f(r^0,F)$ that we call BV (BehaVior) function inspired from [48]. This function can oscillate from hyperbolic to parabolic shape as illustrated in Figure III.3:

• Values on the x axis are positive results of Fisher test. These values lie between 1 and Ft. We consider that Ft corresponds to the maximum sampling rate. Thus, if a node finds F greater than Ft it puts its sampling rate to the maximum.

• The y axis gives the corresponding sampling rate based on the Fisher test results on the x axis and the application criticality level (r^0) (number of sensed measures per unit of time).

We now present the contrast between applications that exhibit high and low criticality level in terms of the BV function.

1) Class 1 ”low criticality”, $0 \leq r^0 < 0.5$: this class of applications does not need high sampling rate. This characteristic is represented by hyperbolic projections of x values that are gathered close to zero (i.e. the majority of the sensors will preserve their energy by sampling slowly).

2) Class 2 ”high criticality”, $0.5 \leq r^0 \leq 1$: This class of applications needs high sampling rate. This characteristic is represented by a parabolic BV function. As illustrated in figure III.2, most projections of x values are gathered close to the max frame capture rate (i.e. the majority of nodes capture at a high rate).

3) The behavior function:

We use Bezier curve to model the BV function. Bezier curves are flexible and can plot easily a wide range of geometric curves.

Definition III.1: Bezier Curve

The Bezier curve is a parametric form to draw a smooth curve. It is fulfilled through some points P_0, P_1 ...P_n, starting at P_0 going towards P_1 ...P_{n-1} and terminating at P_n.

In our model we will use a Bezier curve with three points which is called a Quadratic Bezier curve. It is defined as follows:

Definition III.2: Quadratic Bezier Curve

A quadratic Bezier curve is the path traced by the function B(t), given points P_0 , P_1 , and P_2 .

$$B(t) = (1 - t)^2 * P_0 + 2t(1 - t) * P_1 + t^2 * P_2 . (3)$$

The BV function is expressed by a Bezier curve that passes through three points:

• The origin point (P_0 (0, 0)).

• The behavior point (P_1 (b_x, b_y))

• The threshold point (P_2 (h_x , h_y)) where h_x represents F_t and h_y represents the maximum sampling rate determined by the sensor node hardware capabilities.

As illustrated in Figure 3.3, by moving the behavior point P_1 inside the rectangle defined by P_0 and P_2, we are able to adjust the curvature of the Bezier curve. The BV function describes the application criticality. It takes F value as input on the x axis and returns the corresponding “sampling rate” on the y axis. To apply the BV function with the Bezier curve, we modify this later to obtain y as a function of x, instead of taking a temporal variable t as input to compute x and y. Based on the Bezier curve, let us now define the ”BV function”:

Definition III.3: Bezier Curve function

The BV function curve can be drawn through the three points P_0 (0, 0), P_1 (b_x , b_y) and P2 (h_x , h_y) using the Bezier curve as follows:

$$BV : [0, h_x] \rightarrow [0, h_y]$$
$$X \rightarrow Y$$

$$BV_{P_1P_2}(X) = \begin{cases} \frac{(h_y - 2b_y)}{4b_x^2} + \frac{b_y}{b_x} X \; if \; (h_x - 2b_x = 0) \\ (h_y - 2b_y)(\alpha\,(X))^2 + \; 2b_y \alpha\,(X), if \; (h_x - 2b_x \; \neq 0) \end{cases} \quad (4)$$

Where $\alpha\,(X) = \frac{-b_x + \sqrt{b_x^2 - 2b_x * X + h_{x*X}}}{h_x - 2b_x} \wedge \begin{cases} 0 \leq b_x \leq h_x \\ 0 \leq X \leq h_x \\ h_x > 0 \end{cases}$

4) The criticality level r^0: As discussed above, the criticality level r^0 of an application is given into the interval [0, 1]. According to this level, we define the criticality function called C_r which operates on the behavior point P_1 to control the BV function curvature.

According to the position of point P_1 the Bezier curve will morph between parabolic and hyperbolic form. As illustrated in figure III.3 the first and the last points delimit the curve frame. This frame is a rectangle and is defined by the source point $P_0(0, 0)$ and the threshold point $P_2(h_x, h_y)$. The middle point $P_1(b_x, b_y)$ controls the application criticality. We assume that this point can move through the second diagonal of the defined rectangle $b_x = \frac{-h_y}{h_x} * \; b_y + \; h_y$

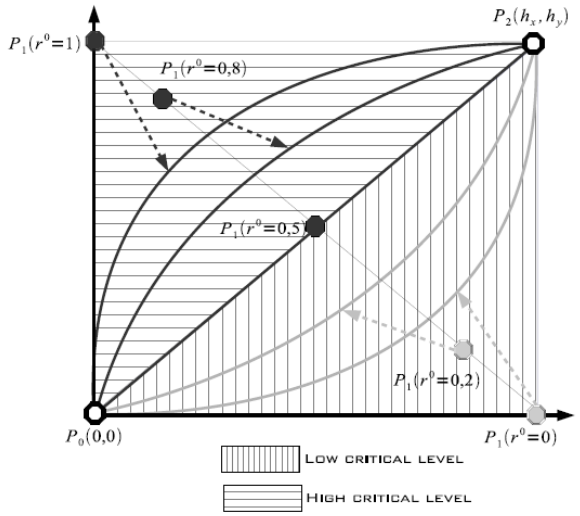


Figure III.3. The Behavior Curve Function

We define the Cr function as follows, such that varying r^0 between 0 and 1 gives updated position for P_1:

$$\begin{aligned} Cr : [0,1] &\rightarrow [0, h_x] * [0, h_y] \\ r^0 &\rightarrow (b_x, b_y) \end{aligned} \qquad (5)$$

$$Cr(r^0) = \begin{cases} b_x = -h_x * r^0 + h_x \\ b_y = h_y * r^0 \end{cases}$$

Level r^0 is represented by the position of point P_1.

If $r^0 = 0$, P_1 will have the coordinate $(h_x, 0)$. If $r^0 = 1$, P_1 will have the coordinate $(0, h_y)$.

B. Adapting Algorithm

The adaptive sampling rate algorithm operates in rounds where each round equals m periods. For each round, every node decides to increase or decrease its sampling rate according to the variance condition and the application risk. The algorithm is presented in algorithm III.1.

Algorithm III.1 : Adapting rate algorithm.
Require: m (1 round = m periods), $Smax$ (maximum sampling speed), r^0
Ensure: S_t (instantaneous sampling speed).
1: $S_t \leftarrow S_{max}$
2: while $Energy > 0$ do
3: for $i = 1 \rightarrow m$ do
4: takes measures at S_t speed
5: end for
6: for each round do
7: compute SR, SF and F.
8: find F_t
9: if $F < F_t$ then
10: $S_t \leftarrow BV(F, F_t, r^0, S_{max})$ (BV behavior function).
11: else
12: $S_t \leftarrow S_{max}$
13: end if
14: end for
15: end while

V. EXPERIMENTAL RESULTS

To verify our suggested approach, we conducted multiple series of simulations using a custom Java based simulator. The objective of these simulations is to confirm that our adaptive data collection technique can successfully achieve desirable results for energy conservation in periodic sensor networks. Therefore, in our simulations we used real readings collected from 45 sensor nodes deployed in the Intel Berkeley Research Lab(see figure III.4) [47].

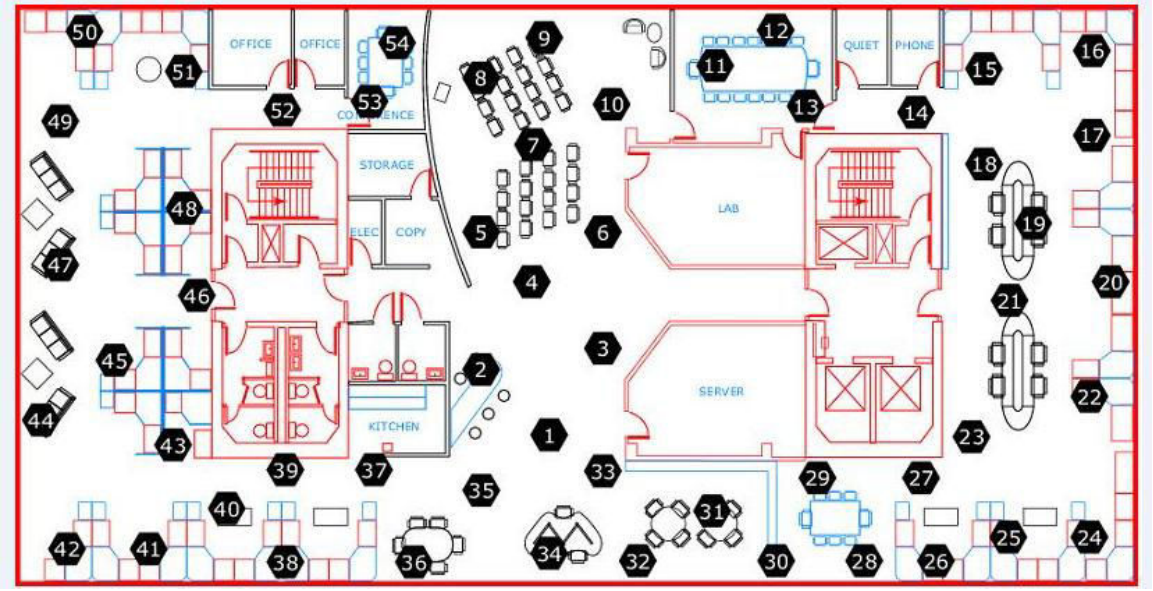


Figure III.4. Sensor Nodes deployed in Intel Berkely Research Lab

Every 31 seconds, sensors with weather boards were collecting humidity, temperature, light and voltage values. In our experiments, we used a file that includes a log of about 2.3 million readings collected from these sensors. Figure III.5 shows a screen capture of this file. Temperature is in degrees Celsius. Humidity is temperature corrected relative humidity, ranging from 0-100%. Light is in Lux. Voltage is expressed in volts.

For the sake of simplicity, in this chapter we are interested in one field of sensor measurements: the temperature. We performed several runs of the algorithms. In each experimental run, each node reads periodically real measures and adapts its sampling rate after each round according to its BV function. We evaluated the performance of the algorithm using the following parameters: a) the time t; b) m the number of periods per round; c) the application criticality level (r^0). We employ two metrics in our simulations:

- the instantaneous sampling speed after each round;
- The overall energy dissipation

	A	B	C	D	E	F	G	H	I
1	Date	Time	Slot	Node id	Temperature	Humidity	Light	Voltage	
2	03/03/2004	00:27,0	12005	1	18,3812	29,9691	1,38	2,63964	
3	03/03/2004	01:25,6	12007	1	18,4008	29,8271	1,38	2,63964	
4	03/03/2004	01:56,5	12008	1	18,4008	29,7561	1,38	2,63964	
5	03/03/2004	02:25,8	12009	1	18,4008	29,8271	1,38	2,63964	
6	03/03/2004	02:59,0	12010	1	18,391	29,8271	1,38	2,63964	
7	03/03/2004	03:27,7	12011	1	18,3812	29,7561	1,38	2,63964	
8	03/03/2004	03:57,7	12012	1	18,3812	29,7916	1,38	2,63964	
9	03/03/2004	04:28,7	12013	1	18,3812	29,8271	1,38	2,63964	
10	03/03/2004	05:57,4	12016	1	18,3714	29,8981	1,38	2,63964	
11	03/03/2004	06:28,1	12017	1	18,3616	29,8981	1,38	2,63964	
12	03/03/2004	07:00,1	12018	1	18,3616	29,8981	1,38	2,63964	
13	03/03/2004	07:55,2	12020	1	18,3616	29,8981	1,38	2,63964	
14	03/03/2004	08:25,3	12021	1	18,3616	29,8981	1,38	2,63964	
15	03/03/2004	08:59,9	12022	1	18,3714	29,8981	1,38	2,62796	
16	03/03/2004	09:55,3	12024	1	18,3616	29,8271	1,38	2,63964	
17	03/03/2004	10:25,3	12025	1	18,3616	29,7916	1,38	2,63964	
18	03/03/2004	10:55,8	12026	1	18,3518	29,8981	1,38	2,63964	
19	03/03/2004	11:27,0	12027	1	18,3616	29,9336	1,38	2,63964	
20	03/03/2004	11:58,4	12028	1	18,3518	29,9691	1,38	2,63964	
21	03/03/2004	13:27,0	12031	1	18,3518	29,9691	1,38	2,63964	
22	03/03/2004	14:01,4	12032	1	18,3518	29,9691	1,38	2,62796	
23	03/03/2004	14:25,9	12033	1	18,3518	30,0401	1,38	2,63964	

Figure III.5. Snapshot of real data

The main goal here is to show how our approach is able to adapt the sampling rate of the sensor nodes according to the changing dynamics of the environment and to the application criticality level. Our simulation results were obtained for the following parameters:

- a period is equal to 500 measures (' 4 hours)
- S_{MAX} = 150 or 250
- m = 2,
- α= 0.05
- r^0 = 0.2 and 0.9

Figures III.6 and III.7 confirm our previous analysis and show that the sampling rate is changing along the time and is able to adapt itself to application criticality i.e. r^0. Now from an energy preservation point of view (figures III.8 and III.9), if we assume that each sensor has an energy level arbitrarily fixed to 5000 units and that each measure consumes 0.125 unit our simulation results are again very encouraging. For example, for r^0 = 0.2 and S_{MAX} =150, our approach is able to provide a gain of more than 25% of sensors lifetime (comparing to a non-optimized sampling rate).

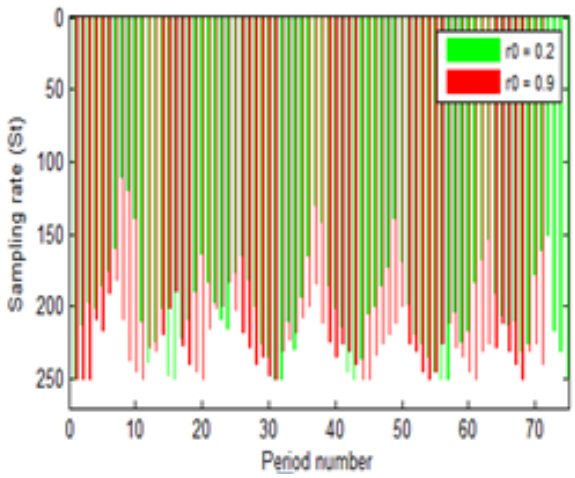


Figure III.6. The sampling rate adaptation for SMAX=250

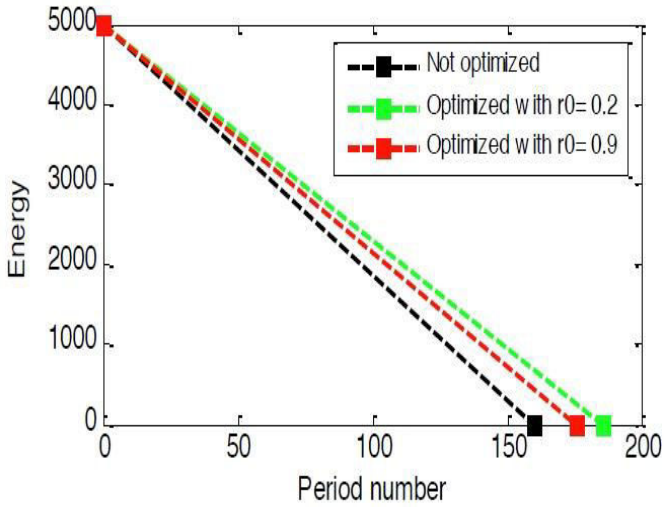


Figure III.8. The energy consumption for SMAX=250.

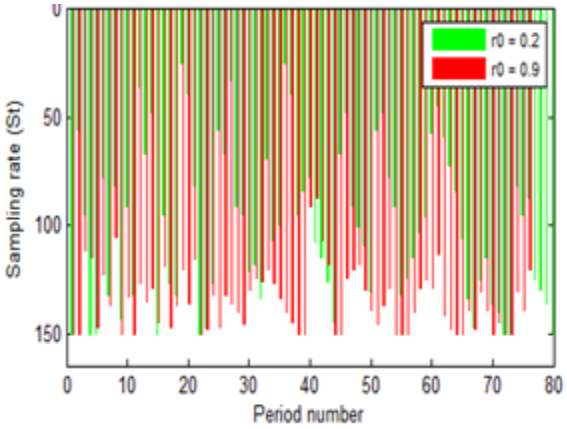


Figure III.7. The sampling rate adaptation for SMAX=150

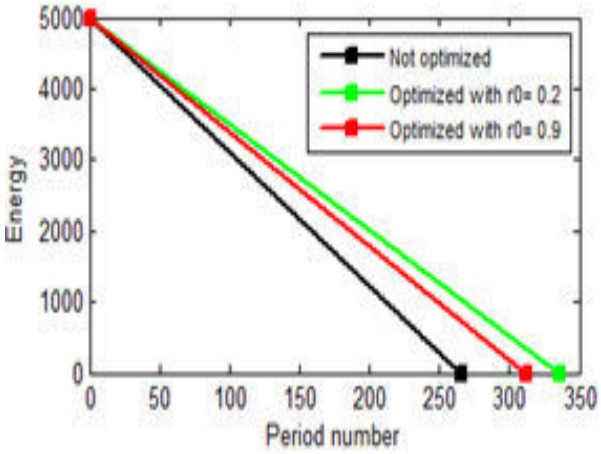


Figure III.9. The energy consumption for SMAX=150

VI. CONCLUSION

We provided an adaptive sampling approach for energy efficient periodic data collection in sensor networks. We described two main mechanisms that form the core of our approach. First we study the sensed data between periods based on the dependence of conditional variance on measurements varies over time. Then, we proposed a multiple levels activity model that uses behavior functions modeled by modified Bezier curves to define application classes and allow each node to compute its sampling rate. We showed that our approach can be effectively used to increase the sensor network lifetime, while still keeping the quality of the collected data high.

Chapter IV Energy Efficient 2 tiers in-Sensor weighted data aggregation

Exploiting sensors data should respect the characteristics of sensor networks in terms of energy and computation constraints, network dynamics, and faults. Reducing packet size transmitted and preparing the data for an efficient and scalable data mining is very crucial. Such approach, leads us to think of a periodic data aggregation as a preprocessing phase to achieve this goal. This chapter introduces a tree-based bi-level periodic data aggregation approach implemented on both the source node and the aggregator levels. Our contribution in this chapter is two folds. First we look on a periodic basis at each data measured. Secondly, we clean it periodically while conserving the number of occurrences of each measure captured. Then, data aggregation is performed between groups of nodes on the level of the aggregator. The quality of the information should be preserved during the in-network transmission through the number of occurrence of each measure called weight. The experimental results show the effectiveness of this technique in terms of energy efficiency and quality of the information.

I. INTRODUCTION

The need of unattended operations in remote or hostile locations became an eminent demand nowadays. Information collection and prediction for controlling and predicting natural disasters, preventing failures, improving food production, and improving human well-being are intended to wireless sensor networks. However as presented in chapter II, sensor nodes are not expected to carry huge amount of data or complex computations due to their presented constraints. It is important to remind that a sensor network usually consists of thousands or ten thousands of nodes deployed redundantly in order to ensure reliability. Subsequently, the collected data is partially

redundant and is subject to aggregation offering. In this context, data aggregation constitutes energy efficient data management technique for wireless sensor network. Furthermore, data accuracy is another main design concern in wireless sensor networks. The distributed measurements nodes communicate wirelessly to a central gateway, providing "interaction between people or computers and surrounding environment" [51]. To achieve data accuracy we strongly believe that only the right information should be communicated through the wireless sensor networks. Intrigued by such interest, this chapter suggests a periodic multilevel data aggregation algorithm aiming to optimize the volume of data transmitted thus saving energy consumption and reducing bandwidth on the network level. Instead of sending each sensor node's raw data to a base station, the data is cleaned periodically at the first level of the sensor node then another "data aggregator " sensor node collects the information from its associated nodes. We shall call this the first level "in-sensor process periodic aggregation" approach. At the second level, a heuristic data aggregation technique is applied on the level of the aggregator node itself. This technique preserves the quality of the information through the number of occurrences of each measure in the set called weight. The described approach focuses on a periodical data aggregation while taking into consideration the weight of the data captured. The output is a cleaned training set of data. This phase will constitute the preprocessing step to get the perfect data set to be mined in an acceptable timeframe. This will allow an optimization of the data mining algorithms that will be discussed in chapter VI.

The rest of this chapter is organized as follows: the first section presents the different data aggregation taxonomies and accredits data aggregation related work and research. While the second introduces our data aggregation architecture scheme: the first level periodic data aggregation algorithm applied on the sensor node level. At the second level, a heuristic method aiming to aggregate data on the aggregator level and index the data by a weight significant of its redundancy and quality. The Third section shows the experimental results of our suggested bi-level aggregation algorithm and its contribution to the network life in terms of energy consumption optimization. We conclude by emphasizing the added value of our periodic data aggregation approach and its contribution to the world of wireless sensor network research.

II. TAXONOMIES IN DATA AGGREGATION

Data aggregation in wireless sensor networks has been well studied in recent years [52][53]. Data transmission is the most costly operation in sensors [54], compared with it, the energy cost of in-network computation is sometimes trivial and negligible. In consequences, the main challenge is the optimization of the energy consumed during the transmission of the data. Computing and transmitting partially aggregated data to the end user instead of sending the raw data will reduce the number of packets in the network which save the energy of the sensor nodes [55]. Data aggregation techniques consist of exploring how the data is to be routed in the network as well as the processing method that are applied on the packets received by node. There are vast amount of extant works on in-network data aggregation in the literature. Figure IV.1 illustrates the different data aggregation schema existing in the WSN world. Actually, various structured and unstructured algorithmic techniques have been proposed to allow efficient aggregation without increasing the message size [62].

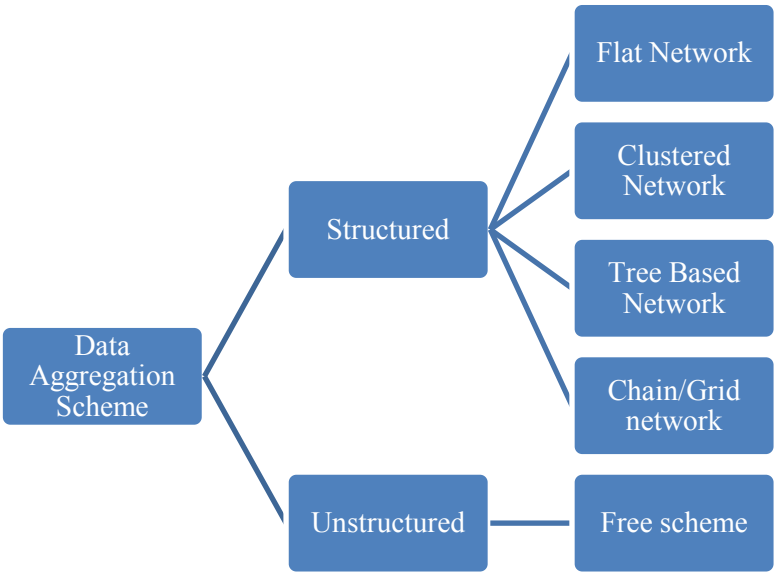


Figure IV.1 WSN Taxonomies

Four different topologies illustrated in Figure IV.1 can constitute the structured data aggregation world: flat network, clustered network, tree based network and chain/grid network.

A. Flat Network

Flat network based is a network composed of sensor nodes equipped with same battery power and belonging to the same broadcast area. Figure IV.2 shows a representation of a flat network. Some of the methods reported recently in such type of network are query based methods [63] [64]. A query is generated at the sink and then broadcasted through the network via multi-hop routes by using peer nodes as relays. Some nodes just process the query, while others propagate it, receive partial results, aggregate results, and send them back to the sink. A query is generated at the sink and then broadcasted through the network. All protocols respecting this topology use a technique that rely on a given node to broadcast received data and control packets to the rest of the nodes in the network. This technique is called flooding and aims to find a good-quality route from sources nodes to sink nodes. The main problem in this technique is the implosion and overlap during routing since it doesn't take into account the energy constraint. Neighbors may also receive duplicate packets when two sensors sense the same region and broadcast their sensed data at the same time. Different protocols exist in this regard depending on the type of application aiming to restrict the flooding to localized regions. Some examples of routing protocol based on flat topology are Sensor Protocols for Information via Negotiation (SPIN) [52] [63], Directed-Diffusion[53], Rumor-Routing[55],etc. The main advantages in the flat based topology are that no big effort is needed to maintain and manage the network since non-complex switches or routers are used. In addition, these protocols include a good quality routes from source to sink. Unfortunately, flooding doesn't respect the constraints imposed by sensor networks since it is an expensive operation. To add also that the lifetime of a sensor network decreases due to the unbalanced energy distribution and to the redundancy of packets transmitted. High delay and unreliability also occur in such topology in case of large network.

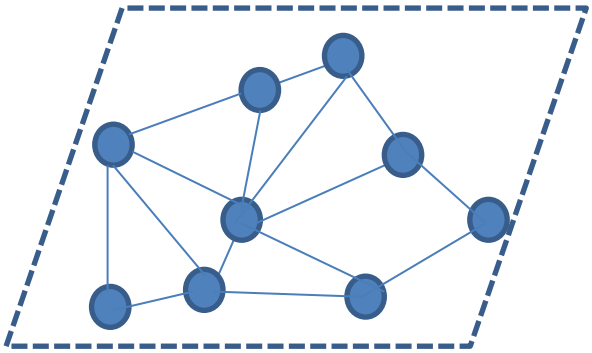


Figure IV.2 Flat Topology Architecture

B. Clustered Network

In a clustered network, the nodes are organized into clusters and a local aggregator is introduced as a cluster head. The main function of a cluster head is to aggregate data collected by all sensors existing in the same cluster before transmitting them to the sink. This topology illustrated in figure IV.3 overcomes the constraint imposed by large size network. It helps also in load balancing applications that require scalability to thousands of nodes.

Some works, such as [65] [66] [67], use the clustering methods for aggregating data packets in each cluster separately. Among these methods, the low-energy adaptive clustering hierarchy (LEACH) protocol [68] [69] constitutes an example. LEACH generates clusters based on the size of the sensor network. A drawback in this protocol is the prior knowledge of the topology of the network. In [66], the authors propose a self-organizing method for aggregating data based on the architecture CODA (Cluster-based self-Organizing Data Aggregation). CODA relies on Kohonen Self-Organizing Map to aggregate sensor data in cluster. Then clusters are combined or partitioned. Before deployment, the nodes are trained to have the ability to classify the sensor data. [66] proves that his method increases the quality of data and reduces data traffic as well as conserves energy. An adaptive data aggregation (ADA) scheme for clustered sensor networks has been also proposed in [67]. In this scheme, a time based as well as spatial aggregation degrees are introduced. They are controlled by the reporting frequency at sensor nodes and by the aggregation ratio at cluster heads (CHs) respectively. The function of the ADA scheme is mainly performed at the sink node, with a little function at CHs and sensor nodes.

At the end, all protocols adopting the clustered topology will have to choose a cluster head, construct the cluster then transmit the data. The difference exists in the implementation of these stages either through a fixed distribution or a dynamic one to locate the sensor nodes and the cluster head.

The main advantage of a cluster based topology is the high scalability and the optimization of energy consumption that extend the network lifetime. The channel bandwidth is well utilized since the network is well organized. However we might face cases were cluster heads are grouped on the same side of the network which lead to non-uniform clustering. In consequences, no balanced energy distribution exists and energy might be depleted to the long channel of communication between the cluster member and the cluster head which lead to a decrease in the network lifetime.

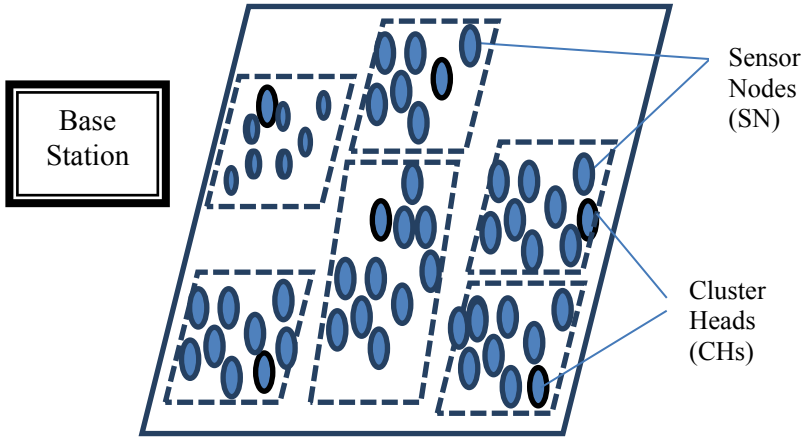


Figure IV.3 Cluster Based Topology architecture. Clusters boundaries referred by dotted line

C. Tree Based Network

In a tree based network, as illustrated in figure IV.4, a tree is constituted of sensor nodes where data aggregation is performed at aggregators along the tree to arrive to the sink. Tree based data aggregation approaches are suitable for in-network data aggregation and aim to consume the lowest energy of the network. However, the aggregation tree doesn't share fairly the load of data packets to the transmitting nodes which sometimes leads to heavily loaded nodes and results with the death of the network. The authors in [70] [71], have proposed Tree on DAG (ToD) for data aggregation, a semi structured approach that uses Dynamic Forwarding on an implicitly constructed structure composed of multiple shortest path trees to support network

scalability. The key principle behind ToD is the adjacent nodes in a graph which will have low stretch in one of these trees in ToD thus resulting in early aggregation of packets. An energy aware spanning tree (ESPAN) algorithm is proposed in [72] that choose the node that has the highest residual energy as the root. Parent nodes are chosen from neighbor nodes based on the residual energy and the distance to the root.

[73] proposes an energy-aware data aggregation tree (EADAT) algorithm. A broadcast control message is sent periodically from the base station. A timer will start on the level of each node once the message is received. When a node receives a message, the timer is refreshed. The expiration time is inversely proportional to the node's residual energy. Therefore some nodes will be heavily loaded which will cause depletion of energy and in consequences the death of the network. To overcome this problem, [74] uses the genetic algorithm to calculate the possible routes represented by the aggregation trees in order to balance the residual energy among the nodes. The optimum tree is the adopted and the data load and the energy in the network are balanced. This method can work only in case of homogeneous WSN with some spatial correlation to monitor the environment. The most inconvenient point in this topology is that the construction of the tree is time consuming and costly and if one parent node is dead, the entire sub-tree is dead. The node in the leaf level are more likely to save energy than the one closer to the base station that consume a lot of power when forwarding packets received from the different nodes in the sub tree.

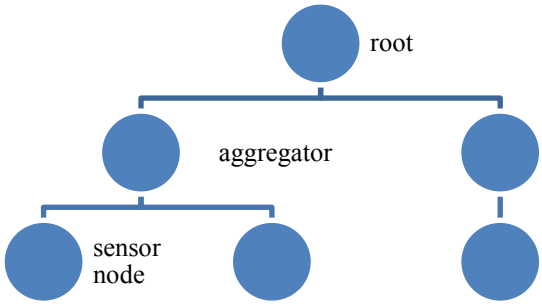


Figure IV.4 Tree based topology

D. Grid/Chain Based network

In a grid based data aggregation, the region to be monitored is divided into a grid. Fixed regions of sensor networks contain a set of sensors assigned as data aggregators.

Sensors dispersed on the same grid transmit the data to the aggregators belonging to this grid [75]. Communication is done only inside the grid and not among different grid like the in network aggregation. The aggregator can be any node inside the grid on a round basis till the death of the last node.

Some protocols such as PEGASIS [74] save energy dissipation of data transmission by constructing transmission chain that connects the sensor nodes (figure IV.5). One of the sensor nodes will lead the chain in a specific time-frame. Sensor nodes communicate by choosing the closest node along the chain in direction of the leader till data is received by the leader. The main objectives reached by PEGASIS are the enhancement of the lifetime of each node through the collaborative technique, and the optimization of the bandwidth consumed during communication.

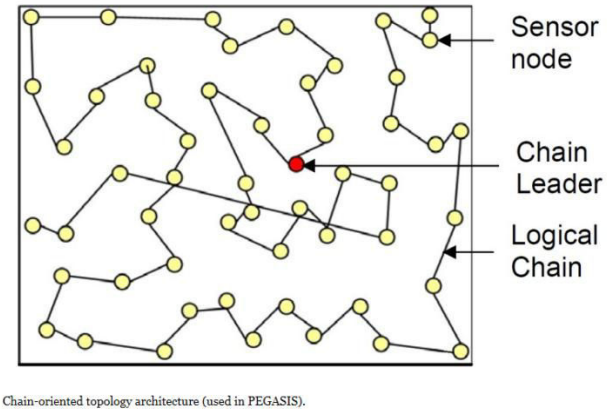


Figure IV.5 Chain based topology

E. Structure free data aggregation

In a structure free data aggregation, no structure is adopted. Event driven models are the typical example where we can adopt such structure since many changes are done on the level of the event imposing several architectural reconstruction. However in a structure free architecture, routing decisions need to be made on the fly. In addition, the nodes ignore their upstream nodes and forward their own data without waiting to receive data from other node. However, the positive side of this architecture, there is no need to worry about the construction of the structure when some nodes fail. The first work done on this point was by [68] where a MAC layer protocol for spatial convergence called data-aware anycast (DAA) is proposed. DAA aggregates packets early on their route to

the sink. Then, another angle is tackled allowing some sensor nodes to wait for others through a randomized waiting (RW) before sending data. It works as follow:
The node sends a "request to send" (RTS) packet with the type of data to its neighbor. In his turn, the neighbor sends the "clear to send" (CTS) packet that have similar type of data. After receiving the CTS from more than one neighbor, the source node selects only one of them according to instantaneous channel condition. DAA is based on MAC layer where in any casting we have the situation to select only one next hop among many. A combination of the DAA and RW improves the performance in comparison with structure approach.

F. Metrics for data aggregation in WSN

The efficiency of a data aggregation technique can be calculated using the below different metrics:

1. The network lifetime prolongation that constitutes the target of any data aggregation scheme since once all sensor nodes have died, the whole network is dead. Efficient Energy consumption constitutes a main challenge for data aggregation as it affects the network lifetime.
2. Minimizing latency which is very important since delay in data transmission may consume more energy.
3. Enhancing data accuracy and avoiding data loss thus having better decision making.

TableIV.1 shows a comparison between the different taxonomies of data aggregation in a structure based topology taking into consideration the above metrics:

	Advantages	Drawbacks
Flat network	• Good quality routes from source to sink. • No topology maintenance overhead	• Implosion problem due to duplicate packets • Sink node might lead to the breakdown of the entire network • High latency • Energy constraint not respected
Tree based	• Less power consumed • Optimization of energy	• Unbalanced power consumption between the closest nodes to the based station and the nodes in the sub tree

		• Long delay for sending data from leaf to root node. • Tree maintenance overhead is high. • Tree construction is time consuming and costly.
Cluster based	• Enhanced scalability • Optimization of energy consumption • Efficient data aggregation that in consequences lead to better utilization of the channel bandwidth • The failure of a cluster head doesn't affect the whole network	• Non uniform clustering leading to not having cluster heads in some side of the network • Failure of the sink node may breakdown the entire network • Higher latency is involved in the data transmission to the sink via multihop • Energy dissipation rate is highly different from one sensor to another sensor, even if they are in the same cluster. Thus energy distribution is not even. • Total energy dissipation increases due to the long way communication between a cluster member and cluster head. • Because of very long-way communications, some sensors consume energy rapidly and die. As a result, network lifetime decreases. • Network connectivity may not be guaranteed.
Chain Based	• Optimization in energy • Balancing in energy distribution • Prolongevity of the network lifetime	• Too much delay for data collection. • High Topology management overhead

Table IV.1. Data Aggregation Taxonomies

In this chapter we will study a tree based data aggregation algorithm for periodic sensor networks, where each sensor node takes measurements at regular time intervals prior to send it to the aggregator. To the best of our knowledge, previous works didn't take into consideration the accuracy of the information affected by the number of similarity between measures. Our aim is to periodically aggregate the data captured from noisy and redundant measures while maintaining an acceptable level of quality and accuracy of the information. The measures' occurrences are called weighted measures in this chapter and will serve as a parameter passed to all data aggregation levels and subsequently saving accuracy of the purged data. When applying the suggested algorithm, it aggregates periodically the data while assigning to each measure its proper weight. Such scheme will form an optimized training set for the classifier, predicting

with reasonable accuracy the class of each instance fed. The next section describes in more details our proposed approach.

III. DATA AGGREGATION SCHEMA

Our proposed approach for data aggregation in periodic sensor network is a tree based approach divided into two levels: the source node will constitute the first level whereas a special sensor node called aggregator receiving the data from different source nodes will be the subject of data aggregation at the second level. Figure IV.6 illustrates our tree based data aggregation scheme.

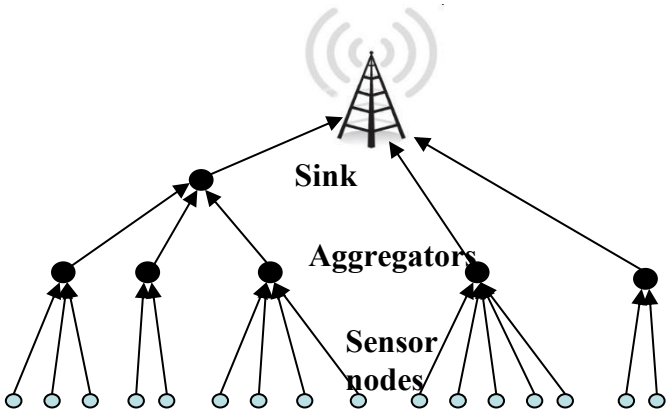


Figure IV.6. Tree based data aggregation scheme

The following section outlines the main definitions and notations, together with our approach that will be used for an efficient and accurate in sensor nodes data aggregation.

A. Definitions and Notations

The set of sensor nodes is denoted by N = {1, 2, …, n}, where n is the number of nodes. Each node is composed of many sensors S that produce a measurable response to a change in a physical condition like temperature or pressure or humidity, etc. Each sensor node takes a matrix of measurements $M[t] = (m[t_1],\ldots m[t_{\Pi-1}]) \in \Re^{\Pi}$ at regular time

interval t during a period ∏. The unit time is called slot, whose length is the time interval between two measurements. After ∏-1 slot, each sensor node N_i will have a matrix of measurements M_i as follows:

$$\begin{array}{c} M_1 \\ M_2 \\ M_3 \\ \\ \\ M_s \end{array} \begin{bmatrix} m_1[t_1] & m_1[t_2] & \ldots\ldots & m_1[t_{\pi-1}] \\ m_2[t_1] & m_2[t_2] & \ldots\ldots & m_2[t_{\pi-1}] \\ m_3[t_1] & m_3[t_2] & \ldots\ldots & m_3[t_{\pi-1}] \\ & & & \\ & & & \\ m_s[t_1] & m_s[t_2] & \ldots\ldots & m_s[t_{\pi-1}] \end{bmatrix}$$

Definition IV.1: link between two measures

We define a link function link(m[t_i], m[t_j]), the degree of similarity between two measures m[t_i] and m[t_j] collected at two slots i and j. This function returns either 0 or 1. A higher similarity value indicates that the measures are more similar.

$$\text{link}\big(m[t_i], m[t_j]\big) = \begin{cases} 1 \text{ if } ||m[t_i] - \dot{m}[t_j]|| \leq \delta \\ 0 \text{ otherwise.} \end{cases} \quad 1)$$

Where δ is a threshold fixed by the application.

Definition IV.2: Weight of a measure

Intuitively, redundancy gives more importance to some information which, are represented by many features and may occult less than others that are less present. We define weight λ of a measure m at a time t the total number of measures captured after the time t and can be similar to m.

$$\lambda_i = \text{Weight}(m[t_i]) = \Sigma^{\Pi-1}{}_{j=t_{i+1}} \text{link}(m[t_i], m[t_j]) \quad (2)$$

Definition IV.3: Cell's measure

On the level of an aggregator A, we define a cell of a measure $Ca[i] = A[i](\lambda_i, m_i)$, a cell that contains the received measure m_i from the node n_i with its corresponding weight λ_i. We refer to Ca[i](m) as the measure in a cell while the respective weight is Ca[i](λ).

B. First Tier: Periodic data aggregation at the node's level

At this level, our technique consists on evaluating the link function between two measures taken at the same period before sending them to the aggregator. Hence, during a period, when a node takes a new measure it calculates the link function with the previous measure already captured during this period. If the link is equal to 1, this means that the new measure can be aggregated with the existing measure on which we are performing the link function. The weight of the existing measure is incremented by 1 and the new measure is disregarded. For sake of simplicity and without loss of generality, Algorithm IV.1 illustrates the first tier with one field of measure (i.e: temperature). At the end of this algorithm, no redundant measures will exist. Each sensor will send to the aggregator a set of reduced measures associated to their corresponding weight and ready for the second tier data aggregation algorithm.

Algorithm IV.1: First Tier Data Aggregation

Input: New measure $m[t_i]$.

Output: Reduced set of measurements M.

Initialization: Get first measure $m[t_1]$

1: $\lambda_1 \leftarrow 0$

2: Foreach slot t_i during a period ∏ do

3: Get a measure $m[t_i]$

4: Foreach existing measure $m[t_j]$ do

5: If link $(m[t_i], m[t_j]) = 1$ then

6: $\lambda_j \leftarrow \lambda_j + 1$ // λ_j is the weight($m[t_j]$)

7: Disregard $m[t_i]$

8: Else $\lambda_i \leftarrow \lambda_i + 1$ // λ_i is the weight($m[t_i]$)

9: Add $m[t_i]$ to M: M←{(M ∪(λ_i, $m[t_i]$)}

10: End if

11: End for

12: End For

C. Second Tier: weighted data aggregation at the aggregator level

At this level of aggregation, each aggregator has received k measures and their frequencies. The idea here is to identify all pairs of measures whose similarities are above a given threshold t. For this reason we use the same similarity function used at the first tier. Thus we can treat pairs of measures with high similarity value as duplicates and reduce the size of the final data set that will be sent to the sink.

Our approach aims at reducing data transmitted from the aggregators to the sink subsequently reducing energy consumption. The obvious idea will suggest looping each list comparing its measures with the remaining lists looking for redundant data. Such approach proved to be costly in terms of data processing since it will scan the whole existing set many times and is attributed a complexity of O(n!). Our approach, illustrated in Algorithm IV.2, suggests building progressively a dynamic array list as follows:

We define A = Union of all existing lists in the aggregator: A = (∪(λ_i, $m[t_i]$)|i∈N). Then we select a random measure with its related weight from A in order to create the first cell of our dynamic array list by placing the above random value in it. We continue by selecting value (λ_i, m_i) from A and calculating the link function for each selected value m_i with the array list values { (λ_j, m_j), j∈array list values}. The first measure m_j answering link (m_i, m_j) = 1 is observed and the weight of matched values are added. If no match occurs the value is added to the dynamic array list by creating a new cell. Finally, the selected value m_i is deleted from A. As we proceed in the algorithm an array list is built up.

Algorithm IV.2: Second Tier Data Cleaning

Input:

N: number of nodes associated to one aggregator A.

K: number of measurements received by the aggregator A.

A= ($\cup_{nk}\lambda$,m| n∈N, k∈K)= {(λ_{nk}, m_{nk})| n∈N, k∈K} = {(λ_{11}, m_{11}),(λ_{12}, m_{12}) ,.., (λ_{21}, m_{21}), …., (λ_{nk}, m_{nk})}.

Output: Final dataset sent to the sink.

Initialization: We create a cell $C_a[1]$ which contain a random value from the set A.

1: L←K
2: T←1 //T is the number of cells created
3: For i←2 to L do
4: Remove←False
5: For j=1 to T do
6: Compute link(C_a[j](m),A[i](m))
7: If link(C_a[j](m),A[i](m)) =1 Then
8: $C_a[j](\lambda) \leftarrow C_a[j](\lambda) + A[i](\lambda)$
9: Remove A[i](λ, m) from the set A
10: Remove←True
11: End if
12: End For
13: If remove ←False Then
14: Build a cell C_a[j+1] to contain A[i](λ, m)
15: Remove A[i](λ, m) from A
16: Remove←True
17: End if
18: L← length (A)
19: T← number of cells created for an aggregator.
20: End For
21: Built Array list of measures and weights.

---

1. Illustrative Example:

Let AM be the set of values related to one type of measures received from different nodes connected to an aggregator A.

AM = {(λ_{11}, m_{11}),(λ_{12}, m_{12}), .., (λ_{21}, m_{21}), …., (λ_{nk}, m_{nk})}.

We create the first cell $C_a[1]$ in the array list where the first value (λ_{11}, m_{11}) collected is placed. For each (λ_{ij},m_{ij})we compute link ($C_a[1](m)$, m_{ij}) where m is a measure from AM.

If the function returns 1 it means that these two measures are similar. Then the weights are added to each other and we remove (λ_{ij}, m_{ij}) from the set A, else we create a cell $C_a[2]$ for m_{ij} affected of the weight λ_{ij} as shown in Table IV.1. for ($\lambda_{12,}$ m_{12}) . At the end we remove (λ_{ij}, m_{ij}) from the set A.

Cells	***C_a[1]***	***C_a[2]***
	λ_{11},m_{11}	$\lambda_{12,}$ m_{12}

Table IV.2. Array List under creation.

Supposing we are in the case where the measures are not similar we continue as follows: We move to (λ_{13}, m_{13}), then we check if the similarity is reached with the measure m. If so, the weights are added as follows: $C_a[1](\lambda) = C_a[1](\lambda) + \lambda_{13}$ and $m=m_{13}$ is removed from the set A. Otherwise we continue checking the similarity with the measure existing in the second cell. If link ($C_a[2](m)$, m_{13}) =1 then $C_a[2](\lambda) = C_a[2](\lambda) + \lambda_{13}$ and m_{13} is removed from the set A. If the measure is not similar with any of the existing measure in the array we create a cell $C_a[3]$ for m_{13} affected by its weight λ_{13} before we remove (λ_{13}, $m_{13)}$ from the set A. Instead of looping through the entire set of values in A, we are only scanning the cells progressively created in the dynamic array list while computing the link function and reducing the original set size. If the latter is not verified then we create a new cell containing the measure with its related weight otherwise we are only adding the weight to an existing slot as in Table IV.2.

Cells	*C_a[1]*	*C_a[2]*
Weight	$\lambda_{11,}$ m_{11}	(λ_{12}+λ_{13}),m_{12}

Table IV.3. Sample of the Result Set sent to the aggregator

IV. EXPERIMENTAL RESULTS

To validate the approach presented in this chapter, we developed a C# based simulator that we ran on the same readings collected from 46 sensors deployed in the Intel Berkeley Research Lab [47] mentioned in chapter III. Every 31 seconds, sensors with weather boards were collecting humidity, temperature, light and voltage values. In our experiments, we are interested in two sensors measurements: the temperature and the humidity. Each node reads an average of 83000 values of each measurement per day and per field. All the results presented below are the average of 25 runs.

Output of our two tiers aggregation approach is presented below and include: (1) output of first tier where the aggregation is done on a periodic basis every 31 seconds (2) output of the second tier where the aggregation is done on the level of the aggregator that receives the input from a group of nodes.

A. First tier: periodic data aggregation at the node's level

At the first tier, data is filtered on a periodic basis where each period is constituted of 31 seconds. At each period, each measure is affected by its weight. In these series of simulations, we computed the percentage of the measurements sent by the nodes to the aggregators after local aggregation. We varied the threshold delta between 0.01 and 0.07 based on the variation of measurements. Figure IV.9 shows the percentage of data sent to the aggregator. Obviously the data size is disproportional to the threshold data. The goal of this tier is to reduce the size of the data collected by each node while preserving the frequency of each value as to not affect the analysis on the sink level. The experimental results show that a minimum of 5% of the total set for each type of measure is sent. The size of the affected weight for each measure is equal to the number of items existing in the message to be sent to the aggregator. The total size of the messages sent to the aggregator is then equal to the total number of measures to be sent in addition to the total number of affected weight. As per the experimental results displayed in figure IV.7, minimum of 10% for each measure is sent to the aggregator.

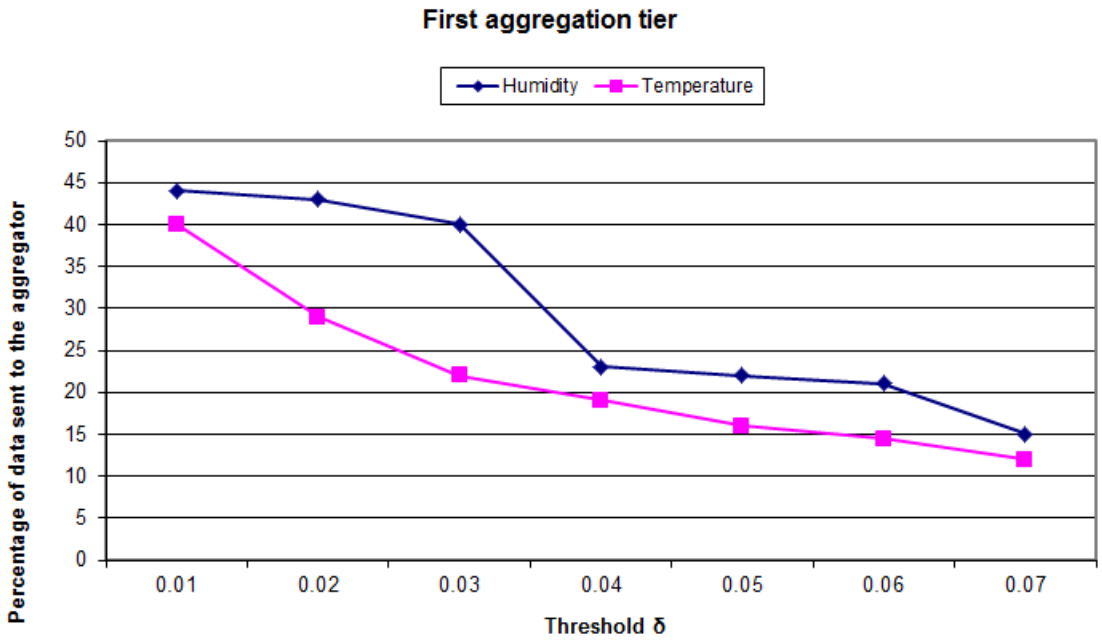


Figure IV.7. Percentage of total data sent to the aggregator

B. Second tier: weighted data aggregation at the aggregator's level

At this level, weighted data measures are received by the aggregator. Weighted data aggregation between all measures is performed at the level of the aggregator. It takes as input the measures with their weight and gives as output one reduced set. This set contains the aggregated measures associated to their weight. The weight of each measure can define the number of occurrence of the data measure existing in this aggregator. Results in Figure IV.8 show that maximum 13% of the data is sent to the sink adding to it 13% related to their respective number of occurrence. We conclude that only 26% of the size of messages received by each aggregator A will be the aggregated data generated by algorithm IV.2.

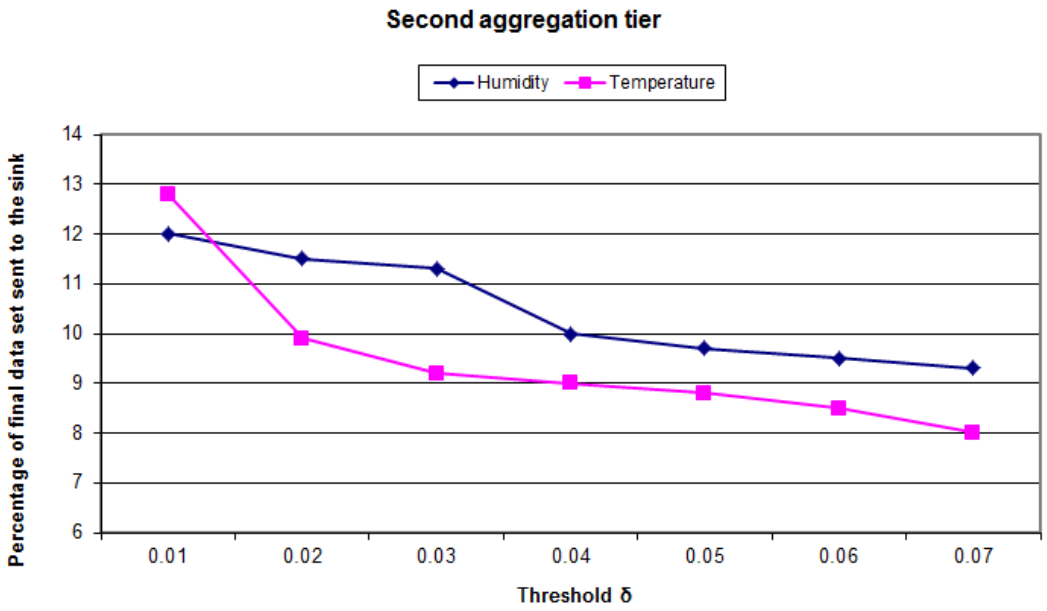


Figure IV.8 Second Tier Data Aggregation

C. Energy study

Sensor nodes used to form a sensor network are normally operated by a small battery which has small amount of energy. Therefore, in wireless sensor networks reducing energy consumption of each sensor node is one of the prominent issues to address in the network lifetime. Since wireless communications consume significant amount of battery power, sensor nodes should be energy efficient in transmitting data. Protocols can reduce transmitted power in two ways. First where nodes can emit to short distances such as data sinks or cluster nodes. The cluster node can then send the data over a larger distance preserving the power of the smaller nodes. The second is by reducing the number of bits (amount of data) sent across the wireless network. Our approach reduces the overhead by detecting and aggregating redundant measures while preserving the information integrity. To evaluate the energy consumption of our approach we used the same radio model as discussed in [79]. In this model, a radio dissipates E_{elec} = 50 nJ/bit to run the transmitter or receiver circuitry and βamp = 100 pj/bit/m^2 for the transmitter amplifier. The radios have power control and can expand the minimum required energy to reach the intended recipients as well as they can be turned off to avoid receiving unintended transmissions. The equations used to calculate

transmission costs and receiving costs for a k-bit messages and a distance d are respectively shown below in (3) and (4):

$$E_{TX}(\kappa, d) = E_{elec} * \kappa + \beta_{amp} * \kappa * d^2. \quad (3)$$

$$E_{RX}(\kappa, d) = E_{elec} * \kappa. \quad (4)$$

Receiving is also a high cost operation, therefore, the number of receptions and transmissions should be minimal. In our simulations, we used a measure length k of 64 bits which, corresponds to a packet length. With these radio parameters, when d^2 is 500 m^2, the energy spent in the amplifier part is equal to the energy spent in the electronics part, and therefore, the cost to transmit a packet will be twice the cost to receive.

At the first level, and at the end of the period, each node will contain m messages affected each by a weight λ. The size of the message sent by each node is equal to the number of weight sent in addition to the number of values sent. We consider that each value is equal to 64 bits. The total energy consumed is equal to the sum of the energy consumed by each node when the packet is sent to the aggregator from the source nodes and can be calculated as follows:

$$E_{agg}(\kappa, d) = \Sigma E_{Tx}(\kappa, d) + E_{Px}(\kappa) = \Sigma(E_{elec} * \kappa + \beta_{amp} * \kappa * d^2) + E_{elec} * \kappa. \quad (5)$$

At the second level, the energy consumption will be equal to the energy consumed when the aggregator send the data to the sink in addition to the energy consumed by the sink when receiving the data as shown in (6).

$$E_{sink}(\kappa, d) = \Sigma E_{Tx}(\kappa, d) + E_{Rx}(\kappa) = (E_{elec} * \kappa + \beta_{amp} * \kappa * d^2) + E_{elec} * \kappa \quad (6)$$

The total energy consumed on the level of the network is calculated as follows:

$$E = E_{agg}(\kappa, d) + E_{sink}(\kappa, d). \quad (7)$$

To evaluate the energy consumption of our approach we compared it to a classical clustering approach, where every node sends all its measures to a cluster head which, in his turn relays all the received data to the sink. Figure IV.9 shows that our approach

outperforms clustering approaches and minimizes the energy consumption by at least 50%.

Our approach is efficient since the information integrity is fully preserved. All taken measurements appearing in the final set arrived to the sink along with their weight. Therefore, we can consider that our approach decreases the amount of redundant data forwarded to the sink and performs an overall lossless process in terms of information and integrity by conserving the weight of each measure.

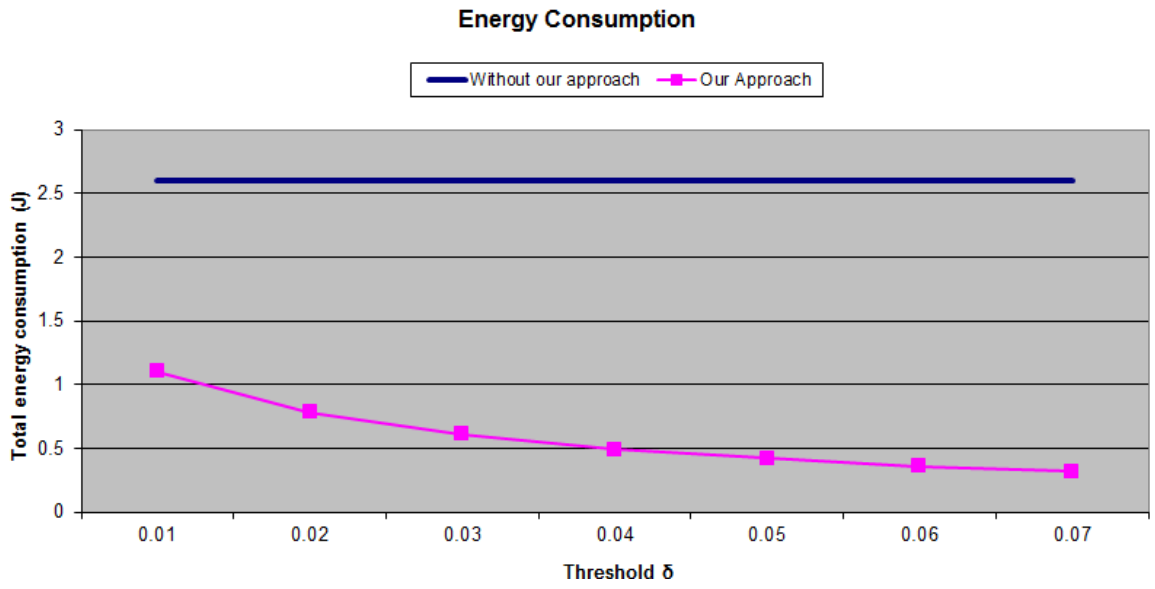


Figure IV.9. Energy Consumption

V. CONCLUSION

Data aggregation is a well-known technique to achieve energy efficiency, in wireless sensor networks, when propagating data from sensor nodes to the sink. The objective is rather than sending all captured data from sensors to the sink, multiple redundant data are aggregated as they are forwarded by the sensor network. We provided a two levels data aggregation scheme. At the first level we provided an aggregator for simple captured measurements based on a link similarity function while at the second one our objective was to detect and aggregate multiple data sets generated

by different neighboring nodes. It was shown through simulations on real data measurements that our method reduces drastically the redundant sensor measures. In the next chapter, another approach will be presented at the second tier relying on the sets similarity in sensor networks.

Chapter V Data Aggregation in periodic sensor networks using sets similarity

This chapter objective is to propose a new data aggregation approach aiming to identify near duplicate nodes that generate similar sets of collected data in periodic applications. We propose a new prefix filtering approach that avoids computing similarity values for all possible pairs of sets. We define a new filtering technique based on the quality of information. To the best of our knowledge, the proposed algorithm is a pioneer in using "sets similarity functions" for data aggregation in sensor networks. To evaluate the performance of the proposed method, experiments on real sensor data have been conducted. The analysis and the results show the effectiveness of our method dedicated to period sensor networks.

I. INTRODUCTION

An important topic addressed by the sensor networks community over the last several years has been in-network aggregation. The idea is that cumulate time intervals, or summaries can be computed directly within the network by sensor nodes, endowed with computational power, thus avoiding the expensive transmission of all sensor data to the sink. Previous work studied the data aggregation as the computation of statistical means and moments, as well as other cumulative quantities that summarize the data obtained by the network. To some extent these concerns can be alleviated by providing tools for filtered aggregation, where only a selected subset of nodes participate in the aggregation, according to the values of some of their sensors, their geographic location, etc.

In this chapter we are interested in exploring a new part of the filtering aggregation problem, by focusing on identifying the similarity between sets of data generated by neighboring nodes further to a local processing technique. As highlighted, one of the issues accompanying the growth of sensed data in periodic sensor networks is the

existence of near duplicate sets of data. Our objective is to identify similarities between near sensor nodes, and integrate their sensed data into one record while preserving information integrity. A quantitative approach in identifying two similar sets of sensed data is by using a similarity function. Such function measures the degree of similarity between two sets and returns a value between 0 and 1. A higher similarity value indicates that the sets are more similar, thus we can treat pairs of sets with high similarity values as duplicates, and send only one set to the sink instead of sending both. Similarity functions were used in various domains and applications in order to identify near duplicate objects (data). For instance, for Web search engines [53], Web mining applications [54], detecting plagiarism [55], collaborative filtering in data mining [56], etc.

We provide a new prefix filtering method to study the sets similarity in sensor networks. We propose frequency filtering optimization techniques, which exploits the ordering of measurements according to their frequencies. A frequency of a measure is defined by the number of occurrences of this measure in the set defined at the first aggregation level. Furthermore, we provide a new optimization method for early termination of sets similarity computing.

Our method is divided into two phases: the first one is done at the nodes level, where each node compacts its measurements set according to a *link* function. The second is defined at the aggregator level where the frequency filtering technique will be applied. To evaluate our approach we conducted extensive experimental study using real data measurements and we compare our approach to the existing ToD protocol [70, 71] for data aggregation in sensor networks. The obtained results compared to the existing algorithms show the effectiveness of our method which significantly reduces the number of duplicate data.

The rest of this chapter is organized as follows: The first section gives an overview on related works reported on the similarity between objects or records.. The second introduces our data aggregation tree architecture scheme: the first level periodic data aggregation algorithm applied on the sensor node level. At the second level, a heuristic method based on the frequency ordering is proposed. Two optimization techniques based on frequency filtering extension aiming to find similar data sets efficiently are presented. The Third section shows the experimental results of our suggested data aggregation algorithm and its contribution to the network life through optimizing energy

consumption. We conclude by emphasizing the added value of our approach and its contribution to the world of wireless sensor network research.

II. PREVIOUS WORK

In this chapter we will follow the same hierarchical multilevel data aggregation scheme presented in chapter IV aiming to optimize the volume of data transmitted thus saving energy consumption and reducing bandwidth on the network level.
We are not aware of previous work that specifically addresses the set joins similarity aggregation problem in sensor networks. Recently, many studies have proposed new algorithms that define the similarity between objects or records. These algorithms are classified into three categories, inverted index based methods [82], prefix filtering methods [65], and signature based methods [83]. The most of these methods seem to be pretty complex for wireless sensor networks usually generating large amount of candidate pairs, all of which need to be verified by the similarity function. [87] applied the Euclidean distance and cosine distance to reduce the packet size and minimize the data redundancy of cluster-based underwater wireless sensor networks.

III. DATA AGGREGATION – OUR APPROACH

In this section we present our approach for data aggregation in sensor networks. We consider the same tree based network adopted in previous chapter, where sensed data needs to be aggregated on the way to their final destination. Sensor nodes collect information from the region of interest and send it to aggregators. The aggregators can either be special (more powerful) nodes or regular sensors nodes, or mobile agents like robots that traverse the region of interest and collect the data sets. Each aggregator then condenses the data prior to sending it. Our data aggregation method works in two phases, the first one at the nodes level, which we call local aggregation and the second at the aggregators' level. At each period *p* each node sends its aggregated data set to its proper aggregator which subsequently aggregates all data sets coming from different sensor nodes and sends them to the sink.

A. Local aggregation

In periodic sensor networks, we consider that each sensor node i at each slot s takes a new measurement y_{is}. Then node i forms a new set of captured measurements M_i with period p, and sends it to the aggregator. It is likely that a sensor node takes the same (or very similar) measurements several times especially when s is too short. In this phase of aggregation, we are interested in identifying locally duplicate data measurements in order to reduce the size of the set M_i. Therefore, to identify the similarity between two measures, we provide the two following definitions:

Definition V.1: link function

We define the link function between two measurements as:

$$\text{link}(y_{is1}, y_{is2}) = \begin{cases} 1 \text{ if } ||y_{is1} - y_{is2}|| \leq \delta \\ 0 \text{ otherwise.} \end{cases} \quad 1)$$

Where δ is a threshold fixed by the application.

Definition V.2: Measure's frequency

The frequency of a measurement y_{is} is defined as the number of the subsequent occurrence of the same or similar (according to the link function) measurements in the same set. It is represented by $\mathbf{f}(y_{is})$.

Using the notations defined above we present the local aggregation algorithm which is run by the nodes themselves (see Algorithm V.1). For each new sensed measurement (at each slot), a sensor node i searches for similarities of the new taken value. If a similar measurement is found, it deletes the new one while incrementing the corresponding frequency by 1.

Algorithm V.1: Aggregation at the nodes level.

Require: New measure y_{isk}, set of previous measures M_i.

Ensure: searching for similarities in M_i.

1: **for** every measure $y_{isl} \in M_i$ **do**

2: **if** ($link_{is}$ (y_{isk} , y_{isl}) = 1 **then**

3: f (y_{isl}) ← f (y_{isl}) + 1

4: delete y_{isk}

5: **else**

6: add y_{isk} to the set M_i

7: f (y_{isk}) ← 1

8: **end if**

9: **end for**

At the end of the period *p*, each node *i* possesses a local aggregated set M_i. The second step is to send it to the aggregator which in his turn aggregates the data sets coming from different sensor nodes.

B. Aggregation using similarity functions

At this level of aggregation, each aggregator has received k sets of measurements and their frequencies. The idea here is to identify all pairs of sets whose similarities are above a given threshold t. For this reason we use a similarity function which measures the degree of similarity between the two sets and returns a value in [0, 1]. A higher similarity value indicates that the sets are more similar. Thus we can treat pairs of sets with high similarity value as duplicates and reduce the size of the final data set that will be sent to the sink.

I. Similarity Functions

A variety of similarity functions have been used in the literature such as overlap threshold, Jaccard similarity and Cosine similarity [84–86]. We denote $|M_i|$ as the number of elements (measures) in the set M_i . The following functions can be used to measure the similarity between two sets of measurements M_i and M_j :

Overlap similarity: $O(Mi , Mj) = |Mi \cap Mj|$

Jaccard similarity: $J(M_i , M_j) = \frac{|M_i \cap M_j|}{|M_i \cup M_j|}$

Cosine similarity: $C(M_i, M_j) = \frac{|M_i \cap M_j|}{\sqrt{|M_i| * |M_j|}}$

Dice similarity: $J(M_i, M_j) = \frac{2*|M_i \cap M_j|}{|M_i| + |M_j|}$

All these functions are commutative and can be transformed to the Overlap similarity easily. For instance, we can present the Jaccard similarity function as follows:

$$J(Mi, Mj) = \frac{|Mi \cap Mj|}{|Mi \cup Mj|} = \frac{O(Mi, Mj)}{|Mi| + |Mj| - O(Mi, Mj)}, where\ O(Mi, Mj) = |Mi \cap Mj|$$

In our approach, we will focus on the Jaccard similarity. It is one of the most widely accepted functions because it can support many other similarity functions [85]. In our application, two given sets M_i and M_j are considered similar if and only if:

$$J(Mi, Mj) \geq t$$

where t is a threshold given by the application itself. This equation can be transformed as:

$$J(Mi, Mj) \geq t \Leftrightarrow O(Mi, Mj) \geq \alpha \quad (1)$$

where $\alpha = \frac{t}{1+t}(|Mi| + |Mj|)$

In order to study the similarity functions for data aggregation in sensor networks, we define a new function for overlapping "∩s " between two sets of measurements as follows:

Definition V.3: Overlap function

Consider two sets of measurements M_1 and M_2, then we define:

$M_1 \cap_S M_2 = \{(y_1, y_2) \in M_1 \times M_2 / \ link(y_1, y_2) = 1\}$; *and* $O_S(M_1, M_2) = |M_1 \cap_S M_2|$.

For instance, we consider the following example:

Example1:

Consider 2 sets of measurements:

$$M_1 = \{y_{11}, y_{12}, y_{13}, y_{14}, y_{15}\}$$

$$M_2 = \{y_{21}, y_{22}, y_{23}, y_{24}, y_{25}\}$$

Such that:

$M_1 \cap_S M_2 = \{(y_{12}, y_{21}), (y_{13}, y_{22}), (y_{14}, y_{23}), (y_{15}, y_{24})\} \Rightarrow O_S(M1, M2) = 4$

To evaluate the similarity between two sets we obtain:

$$J(Mi, Mj) \geq t \Leftrightarrow |Mi \cap s\ Mj| \geq \alpha = \frac{t}{1+t}(|Mi| + |Mj|) \quad (2)$$

II. Sets similarity computation

In this section we provide techniques for computing the similarity between the received sets. A naïve solution to find all similar sets is to enumerate and compare every pair of sets as shown in algorithm V.2. This method is obviously prohibitively expensive for large data sets (such the case of sensor networks), as total number of comparison is $O(n^2)$.

Algorithm V.3: Naïve method for similarity computation.

Require: Set of measures' sets $M = \{M1, M2 \ldots Mn\}$, and a threshold t.

Ensure: All pairs of sets (Mi, Mj), such that $J(Mi, Mj) \geq t$.

1: $S \leftarrow \emptyset$
2: **for** i=2 to n **do**
3: **for** j=1 to i-1 **do**
4: **if** $O_s(M_i, M_j) \geq \alpha$ **then**
5: $(S \leftarrow \{(M_i, M_j)\})$
6: **End if**
7: **End for**
8: **End for**
9: Return S

To reduce the number of comparisons between sets, a prefix filtering method has been proposed. Several approaches for traditional similarity join between sets are based on the prefix filtering principle [84] [86] [9]. This method is based on the intuition that if

all sets of measures are sorted by a global ordering, some fragments of them must share several common tokens with each other in order to meet the threshold similarity. An inverted index maps a given measurement m to a list of identifiers of sets that contain m_i such that $\mathrm{link}(m_i, m) = 1$. After inverted indices for all measures in the set are built, we can scan each one, probe the indices using every measure in the set M, and obtain a set of candidates; merging these candidates together gives us their actual overlap with the current set M; final results can be extracted by removing sets whose overlap with M is less than $\lceil \frac{t}{1+t}(|Mi| + |Mj|) \rceil$ (Equation 1).

This intuition is formalized by the following Lemma inspired from [86]:

Lemma V.1:

Consider two sets of sensor measures M_i and M_j, such that their elements are ordered by a global defined ordering. Let the p-prefix be the first p elements of M_i. If $|M_i \cap_S M_j| \geq \alpha$, then the $(|M_i| - \alpha + 1)$-prefix of M_i and the $(|M_j| - \alpha + 1)$-prefix of M_j must share at least one element.

Proof: Lemma V.1 can be proven similarly to the lemma of page 6 in [86].

To ensure the prefix filtering based approach does not miss any similarity set result, as shown in Lemma V.1 we need a prefix of length $|M_i| - \lceil t.|M_i| \rceil + 1$ for every set M_i [9]. The algorithm for finding similarity sets based on prefix filtering technique is given in Algorithm V.3. It takes as input a collection of datasets coming from different sensor nodes already sorted according to a defined ordering. It scans sequentially each set M_i, selects the candidates that intersects with its prefix. Afterwards, M_i and all its candidates will be verified against the Jaccard similarity threshold to finally return the set of correct similar measurements sets.

Algorithm V.3: Prefix-filtering based algorithm.

Require: Set of measures' sets $M = \{M_1, M_2 \ldots M_n\}$, and a threshold t.

Ensure: All pairs of sets (M_i, M_j), such that $J(M_i, M_j) \geq t$.

1: $S \leftarrow \emptyset$

2: $I_i \leftarrow \emptyset$ $(1 \leq i \leq$ total number of measures)

3: **for** each set $M_i \in M$ **do**

4: $p \leftarrow |M_i| - \lceil t \times |M_i| \rceil + 1$

5: $X \leftarrow$ empty map from set id to int

6: **for** $k \leftarrow 1$ to p **do**

7: $w \leftarrow M_i[k]$

8: **if** (I_{ws} exists such that $link(w, w_s) = 1$) **then**

9: **for** each Measurement ($M_j[l]$), $f(M_j[l]) \in I_{ws}$ **do**

10: $X[M_j] \leftarrow X[M_j] + 1$

11: **end for**

12: $I_{ws} \leftarrow I_{ws} \cup \{M_i\}$

13: **else**

14: create I_w

15: $I_w \leftarrow I_w \cup \{M_i\}$

16: **end if**

17: **end for**

18: **for** each M_j such that $X[M_j] > 0$ **do**

19: **if** $O_s(M_i, M_j) \geq \alpha$ **then**

20: ($S \leftarrow \{(M_i, M_j)\}$)

21: **end if**

22: **end for**

23: **end for**

24: return S

Prefix filtering algorithm helps prune out unfeasible sets of measures, however, in practice the number of non-similar sets surviving after this technique is still quadratic growth [88]. Following the prefix filtering, many optimization methods [88] [89] were proposed to prune out further the unfeasible non-similar sets. A trade-off of these prefix filtering optimizations is that usually require more computational efforts which is unsuitable by heavy resources sensor networks. In our approach, we provide some optimizations for prefix filtering techniques based on measures frequency while taking into account this trade-off.

III. Frequency filtering approach

In this section, we present our frequency filtering method based on prefix extension. We begin by introducing some definitions and notations which will be the basis of what follows. In periodic sensor networks, two data sets are similar if their measurements overlap with each other, and especially the ones having *higher frequencies values*.

Definition V.4: Ordering O

We define an ordering O which arranges the measurements of a given set by the decreasing order of their frequencies.

For two similar measures m_i and m_j, such that $\text{link}(m_i, m_j) = 1$, we denote $f_{min}(m_i, m_j) = Min((f(m_i), \text{f}(m_j))$ the minimum value of the frequency of these measures.

Definition V.5: $fs(Mi, Mj)$

Consider two sets of measures $\mathbf{M_i}$ and $\mathbf{M_j}$, we define

$$fs(Mi, Mj) = \sum_{k=1}^{Os(Mi,Mj)} (fmin\left((m_i, m_j) \in Mi \cap_s Mj\right))$$

In this chapter, we consider that all sensor nodes operate with the same sampling rate, and every node captures τ measures with each period p. Thus we can deduce that for every received set $\mathbf{M_i}$ from node i we have: $\sum_{k=1}^{|M_i|}(f(m_k \in M_i) = \tau$

Using the Jaccard similarity function, two sets $\mathbf{M_i}$ and $\mathbf{M_j}$ are similar if and only if:

$$\mathbf{O_S}(\mathbf{M_i}, \mathbf{M_j}) \geq \alpha \text{ where } \alpha = \frac{t}{1+t}(|Mi| + |Mj|) \quad (2)$$

Supposing that the sets were sent to the aggregators without applying the first aggregation phase and without computing measures frequencies, thus we can observe that:

$$|\mathbf{M_i}| = |\mathbf{M_j}| = \tau \text{ and } \mathbf{f_S}(\mathbf{M_i}, \mathbf{M_j}) = \mathbf{O_S}(\mathbf{M_i}, \mathbf{M_j}). \quad (3)$$

Hence, from Equation (2) and Equation (3) we can deduce that:

$\mathbf{M_i}$ and $\mathbf{M_j}$ are similar iff:

$$fs(Mi, Mj) \geq \frac{2 \times t \times \tau}{1+t} \quad (4)$$

IV. Frequency filter principle

Lemma1 states that the prefixes of two sets of measures must share at least one measure in order to satisfy the prefix filtering condition (P F C). Nevertheless, in sensor networks this condition is easily satisfied. In this section, we will present an extension of the prefix filtering technique making the P F C condition more difficult to be satisfied.

***Lemma V.2*:**

Assume that all the measures in the sets $\mathbf{M_i}$ and $\mathbf{M_j}$ are ordered according to the global ordering O. Let the p-prefix be the first p elements of $\mathbf{M_i}$:

$$If\ fs(Mi, Mj) \geq \frac{2 \times t \times \tau}{1+t},$$

$$Then\ fs(r-Mi, r-Mj) \geq \frac{2 \times t \times \tau}{1+t} - \sum_{k=1}^{|p-Mj|} (f(mk \in p-Mj))$$

Proof:

We denote by p-$\mathbf{M_i}$ the prefix of the set $\mathbf{M_i}$ and r-$\mathbf{M_i}$ the set of reminder measures where $\mathbf{M_i} = \{\text{p-}\mathbf{M_i} + \text{r-}\mathbf{M_i}\}$. We have:

$$fs(Mi, Mj) = fs(p-Mi, Mj) + fs(r-Mi, Mj)$$

$$= fs(p-Mi, p-Mj) + fs(p-Mi, r-Mj) + fs(r-Mi, Mj)$$

$$\cong fs(p-Mi, p-Mj) + fs(r-Mi, Mj)$$

$$\cong fs(p-Mi, p-Mj) + fs(r-Mi, p-Mj) + fs(r-Mi, r-Mj)$$

$$\leq fs(p-Mi, p-Mj) + fs(r-Mi, r-Mj)$$

$$\leq fs(p-Mi, p-Mj) + \sum_{k=1}^{|r-Mi|} (f(m_k \in r-Mi))$$

In the second line we can omit the term $\mathbf{f_S}$ (p-$\mathbf{M_i}$, r-$\mathbf{M_j}$) because we have assumed that it is negligible compared to the other terms in the equation. Indeed, if the two sets are

similar then the measures having highest frequencies must be in the prefix set and not in the remainder, which means that the overlapping between the p-$\mathbf{M_i}$ and $\mathbf{r}$-$\mathbf{M_j}$ is almost empty. From the above equations and equation (4) (similarity condition) we can deduce:

$$\mathrm{fs}(\mathrm{p}-\mathrm{Mi},\mathrm{p}-\mathrm{Mj})+\sum_{\mathrm{k}=1}^{|\mathrm{r}-\mathrm{Mi}|}(\mathrm{f}(\mathrm{m_k}\in\mathrm{r}-\mathrm{Mi}))\geq\frac{2\times t\times\tau}{1+t} \quad (5)$$

From the following equation:

$$\sum_{k=1}^{|p-Mi|}(f(mk\in p-Mi))+\sum_{\mathrm{k}=1}^{|\mathrm{r}-\mathrm{Mi}|}(\mathrm{f}(\mathrm{m_k}\in\mathrm{r}-\mathrm{Mi}))=\tau \quad (6)$$

We obtain:

$$\mathrm{fs}(\mathrm{p}-\mathrm{Mi},\mathrm{p}-\mathrm{Mj})\geq\sum_{k=1}^{|p-Mi|}\big(f(mk\in p-Mi)\big)-\frac{1-t}{1+t}*\tau \quad (7)$$

The lemma is proved.

Algorithm V.2 describes our method to find similar sets of measures based on the frequency filtering approach. It is a hybrid solution, where we integrate our frequency condition presented in Lemma V.2 to the prefix filtering approach presented in Algorithm V.1.

V. Jaccard similarity computation

Although filtering approaches reduce the number of comparisons between the received sets of measures, the number of candidate sets surviving after this phase is still non negligible. Furthermore, the computation of the Jaccard similarity between two candidates' sets can be very complex, especially when it comes to sensor networks where measures' sets can have ten hundreds or thousands elements. Therefore, to continue filtering out further candidate sets we propose a new frequency filtering constraint in the verification phase. By applying this, we can also reduce the overhead of the Jaccard similarity computation.

Algorithm V.2: Frequency-filtering based algorithm.

Require: Set of measures' sets $\mathrm{M}=\{\mathrm{M1},\mathrm{M2}\ldots\mathbf{Mn}\}$, t, τ.

Ensure: All pairs of sets ($\mathbf{M_i}$, $\mathbf{M_j}$), such that $\mathbf{J}(\mathbf{M_i},\mathbf{M_j})\geq\mathbf{t}$.

1: Replace line 5 in Algorithm V.1 with

2: F s ← empty map from set id to int

3: sumF req ← 0

4: **for** k ← 1 to p **do**

5: sumF req ← sumF req + $\mathbf{f}(\mathbf{m_k} \in \text{p-M}_\mathbf{i})$

6: **end for**

7: Replace line 10 in Algorithm 1 with

8: F s[$\mathbf{M_j}$] ← F s[$\mathbf{M_j}$] + $\mathbf{fmin}$ ($\mathbf{M_i}$ [k], $\mathbf{M_j}$ [l])

9: Replace line 18 in Algorithm V.1 with

10: **for** each $\mathbf{M_j}$ such that F s[$\mathbf{M_j}$] > sumF req − $\frac{1-t}{1+t} * \tau$ **do**

Assume that we want to compute the similarity between two sets $\mathbf{M_i}$ and $\mathbf{M_j}$. Then, these sets are similar if they satisfy the overlap condition $fs(Mi, Mj) \geq \frac{2\times t\times \tau}{1+t}$. We also assume that a measure $m \in \mathbf{M_i}$ divides $\mathbf{M_i}$ into two partitions: one partition containing all the measures having frequencies higher than $\mathbf{f}(m)$ including m denoted by h-$\mathbf{M_i}$ and the second l-$\mathbf{M_i}$ containing all the measures having frequencies less than $\mathbf{f}(m)$. Similarly, we assume that any measure in $\mathbf{M_j}$ divides it in two partitions h-$\mathbf{M_j}$ and l-$\mathbf{M_j}$. The idea of dividing the sets is to find a measure where at this position a similarity upper bound is estimated and checked against the similarity threshold. As soon as the check fails we can stop the overlap computing early. This hypothesis is formalized by the following lemma:

Lemma V.3:

Assume that $|\mathbf{M_i}| < |\mathbf{M_j}|$ and all measures in $\mathbf{M_i}$ are ordered according to the global ordering O. $\mathbf{M_i}$ and $\mathbf{M_j}$ are similar ⇒ for any $m \in \mathbf{M_i}$ dividing $\mathbf{M_i}$ into h-M_i and l-$\mathbf{M_i}$ we have:

$$fs(h-Mi, Mj) \geq \frac{2\times t\times \tau}{1+t} - \sum_{k=1}^{|l-Mi|} \big(f(mk \in l-Mi)\big).$$

Proof. $\mathbf{M_i}$ and $\mathbf{M_j}$ are similar

$$\Rightarrow fs(Mi, Mj) \geq \frac{2\times t\times \tau}{1+t} \quad (8)$$

$$\Rightarrow fs(h - Mi, Mj) + fs(l - Mi, Mj) \geq \frac{2\times t\times \tau}{1+t} \quad (9)$$

$$\Rightarrow fs(h - Mi, Mj) \geq \frac{2\times t\times \tau}{1+t} - fs(l - Mi, Mj) \quad (10)$$

Then we have:

$$fs(l - Mi, Mj) \leq \min\left(\sum_{k=1}^{|l-Mi|}\big(f(mk \in l - Mi)\big), \sum_{k=1}^{|Mj|}\big(f(mk)\big)\right) \quad (11)$$

$$\leq \min\left(\sum_{k=1}^{|l-Mi|}\big(f(mk \in l - Mi)\big), \tau\right) \quad (12)$$

$$\leq \min \sum_{k=1}^{|l-Mi|}\big(f(mk \in l - Mi)\big) \quad (13)$$

From equations (10) and (13) we can deduce that:

$$fs(h - Mi, Mj) \geq \frac{2 \times t \times \tau}{1 + t} - \sum_{k=1}^{|l-Mi|}\big(f(mk \in l - Mi)\big)$$

The lemma is proved.

The algorithm of overlap computation is given in Algorithm V.3

Algorithm V.3: Overlap Computation.

Require: Two sets of measures $\mathbf{M_i}$ and $\mathbf{M_j}$, t, τ .

Ensure: $\mathbf{O_S}$ ($\mathbf{M_i}$, $\mathbf{M_j}$).

1: $\mathbf{O_S} \leftarrow 0$

2: Consider $|\mathbf{M_i}| < |\mathbf{M_j}|$

3: $\mathbf{sumFreqH} \leftarrow 0$

4: $\mathbf{sumFreql} \leftarrow \tau$

5: $\mathbf{M_j} \leftarrow \mathbf{sort}(\mathbf{M_j}, |\mathbf{M_j}|)$ $\mathbf{M_j}$ is sorted in increasing order of the measures

6: **for** k $\leftarrow$ 0 to $|\mathbf{M_i}|$ **do**

7: $\mathbf{sumFreql} \leftarrow \mathbf{sumFreql} - \mathbf{f}(\mathbf{M_i}[k])$

8: Search similar of $\mathbf{M_i}$ [k] in $\mathbf{M_j}$

9: find $\mathbf{M_j}$ [l]/$\mathbf{link}(\mathbf{M_i}$ [k], $\mathbf{M_j}$ [l]) = 1

10: $\mathbf{sumFreqH} \leftarrow \mathbf{sumFreqH} + \mathbf{fmin}\,(\mathbf{M_i}[k], \mathbf{M_j}[l])$

11: **if** $\mathrm{sumFreqH} \geq \frac{2\times t\times \tau}{1+t}\mathrm{sumFreql}$ **then**

12: $O_S \leftarrow O_S + 1$

13: **else**

14: Return $-\infty$

15: **end if**

16: **end for**

17: Return O_S

In this algorithm, we used two kinds of measures ordering depending on the sets sizes. The first one according to the global ordering O (M_i in the above algorithm) and the second is sorted in increasing order of the measures to accelerate a measure search.

IV. EXPERIMENTAL RESULTS

To validate the approach presented in this chapter, we developed a custom C# based simulator. The objective is to confirm that our prefix filtering technique (PFF) can successfully achieve intended results for data aggregation in sensor networks with random distribution of sensor nodes. We performed experiments on the same real sensor data measurements used in previous chapter. We exploited data collected from 46 sensors deployed in the Intel Berkeley Research lab. Mica2Dot sensors with weather boards collected timestamped topology information, along with humidity, temperature, light and voltage values once every 31 seconds. Data was collected using the TinyDB in-network query processing system, built on the TinyOS platform. In our experiments, we used a file that includes a log of about 2.3 million readings collected from these sensors. Temperature is in degrees Celsius. Humidity is temperature corrected relative humidity, ranging from 0-100%. Light is in Lux. Voltage is expressed in volts [47]. In our experiments, we are interested in two sensors measurements: the temperature and the humidity fields since the variation is more frequent than the light and the voltage. Each node reads an average of 1600 measurements per day and per field. The sensor readings are generated based on intervals. According the variation of measurements, we choose to

vary the threshold delta between 0.01 and 0.07. All the results presented below are the average of 7 days readings.

A. Local aggregation

In these series of simulations, we computed the percentage of the measurements sent by the nodes to the aggregators after local aggregation. The results are shown in Figure V.1. We noted the number of the measurements sent by the nodes to the aggregators after local aggregation. The size of the set contains also the values of the frequencies of each measurement. We considered that the size of each frequency value is equal to the size of a sensor reading. In one day, the 46 sensor nodes collect around 8.0*E* + 4 measurements by field. It is well noticed that the size of data improves strongly depending on the threshold δ. It decreases when δ increases.

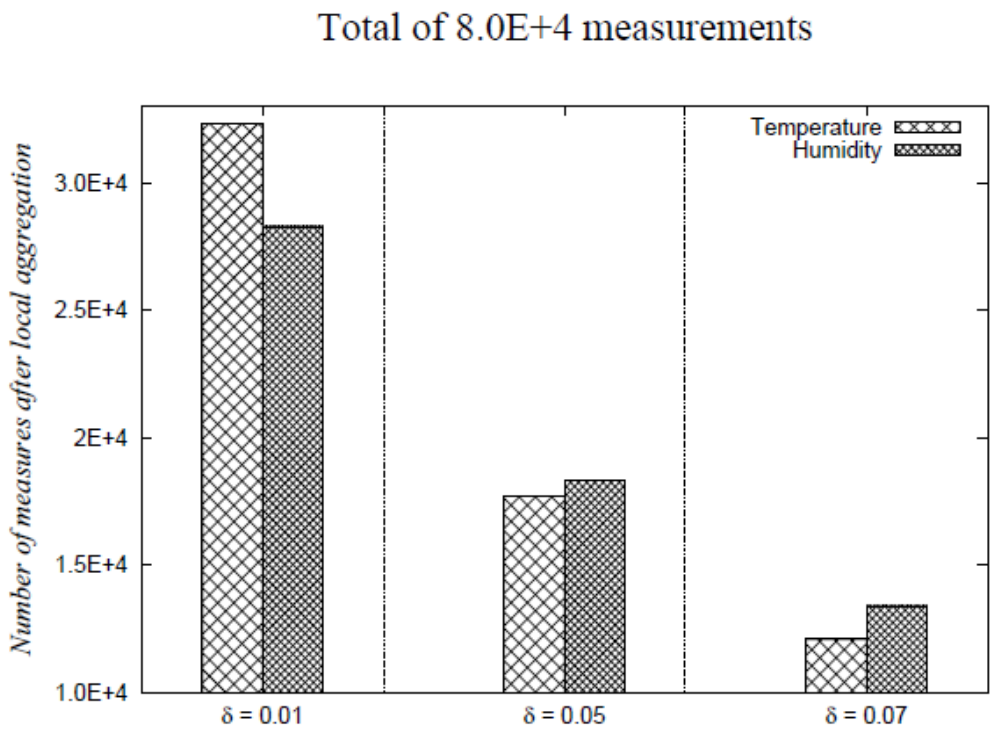


Figure V.1 Percentage of total data sent to the aggregator

B. Aggregation using PFF technique

In this section we show the impact of our frequency filtering technique on data aggregation in sensor networks. As before, we calculated the percentage of aggregated sets as well as the information integrity.

Figures V.2 to V.4 show the percentage of number of sets not sent to the sink depending on similarity and *link* thresholds that vary between 0.8 to 0.9 and between 0.01 to 0.07 respectively. For instance, we noticed that the size of the data set sent to the aggregator is reduced by around 30% in case of $\delta = 0.07$ and $t = 0.8$. The obtained results validated by real data measurements, show clearly the effectiveness of our filtering technique in finding and eliminating redundancy and comparing between two sets of data.

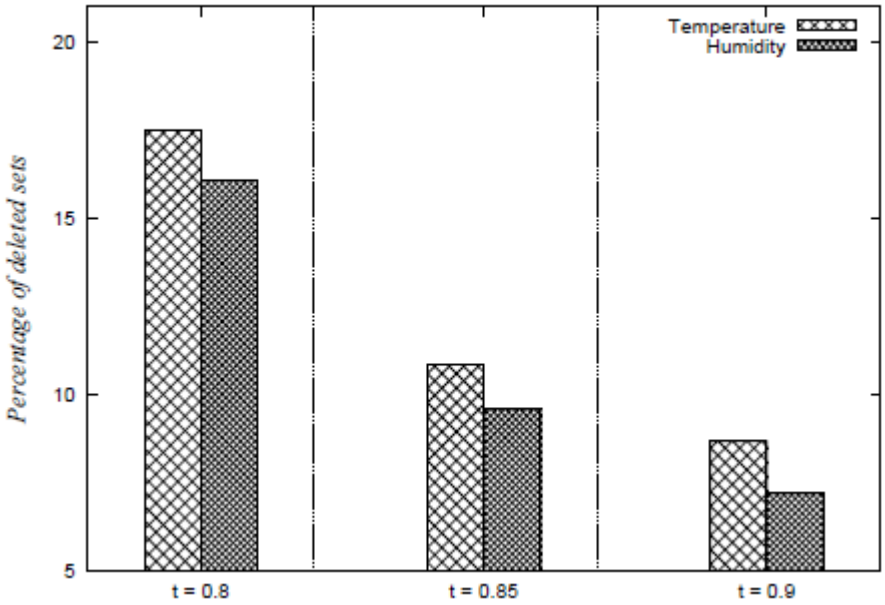


Figure V.2 Percentage of deleted sets, δ= 0.01

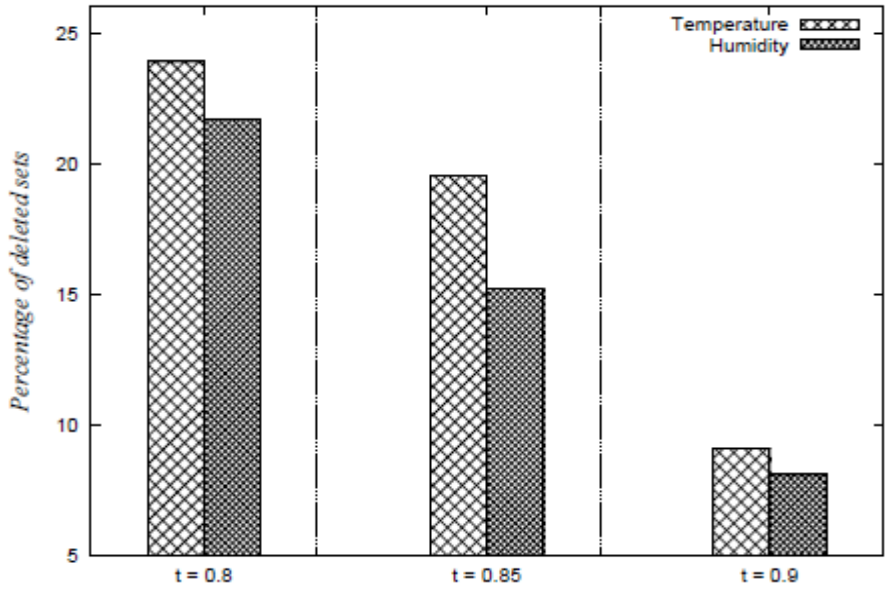


Figure V.3 Percentage of deleted sets, δ= 0.05

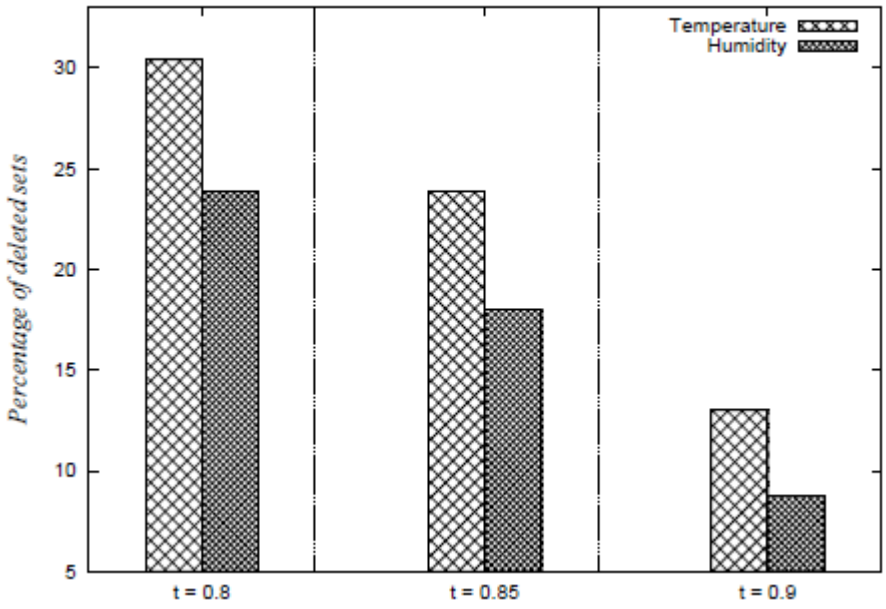


Figure V.4 Percentage of deleted sets, δ= 0.07

C. Data accuracy

We evaluate the impact of data accuracy by calculating the total number of measurements in sets not sent to the sink (the aggregation error). Figures V.5 to V.7 show the percentage of measurements not received by the sink. These results demonstrate clearly that our approach conserves the information integrity. Therefore, we can consider that our

approach decreases the amount of redundant data forwarded to the sink and performs an overall lossless process. In summary, the results obtained from real data sets of sensor reading were qualitatively similar to the one obtained from a random scheme of data measurements.

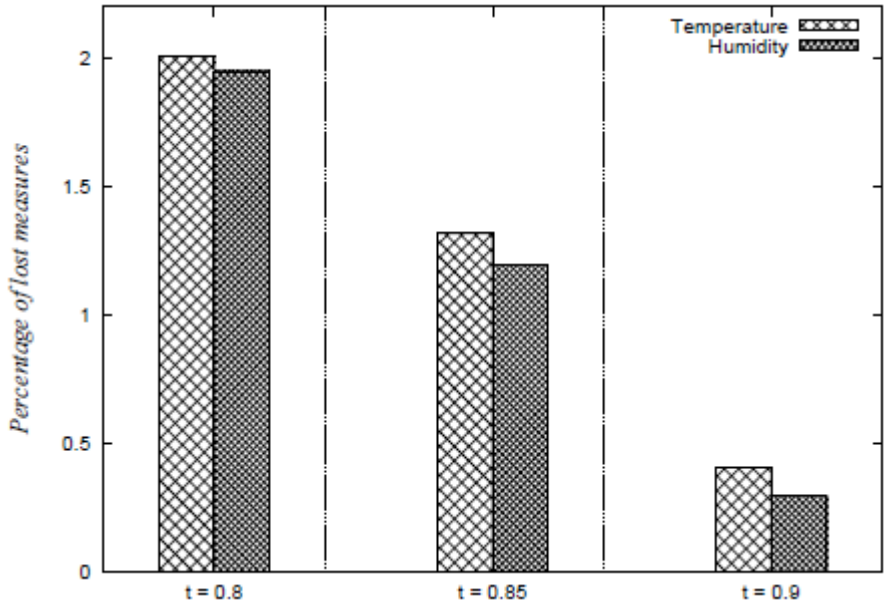


Figure V.5 Percentage of lost measures, δ= 0.01

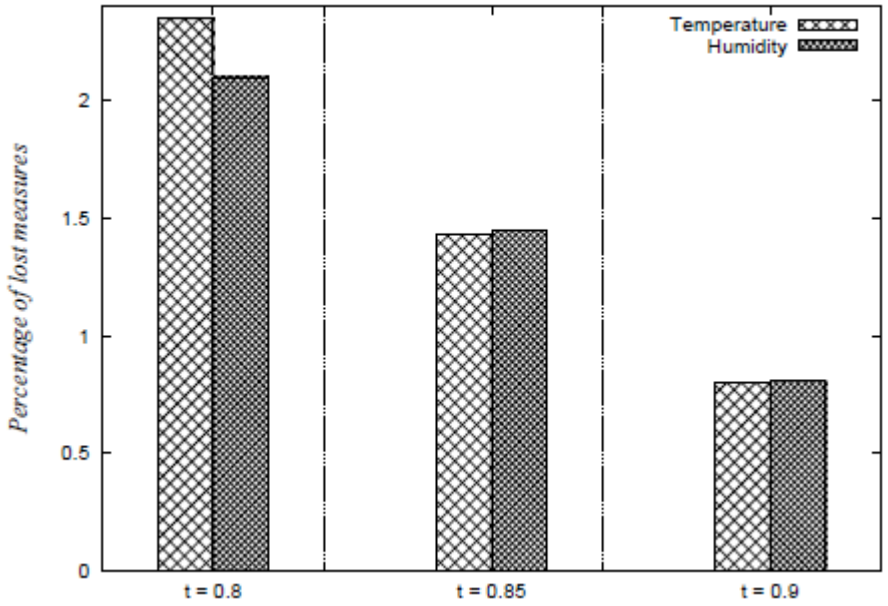


Figure V.6 Percentage of lost measures, δ= 0.05

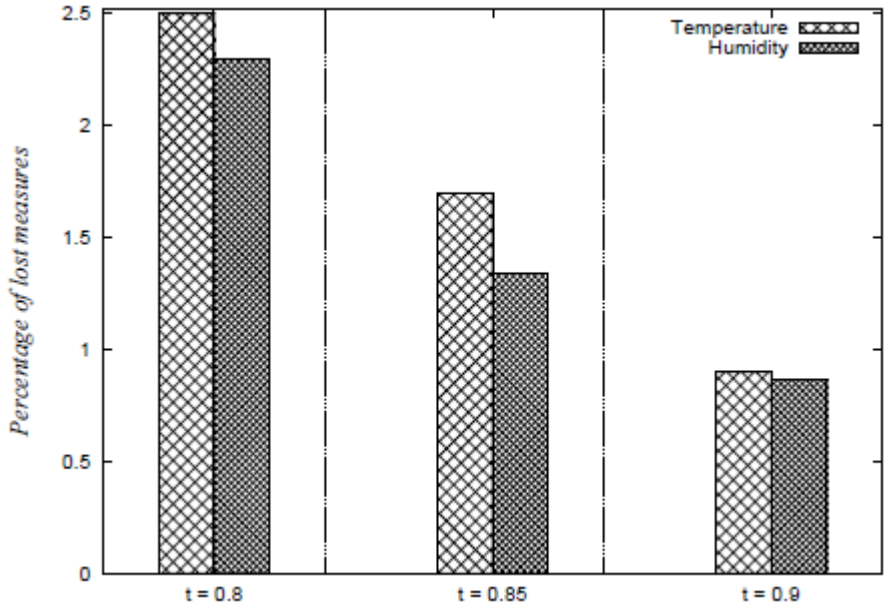


Figure V.7 Percentage of lost measures, δ= 0.07

D. PFF vs ToD aggregation protocols

In these experiments we compare our approach (PFF) to the ToD protocol proposed in [71, 90]. In ToD, the network is divided into square cells, where each cell can contain a number of sensor nodes. Then these cells are grouped into clusters called F-clusters (first cluster). All nodes in F-clusters send their data to F-aggregators (cluster heads). This structure is called F-tree. A second clustering layer (s-clusters) is built. It must interleave with F-clusters so it can cover adjacent cells in different F-clusters. In the ToD approach, the authors present data as events while in our simulations these data are sensor readings. Thus, we consider every new reading as an event-like [71].

As our real data sensor network consists of 46 nodes, we use ToD in a one dimensional Network as explained in [91] and we only divide the network into two F-cluster.

We evaluated the performance of the protocols using the following parameters: a) the number of sensor measurements taken by all nodes during a period τ, and b) the threshold of the Jaccard similarity function t. The threshold δ is fixed to 0.07. The aggregation function used for the ToD protocol is the same used in our approach (PFF) based on the link function (cf section III[A]). We employ four metrics in our simulations:

- The number of candidate sets generated after applying the prefix filtering approach [92], the frequency filtering algorithms with optimizations (PFF) and the final result (the real number of duplicate sets);
- Percentage of received measures: It represents how effective a protocol is in aggregating data. It is the number of measures received by the sink over the number of measures taken by all nodes;
- Data accuracy: represents the measures loss rate. It is an evaluation of measures taken by the source nodes which was not received at the base station (sink). It is defined also as the aggregation error;Overall energy dissipation: is the total energy dissipation of the entire network. To evaluate the energy consumption of our approach we used the same radio model as discussed in [93]. In this model, a radio dissipates Eelec = 50 nJ/bit to run the transmitter or receiver circuitry and βamp = 100 pj/bit/m2 for the transmitter amplifier. The radios have power control and can expend the minimum required energy to reach the intended recipients as well as they can be turned off to avoid receiving unintended transmissions. The equations used to calculate transmission costs and receiving costs for a k-bit messages and a distance d are respectively shown below in (3) and (4):

$$E_{TX}(\kappa, d) = E_{elec} * \kappa + \beta_{amp} * \kappa * d^2. \quad (3)$$

$$E_{RX}(\kappa, d) = E_{elec} * \kappa. \quad (4)$$

E. Percentage of received measures and data accuracy

Figure V.8, V.9 show the percentage of received measures over the total number taken by all nodes for the temperature field. These experiments permit to show how well aggregation protocols do aggregation and reduce redundant measures. PFF performs better than ToD in terms of data aggregation because of it is ability to compare sets of data instead of single packets. In other words, PFF reduces the number of redundant data traveling into the networks better than TOD especially when the number of readings increases (the case of periodic networks). We also notice that, the percentage of received packets remains almost unchangeable while increasing the sensor readings.

Figure V.10, V.11 depicts the results of the aggregation error for temperature and humidity fields respectively. This metric is an important performance index, and the high measures loss rate will impact the use of the data greatly. The obtained results show that the two protocols have good performance regarding the aggregation error. As expected, when we increase the threshold t of the similarity function we reduce the measures loss rate. For instance, we can notice that PFF outperforms ToD in terms of data accuracy for t = 0.9.

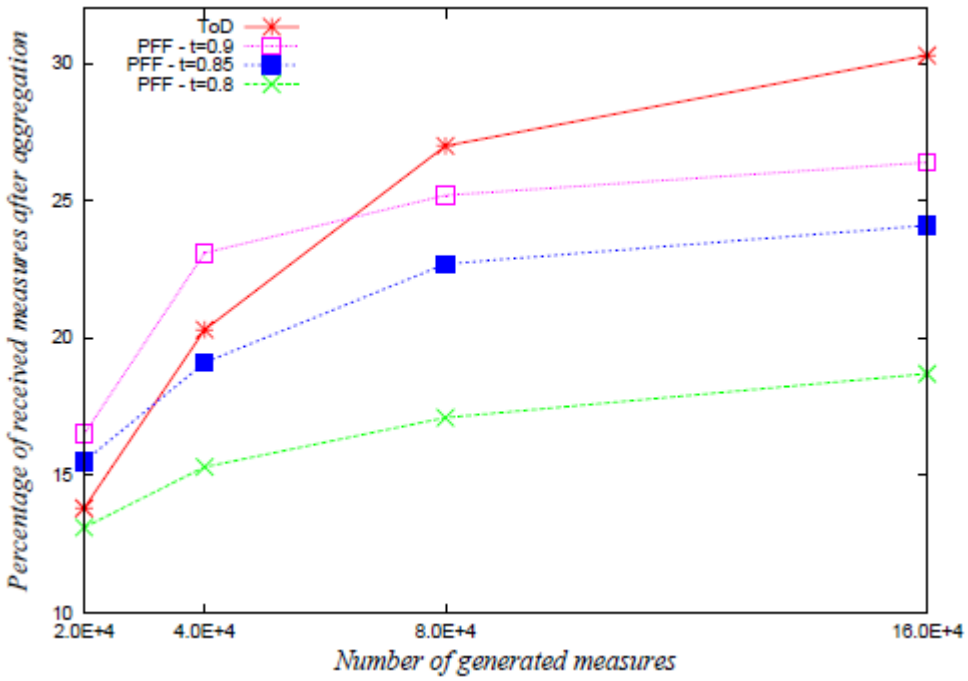


Figure V.8 Received Measure (Temperature)

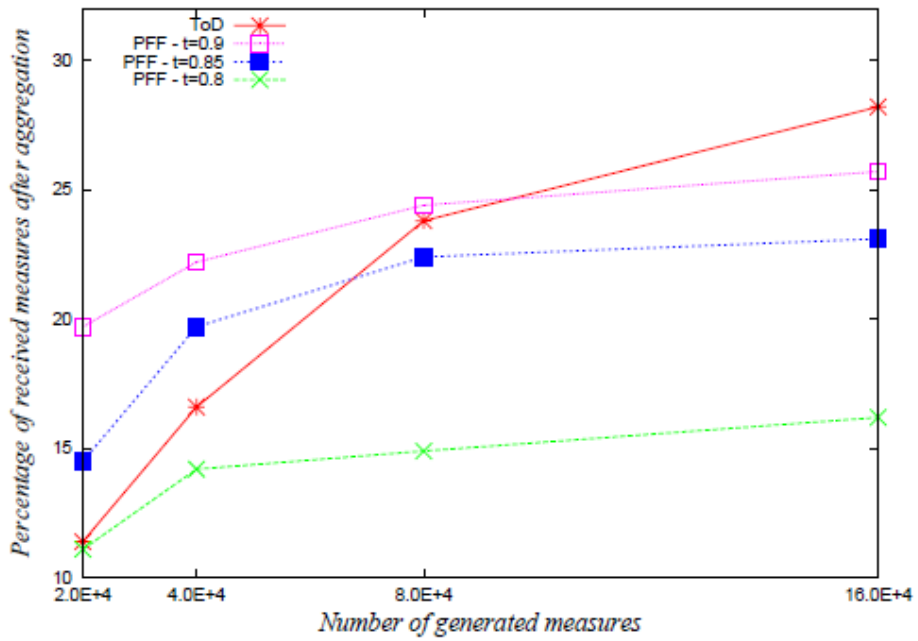


Figure V.9 Received Measure (Humidity)

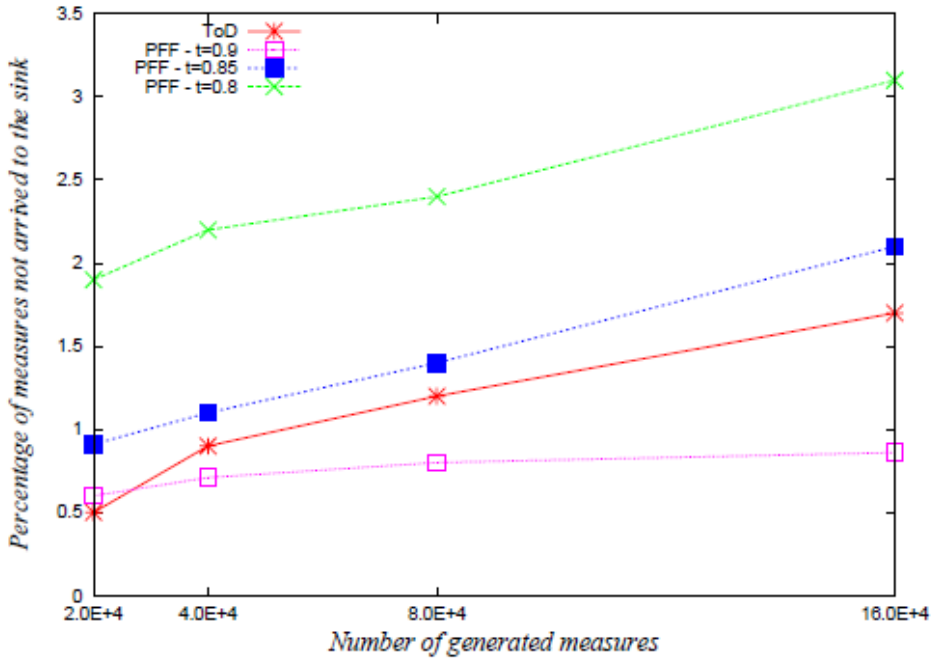


Figure V.10 Data accuracy (Temperature)

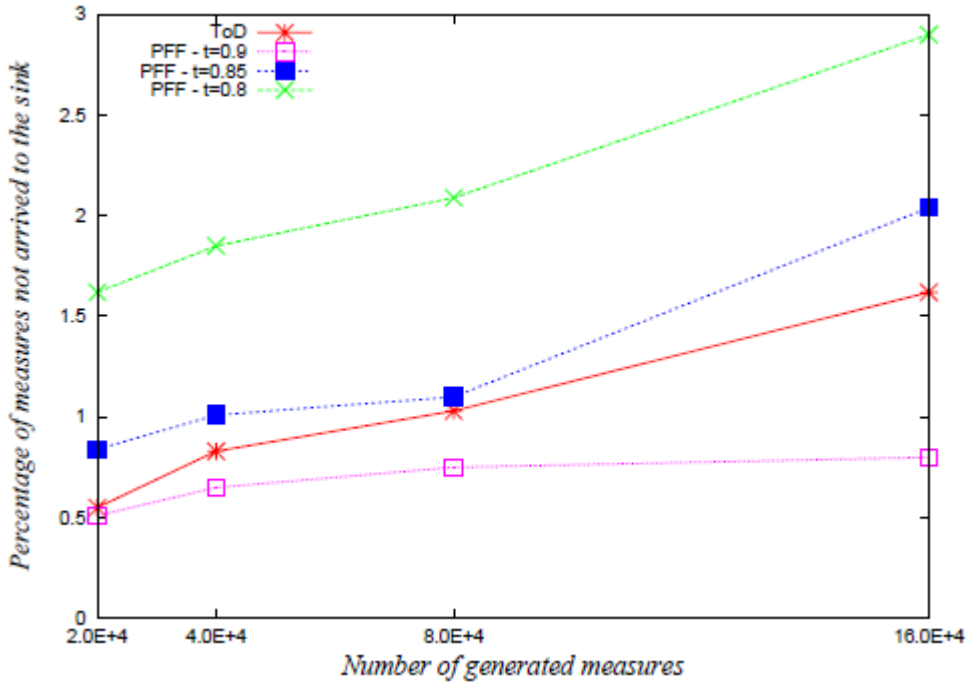


Figure V.11 Data accuracy (Humidity)

F. Overall energy dissipation

The overall energy dissipation is the total energy consumption of the entire network. Figure V.12. shows the results for total energy consumption obtained while varying the total number of sensor readings. The figure shows that the overall energy dissipation for different protocols increases as the number of readings increases. We notice that ToD consumesfairly, but does not scale well as the number of readings increases. For all the values of the threshold t tested, PFF always outperforms the ToD protocol in total energy dissipation. This is because, the packet-packet comparison used in ToD instead of data sets in PFF generates more transmissions in the network, and furthermore, the packet construction in ToD contains additional information required for the aggregation which is not the case in PFF. To conclude, PFF uses a factor of 1.5 to 2.5 less overall energy than ToD as shown in Figure V.12.

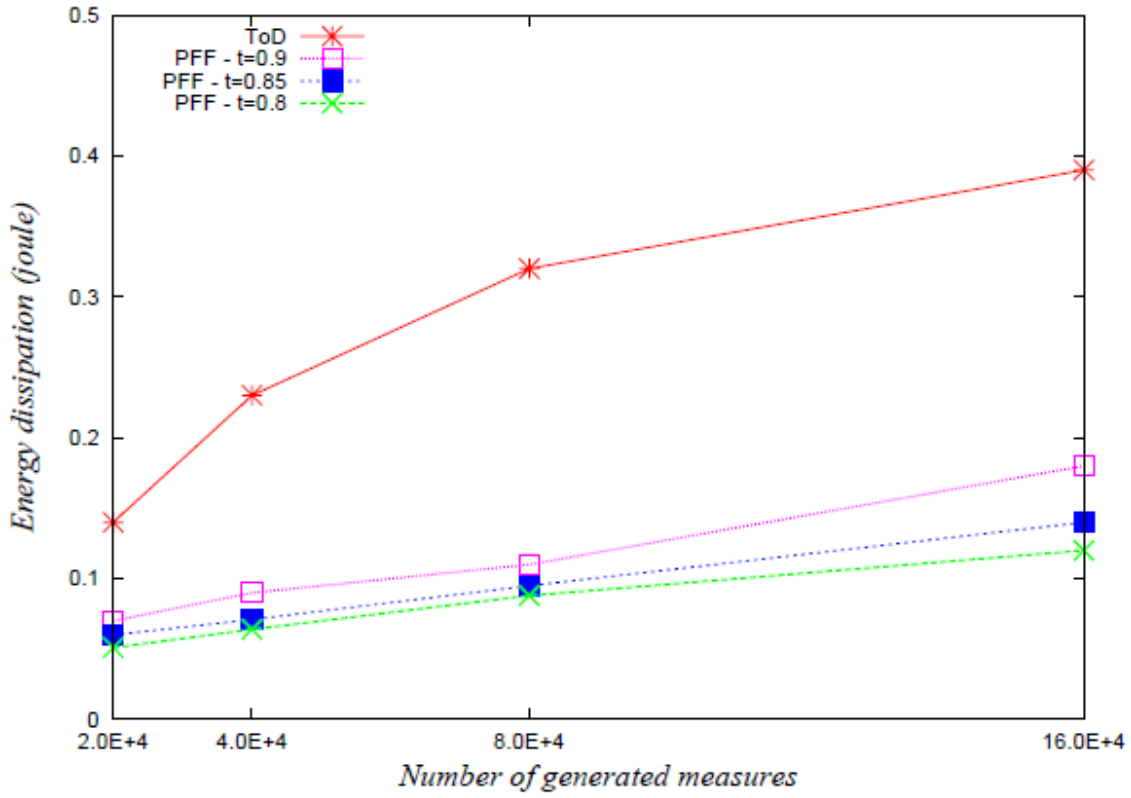


Figure V.12 Total energy dissipation

V. CONCLUSION

Data aggregation is a well-known technique to achieve energy efficiency, in wireless sensor networks, when propagating data from sensor nodes to the sink. The main idea behind is that rather than sending all captured data from sensors to the sink, multiple redundant data are aggregated as they are forwarded by the sensor network. In this chapter, we proposed a new method based on sets similarity functions and prefix filtering technique for data aggregation in periodic sensor networks. In periodic networks, nodes are likely to send multiple correlated data to the sink, thus causing the propagation of redundant information throughout the network which in turn leads to both a waste of energy resources and bandwidth, and increase in network congestion. The objective of our aggregation approach is to reduce the number of redundant data sent to the final user while preserving the data integrity. We have developed a new frequency based prefix filtering technique that avoids computing similarity values for all possible pairs of sets.

We used the Jaccard similarity function to estimate the similarity between sets of data measures. It was shown through simulations on real data measurements that the proposed method reduces drastically the redundant sensor measures while preserving information integrity. Therefore, it saves energy and improves the overall network lifetime.

Chapter VI Data Mining in periodic sensor networks: K-Means clustering

Tides of data captured by sensors networks represent a powerful resource for mining. Data mining is a perfect tool to analyze, categorize data and summarize the relationships identified. However, high computational cost imposed by data mining techniques as well as limitation existing in sensor networks in terms of energy and power constitute a major challenge.

At the same time, big data generated by periodic wireless sensor networks can't be easily mined. All of this has led to the development of new multilevel optimized version of a data mining algorithm named « k-means ». In this chapter we present an efficient prefix mining algorithm in periodic wireless sensor network, both from a statistical and computational point of view.

Periodic preprocessing algorithm based on prefix filtering technique is applied on big data generated by periodic sensor networks. Then a K-means optimization technique in terms of comparison and number of iterations is applied by exploiting prefix subsets of data. The main idea of this technique is to optimize the clustering of observations generated by periodic sensor networks into groups of related readings without any prior knowledge of the relationships between the prefixes sets. Simulations results are presented to validate the performance of the proposed approach.

I. INTRODUCTION

During last years, the main deal of interest reside in applying recognized unsuitability of traditional data warehousing and knowledge discovery methodologies within the challenges posed by sensor networks. Too much data overwhelm the WSN and effectively consume a lot of memory and power when transported. As already stated, it is well known that communicating messages over a sensor network consume far more

energy than processing it. These constraints should be respected by any technique that needs to be applied on the periodic sensor networks. It is therefore mandatory to user request while avoid sending all the data across the network. Thus we introduce the value of applying data mining algorithms on the sensor network.

With the rapidly increasing amount of data gathered over 3 years period, data mining is becoming an increasingly important tool to transform such data into information. Such mining practices are commonly used in a wide range of profiling practices, including marketing, surveillance, fraud detection and scientific discovery. Data mining is generally defined as the process of extracting patterns from data.

Data mining is often associated with analyzing large amounts of data, usually in the form of centralized database table, for useful and interesting information. The current limitation of data mining applications in sensor networks is that existing distributed data mining techniques impose heavy demands on computation and/or communication. Making data mining in sensor networks even more challenging by overcoming the individual sensor constraints of available energy for transmission, computational power, memory, and communications bandwidth undertaking efficiently the data mining process on the sensor network. Centralized data mining in sensor network and distributed data mining in sensor network are two interesting research fields. We summarize the advantages and the differences between the two approaches. The simplest approach is the use of a centralized architecture where a central server maintains a database of readings from all the sensors. The problem arises where the sensor networks is made of thousands of node, the number of messages sent in the system as well as the number of variables of the data mining task will be too large to be managed efficiently. A solution suggests the introduction of intermediary nodes (aggregators) having the capability to fuse the information from different sources before being transmitted along the network [94] [95]. On the other hand, heavy traffic over the limited bandwidth wireless channels will result from central collection of data from every sensor node which will drain a lot of power from the devices. A solution proposed by recent researches consist of a distributed data mining (DDM) approach that pays careful attention to the distributed resources of data, computing, and communication in order to consume them in a near optimal fashion. In such, distributed clustering methods, each sensor collects a set of data (measures) and

aims to design local clustering rules that perform at least as well as global ones which rely on all data being centrally available. However, transmitting the entire collected data to a centralized location consumes a lot of energy. This suggests the development of "in-network" clustering algorithms that only require exchanging information with one hop cluster head or aggregator to solve the unsupervised classification problem in a fully distributed manner. A popular iterative solution to the distributed clustering problem is the k-means algorithm [110]. The algorithm alternates between two major steps (assigning collected data to clusters and computing cluster centers) until a stopping criterion is satisfied.

Our thinking consist of a hierarchical architecture for data mining in periodic sensor network aiming to reduce the communication load and also reduce the battery power more evenly across the different nodes in the sensor network by introducing a preprocessing phase. In this chapter, our hierarchical data mining approach consists of integrating the data aggregation phase presented in previous chapter as a preprocessing step with the traditional k-means algorithm. We applied k-means on prefixes sets of collected data instead of all data sets. Our suggested approach is folded in two steps: the first one is the "pre-processing prefix frequency filtering technique" presented in chapter V, which ensures similar sets of data generated by neighboring nodes. In order to reduce the number of sets comparisons, for each set we compute a prefix subset based on its length and the threshold of a well-defined similarity function. At the second step, we exploit these prefixes to adapt a "k-means clustering, on the prefixes sets in order to cluster observations into groups of related observations without any prior knowledge of the relationships between the prefixes sets. Our main objective is to use solely subsets of data instead of using the whole collected data in a clustering k-means algorithm. In this chapter we design an efficient prefix mining algorithm in sensor network, both from a statistical and computational point of view. On the other hand, we will be addressing the energy problem in sensor network and the problem of mining big data generated sensor networks by mining prefix set of periodic data.

The rest of this chapter is organized as follows: section II gives an overview of related works reported on data mining and k-means clustering in sensor networks. We, then briefly describe k-means algorithm. The problem statement and the mining of prefix

item sets resulted from chapter V are also presented in this section. Simulation results are given in Section IV. Section V concludes the chapter.

II. RELATED RESEARCH

The deployment of data mining techniques in sensor networks is an open research problem. This section will include two parts: first part will present the works and limitations of applying the data mining techniques on a centralized architecture of WSN. The second part will explore the work related to distributed data mining techniques in WSN.

A. Centralized Approach: related research

Mining the large data repository generated by a sensor network for useful information is crucial and challenging. The simplest approach to analyze sensor network data makes use of a centralized architecture where a central server maintains a database of readings from all the sensors. The limitation of this approach appears when the sensor networks is made from thousands of nodes where the number of messages sent in the system as well as the number of variables of the data mining task are too large to be managed efficiently.

Another important issue is that routing may be based on data centric. Such routing, the interest dissemination is performed to assign the sensing tasks to the sensor nodes. The data aggregation is a technique used to solve the implosion and overlap problems in data centric routing [79]. In this technique, a sensor network is usually perceived as a reverse multicast tree where the sink asks the sensor nodes to report the ambient condition of the phenomena. Data coming from multiple sensor nodes are aggregated as if they are about the same attribute of the phenomenon when they reach the same routing node on the way back to the sink. Data aggregation can be perceived as a set of automated methods of combining the data that comes from many sensor nodes into a set of meaningful information [79]. With this respect, data aggregation is known as data fusion [79]. Also, care must be taken when aggregating data, because the specifics of the data, e.g., the locations of reporting sensor nodes, should not be left out.

This solution, however, consumes too much energy because the data volume can be extremely large. A good method should require little data transmission, but still achieves information extraction from the large amount of data distributed across the network. An alternative consists of aggregating systems where the data obtained from different source nodes can be aggregated before being transmitted along the network [101]. Intermediary nodes having capability to fuse the information from different sources are integrated as aggregator in the system. [100] proposes a two layer topology of a sensor network made of a lower level whose task is to organize the sensors in clusters, compress their signals and transmit the aggregate information in the upper level playing the role of a data mining server which uses the aggregate information to carry out the required sensing task. The data mining architecture proposed the Lazy Learning algorithm which is a supervised learning technique. [100] deems that this algorithm is a promising tool in the sensor network context. This algorithm on a query-by-query basis, tunes the number of neighbors using a local cross-validation criterion. In his paper, [100] advocates the idea that the structure of the processing architecture of a sensor network must take into account also criteria related to the accuracy and quality of the data mining task. This means that the organization of the same sensor network may change according to the type of sensing task (e.g. classification or prediction) and the required quality and precision.

[58] considers a very important data mining problem: outlier detection, which defines a process to identify data points that are very different from the rest of the data based on a certain measure. In his paper, [104] consider the problem of finding two types of distance-based outliers in sensor networks. He proposed to use a histogram method to extract hints about the data distribution from the sensor network. The histogram information can help filter out the non-outliers and identify the potential outliers within a certain range. Those potential data ranges can be further refined with more histogram information or identified by individual check. The histogram method reduces the communication cost dramatically versus the centralized scheme. On the other hand, [116] proposes in-network clustering algorithm to detect outlier values and classify them to either noisy data or interesting event in the physical environment.

Other algorithms adopted for in-sensor-network has been developed within the artificial neural-networks tradition [102] [117] where the application demands compressed summaries of large spatio-temporal sensor data and similarity queries, such as detecting correlations and finding similar patterns. Unsupervised learning Artificial Neural Networks such as ART class algorithm typically perform dimensionality reduction or pattern clustering. They are able to discover both regularities and irregularities in the redundant input data by using an iterative process of adjusting weights of interconnections between a large numbers of simple computational units (called artificial neurons). As a result of the dimensionality reduction which is easily obtained from the outputs of these algorithms, lower communication costs leading to considerable energy savings can also be achieved. As a consequence of its stability-plasticity property, the network is capable of learning "on-line", i.e. refining its learned categories in response to a stream of new input patterns, as opposed to being trained "off-line" on a finite training set. Because of its computational advantages, complement coding is used in nearly all ART applications. The strengths of the ART models include its unique ability to solve a stability-plasticity dilemma, extremely short training times in the fast-learning mode, and an incrementally growing number of clusters based on the variations in the input data. The network runs entirely autonomously; it does not need any outside control, it can learn and classify at the same time, provides fast access to match results, and is designed to work with infinite stream of data. All these features make it an excellent choice for application in wireless sensor networks. A neural network algorithm can be implemented in the tiny platform of Smart-It units, which are kind of sensor nodes or motes. Instead of reporting the raw-data, each Smart-It unit can send only the cluster number where the current sensory input pattern has been classified. In that way a huge dimensionality reduction can be achieved depending on the number of sensor inputs in each unit. In the same time communication savings will benefit from the fact that the cluster number is a small binary number unlike sensory readings which can be several bytes long real numbers converted from the analog inputs. The uses of limited resources together with the distributed nature of the sensor-networks has lead also to distributed algorithmic solution for data clustering.

B. Distributed approach: Related Research

With their own processing power, the sensors become active devices allowing the possibility to implement distributed algorithms in a network of sensors. One application is the distributed stream mining system Vedas [97] by Kargupta et al., which monitors data streams obtained in moving vehicles before reporting them to a base. More recently, Banyopadhyay et al. [96] introduced a distributed clustering algorithm based on the k-means clustering algorithm in a peer to peer environment. We briefly discuss classical K-means clustering for readers not familiar with the problem.

K-means clustering: Simply put clustering, is the grouping of similar objects (data points) in a way that minimizes intra-cluster dissimilarity while maximizing inter cluster dissimilarity. K-means clustering is a classical clustering technique where K, the number of clusters, is fixed a priori. The goal is to divide the objects into K clusters minimizing the sum of the average distances to the centroids over all clusters. Finding an optimal clustering is hard (NPcomplete), so the most common approach is to employ an iterative, greedy search as described below:

1. Place K points randomly. These represent the initial cluster centroids.
2. Assign each point to the closest centroid.
3. Recalculate the positions of each centroid (the average of all data points assigned).
4. Repeat Steps 2 and 3 until the centroids do not change. The assignment of points to the final centroids forms the clustering.

Hence, [101] shows that distributed clustering algorithms based on artificial neural networks, seem useful for mining sensor-network data or data steam. An exact local algorithm for majority Voting which is always guaranteed to terminate with precisely the same result that would have be found by a centralized algorithm, show how it can be used as a primitive for monitoring a K-means clustering [106].

Although these algorithms achieve exact solutions eventually, they are limited to problems which can be reduced to threshold predicates. For example it is very difficult (perhaps impossible) to develop an exact local algorithm to compute the mean of a set of

numbers distributed over the network, but not so for evaluating whether the mean lies above a threshold. In light of this, some data mining problems are very difficult, perhaps impossible, to solve with exact local algorithms – in particular, K-means clustering. Following this, an approximate local algorithm offering an approximate solution for incrementally computing a K-means clustering has been developed in [113][114]. The algorithm is initiated with a set of randomly chosen starting centroids distributed over all peers. In each iteration, each peer runs a two-step process. The first step is identical to one iteration of standard K-means where the peer assigns each of its own point to its nearest of k cluster-centroids. In the second step, peer sends a poll message, consisting its id and current iteration number to its immediate neighbors and waits for their responses. Each response message from a neighboring peer contains the locally updated centroids and cluster counts of that peer for the iteration.

[76] proposes a framework for building and deploying predictors in sensor networks that pushes most of the work out to the sensors themselves. [76] Consider only the hubbed sensor networks where the network structure is a tree. In this technique each sensor may collect only a single attribute. A target class is associated with each global reading; for training data, there is a further column containing these target classes. After deployment, the goal is to predict the target class for each global reading. So at the end, each sensor builds a local predictor that predicts the target class based only on the attribute(s) available to it locally. At the root, local predictions are combined using weighted or unweight voting. The network is a tree, with a powerful computation device at the root, and sensors, with limited power, processing, and memory capabilities at the leaves. The bandwidth in the network is a scarce resource, in part because transmission by the sensors consumes power. In this overall approach, the variations depends on the predictive technique being used either it required access to all of the training data at once like decision tree or it requires only one reading at a time like neutral networks. In both cases, sensors must have enough memory to store the model itself and to hold the entire training data for its input attributes. [76] proves that the overall classification accuracy for both the simple and the weighted voting scheme is a good or better than that of the centralized data mining approach. In this approach each sensor learns a local predictive model for the global target classes. Only the predicted target class for each reading is then

transmitted to the root, which determines the appropriate prediction by voting the target classes of the local predictors. The prerequisite of this approach is that the target class prediction should be predefined otherwise this approach is not valid.

Other research related to the distributed data mining introduced the collective data mining[6] where the framework is constituted by the fact that the function to be learned by the data mining algorithm, can be expressed as a sum of basic functions and their corresponding coefficients. By using such technique, the sum is only approximated and the computation is expensive on the sensor. Since it is approximate calculation, this puts an upper boundary on the accuracy that can be achieved.

The existing distributed data mining techniques in sensor networks impose heavy demands on computation and/or communication. We are not aware of previous work that specifically addresses the prefix filtering to mine large item sets problem. Our idea is to reduce the size of data to be mined without losing the main information through our hierarchical approach.

III. PREFIX K-MEANS IN SENSOR NETWORKS

Data mining algorithms are designed for the relational data model. That is why the existing works consider homogeneous schemata containing same set of attributes across different sites. Typically the same algorithm operates on each distributed data site concurrently, producing one local model per site. Subsequently all local models are aggregated to produce the final model. The success of data mining algorithms lies in the aggregation. Each local model represents locally coherent patterns, but lacks details that may be required to induce globally meaningful knowledge. For this reason, many data mining algorithms required a centralization of a subset of local data to compensate it. Therefore, minimum data transfer is another key attribute of the successful data mining algorithm. Our approach consists of considering each sensor as a data site. A feature selection algorithm will first be applied on each data site resulting by minimizing the set of attributes existing in each sensor and producing a local model per site. The main idea of feature selection is to eliminate useless and redundant features. The learning process is then accelerated and the accuracy of learning algorithms may be improved [110].

All the presented work didn't take into consideration the accuracy of the information affected by the number of similarity between measures. Our approach starts with a preprocessing phase that uses the approach presented in chapter V.

In this chapter we shall focus on mining the prefix item sets resulted from the preprocessing phase since such scheme will form an optimized training set for the classifier, predicting with reasonable accuracy the class of each instance fed. However, in data mining the task of finding frequent pattern(FP) in large databases is very important but is computationally expensive, especially when a large number of patterns exist with different set size of attribute. Han & al. [76] propose an FP growth algorithm which use an extended prefix-tree structure for storing compressed and crucial information about frequent patterns named frequent-pattern tree (FP_Tree). In his study, Han proved that his method outperforms other popular methods for mining frequent patterns, e.g. the Apriori Algorithm and the TreeProjection [77]. However the FP growth is expensive to build in terms of CPU and time.

Our work considers a three level tree-based representative network. The first level is the sensor node level where data captured and cleaned on a periodic basis then sent to the aggregator. At the second level, each aggregator condenses the data sets based on prefix frequency filtering technique [9], prior to apply our k-means prefix mining. Our aim is to use the prefix of the frequent item sets collected from the first step as the optimization key for the generation of frequent pattern based on the structure generated on the level of the aggregators as shown in Figure.VI.3.

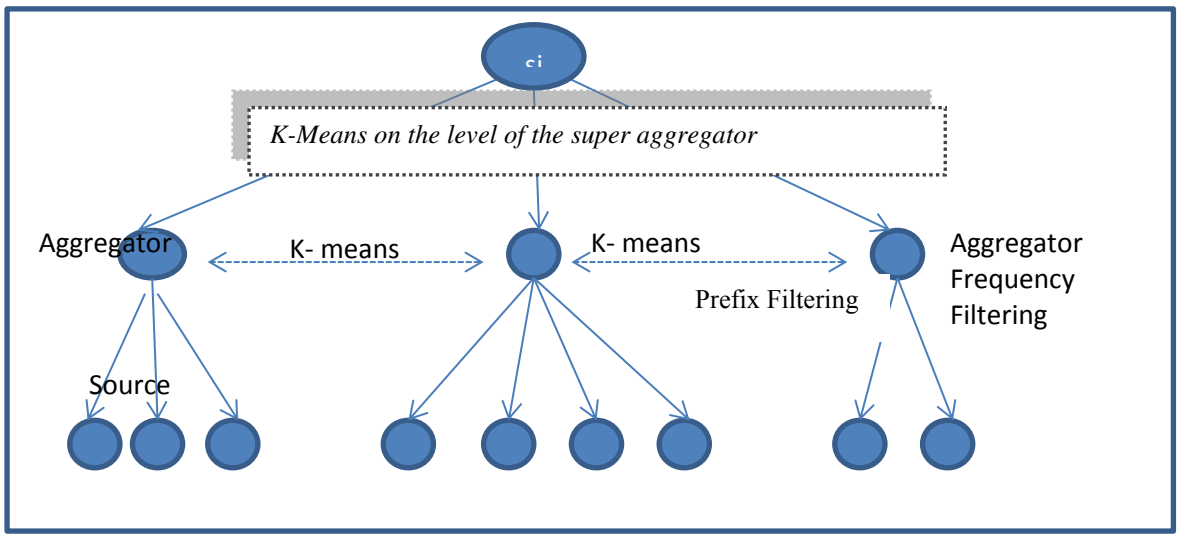


Figure.VI.1 K-Mining similar prefix sets in wsn

A. The k-Means algorithm:

Definition VI.1: K-means

Classifying or grouping data based on attributes/ features into k number of groups is called k-means. k is a positive integer number based on which the number of clusters are defined. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid.

K Means recall

The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early grouping is done. At this point we need to re-calculate k new centroids as barycenter of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be applied between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their

location step by step until no more changes are done. In other words centroids do not move any more.

The steps of the K-means algorithm are presented below.

K-means recall

1: Determine the centroid coordinate by placing K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
2: Assign each object to the group that has the closest centroid according to the minimum distance.
3: When all objects have been assigned, recalculate the positions of the K centroids.
4: Iterate Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

Although it can be proved that the procedure will always terminate, the k-means algorithm does not necessarily find the most optimal configuration, corresponding to the global objective function minimum. The algorithm is also significantly sensitive to the initial randomly selected cluster centers. The k-means algorithm can be run multiple times to reduce this effect. K-means is a simple algorithm that has been adapted to many problem domains.

B. Our algorithm: The prefix set k-means technique

The existing work done in k-means doesn't take into consideration the computational time in periodic sensor networks. Our aim is to respect the constraint imposed by the sensor network and to minimize the computational time for online clustering. The preprocessing phase based on the prefix filtering approach applied in chapterV will output the all pairs of sets (Mi, Mj). This output will be taken as input in our K-means algorithm.

Definitions and Notations

In this section we will introduce some definitions and notations that will be used in our approach.

Definition VI.2: Measure's frequency f

The frequency of a measure is defined as the number of subsequent occurrence of the same similar measurements in the same set.

Definition VI.3: Aggregator of Set AM

We define AM, aggregator of sets as the Union of all sets received by an Aggregator such that for all similar measures between those sets we keep the sum of their frequencies.

Definition VI.4: Means of Set

We define AM_i as means of a set M_i the average of measures existing in the set M_i.

$A M_i = \frac{\sum_{k=1}^{n} m_k}{n}$ such that n is the number of elements

Definition VI.5: General Similarity function

We will use as follows a generalization of the distance of Manhattan to check the similarity between the pairs of set generated by each aggregator:

$$d(i, j) = \sum | AM_i - AM_j |$$

Definition VI.6: Average absolute deviation between pairs of sets:

The average absolute deviation function of pairs of sets is defined by the function Sf as follows:

$$Sf = \frac{1}{n} \sum_{i=1}^{n} | AM_i - m_f |$$

such that

$$m_f = \frac{1}{n} \sum | AM_i - AM_j |).$$

Definition VI.7: Standardization of pairs of sets

The standard function of sets AM_i is defined by the function z_{if} as follows:

$$z_{if} = \frac{AM_i - m_f}{s_f}$$

In a nutshell, we generalize the prefix defined in our previous chapter by the following lemma VI.1.

Lemma VI.1:

Consider two aggregators of sets of sensor measures AM_i and AM_j, such that their elements are ordered by a global defined ordering. Let the p-prefix be the first p elements of AM_i. If $|AM_i \cap_S AM_j| \geq \alpha$, then the $(|AM_i| - \alpha + 1)$-prefix of AM_i and the $(A|M_j| - \alpha + 1)$-prefix of AM_j must share at least one element.

Proof:
The Lemma can be proven similarly to the lemma1 in [8].

This method is based on the intuition that if all sets of measures are sorted by a global ordering, some fragments of them must share several common behaviors with each other in order to meet the threshold similarity and belong to the same cluster. Therefore, the prefix will consist of the most reliable data since it is extracted based on global frequency ordering. This leads us to think of working on the prefix set instead of the whole set. An inverted index maps a given measurement to a list of identifiers of sets that contains mi such that link $(m_i, m) = 1$. After inverted indices for all measures in the set are built, we can scan each one, probe the indices using every measure in the set M, and obtain a set of candidates; Adapting K-Means on these candidates in order to group them together in the same cluster gives us their actual overlap with the current set M; final results can be extracted by clustering all sets. K-means will be adapted then to be

applied on the similar prefix sets results of detecting and aggregating multiple data sets generated by different neighboring nodes instead of applying it on the whole set of data.

C. K-means algorithm on the level of the super-aggregators:

Using the functions defined above we present a new technique of k-means applied on the prefix pairs of sets preprocessed after applying prefix frequency filtering described in Chapter V. This technique is run by one aggregator introduced on the top of all aggregators (algorithm VI.1).

Similar sets are extracted based on the prefix frequency filtering already presented in chapter V which will constitute the preprocessing step of the K means. AM is then constructed on the level of each aggregator as per definition6 where frequency of the similar sets are added to the non-similar sets. Each aggregator will then send AM to the super-aggregator where the K-means is applied as per algorithm1. At the end of the k-means clustering algorithm applied on the prefixes sets we have clustered similar sensor node into groups of related sensed data. Sensor Nodes belonging to the same cluster means that they will generate similar set of data. Using this hypothesis, the network life cycle will be optimized by applying algorithmVI.1.

Algorithm VI.1: k- means on prefix pairs of set

Require: Set of measures' sets AM = {AM_1 , AM_2 ...AM_n }and a number of k random centroids

1: Get prefix of all pairs of sets (AM_i, AM_j) results in different aggregator as per LemmaVI.1.
2: Extract similar sets existing in AM based on the frequency filtering algorithmVI.1
3: Standardization of pairs of sets by calculating AS_f
4: Compute the minimum distance of Manhattan between the means of the prefix pairs of sets.
5: Assign each prefix to the group that has the closest centroid according to the minimum distance between the means.

6: When all objects have been assigned, recalculate the positions of the K centroids.

7: Reiterate steps 5 and 6 until the centroids no longer move. This produces a separation of the prefix pairs of sets into groups of set that will be sent to an aggregator introduced on the top.

Example:

Before standardization we have A1 is more similar to A_2 then A_3.

After standardization we will have the following: A_1 is more similar to AM_3 then AM_2. This means that AM_1 and AM_3 will be in the same cluster subsequently all sensors belonging to AM_1 and AM_3 will behave the same.

	MeansAgg-temp	MeansAgg-Humidity
Agg1	50	11000
Agg2	70	11100
Agg3	60	11122
Agg4	60	11074

d(AM1,AM2)=120

d(AM1,AM3)=132

Conclusion:
AM1 more similar to AM2 then AM3

	MeansAgg-temp	MeansAgg-Humidity
Agg1	-2	-0.5
Agg2	2	0.175
Agg3	0	0.324
Agg4	0	0

Conclusion:
AM1 more similar to AM3 then AM2

d(AM1,AM2)=4,675

d(AM1,AM3)=2,324

Figure VI.2 K-means example

Since the frequency of information for each item sets is preserved through the whole path and clusters of nodes containing prefix sets of data with the same target category are identified, predictions for new data items can be made by assuming they are of the same type as the nearest cluster center. This has two fold benefits:

1. Instead of sending the data to the sink we can send only the predicted result.

2. Instead of having all sensors turned on at the same time and since sensors belonging to the same cluster behave the same, only 1 sensor can be turned on till his battery reach 90%. At this stage the sensor will send its data to the aggregator tagged with an order to its neighbor to start capturing data.This way, lifetime of the sensor network is prolonged and energy is optimized. To proof the above algorithms, experimentations have been conducted in the section below.

IV. EXPERIMENTAL RESULTS

To validate the approach presented in this chapter, we checked k-means on existing datamining software, "tanagra" [109] then we develop our own simulator that implement our suggested algorithm of K-means. We aim at proofing that the result received on the similar prefix item sets leads to same results as applying k-means on the whole set. We study the threshold of data loss when applying k-means on the similar prefix set as well as the performance of the new customized K-means. First of all we ran our program on the same real set of data used in previous chapter collected from 46 sensors deployed in the Intel Berkeley Research Lab [47] where every 31 seconds, sensors with weather boards were collecting humidity, temperature, light and voltage values. In our experiments, we are interested in two sensors measurements: the temperature and the humidity. Each node reads an average of 83000 values of each measurement per day and per field. Then we ran our program on the result sets extract in [9] from the same readings collected that we worked on in the first simulation.

A. Sensors Distribution in clusters.

In order to validate our approach we checked the distribution of sensors measures over the clusters. FigureVI.3 and figureVI.4 show the distribution of sensors on the level of the different clusters based on the variation of delta. Sensors belonging to the same cluster will have same behavior. The experimental results shows clearly between figure VI.3 and figure VI.5 that almost same source node distribution is obtained when applying K-means on the whole set versus when applying it on the prefix set after PFF when delta =0.07. This proof the efficiency of our approach based on the intuition that since all measures are sorted based on the global ordering, several common tokens are

shared. The major information that can be extracted from this dataset are reflected in the prefix. To add also that figureVI.3 and figureVI.4 shows clearly that we don't have the same number of node in all clusters which opens up a new horizon leading to check the best algorithm to adopt regarding the optimal delta to choose. Another window of research can also tackle the energy load balancing subject among sensor nodes within the same cluster by taking a decision which sensor node to turn off and which one to turn on since we should not lose the operation of any cluster and we should have the maximum information accuracy.

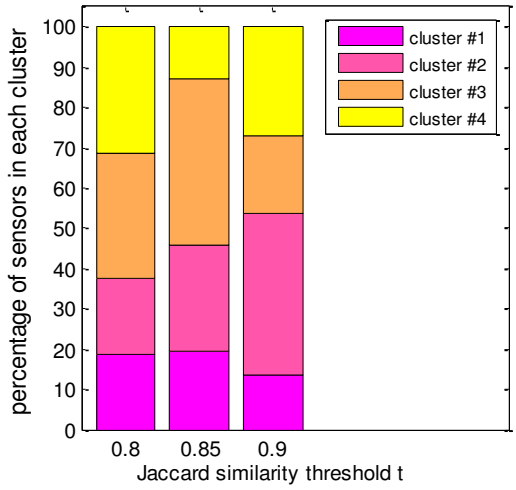


Figure VI.3 Distribution of sensors in clusters, day= 1, delta=0.07

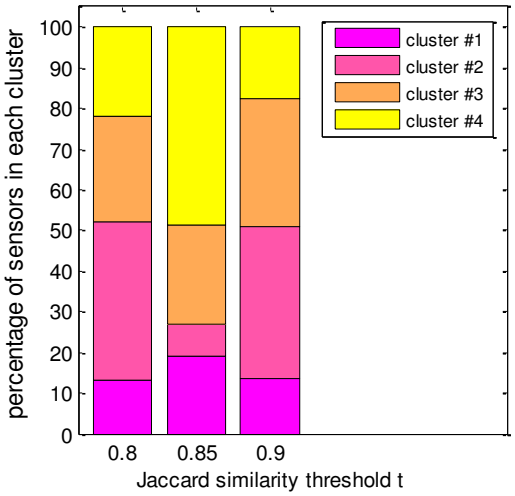


Figure VI.4 Distribution of sensors in clusters, day= 1, delta=0.1

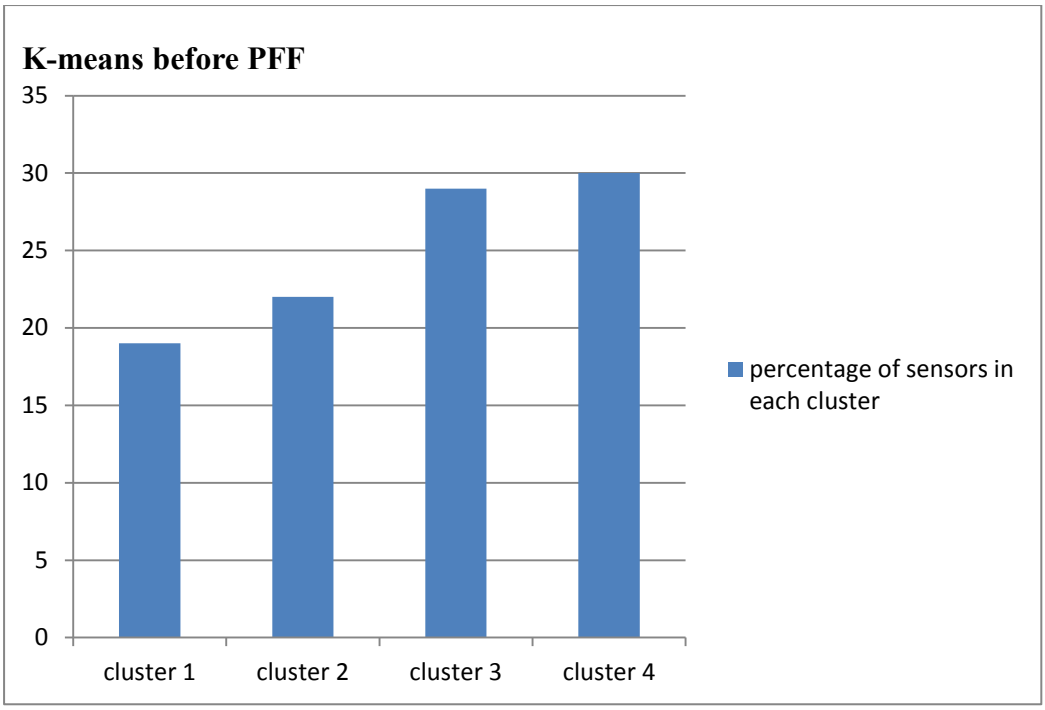


Figure VI.5 Distribution of measurements in clusters based on K-means on data source

B. Energy Consumption

Our aim is to proof that our algorithm is valid in terms of optimization of the energy consumption by decreasing the number of packets sent to the sink. We ran the k-means on the sets results from the preprocessing steps based on the prefix filtering approach versus the original K-means on the data source. Same as in previous chapters, we choose to vary the threshold delta between 0.07 and 0.1. We compared the similarity between k-means on data source and K-means after prefix frequency filtering algorithm at the local aggregator level during 4 consecutive day where each day consist of all measures collected by each sensor in the network. As shown in figureVI.6 and figureVI.7. We reached almost 68% similarities which mean that we can eliminate around 68% of the sets when delta =0.07 and t=0.8. It is well noticed that the size of data improves strongly depending on the threshold *t.* It decreases when *t* increases. For instance, when delta =0.07 and threshold t=0.85 we are reaching of an average of 20 % of similarity which will lead to the optimization of 20% of the total energy consumed on the level of the network.

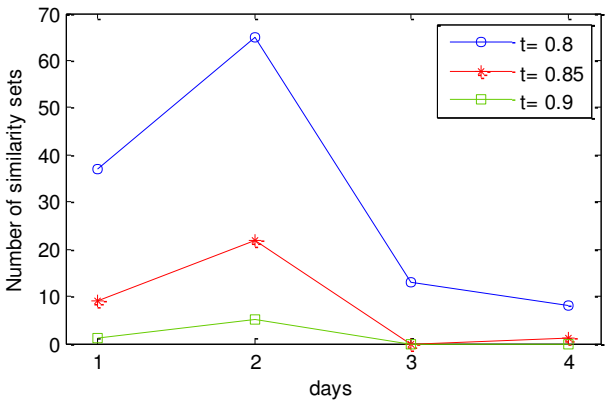


Figure VI.6 Similarity sets, delta=0.07

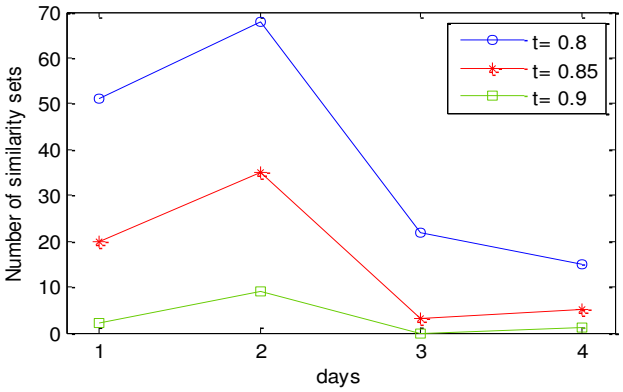


Figure VI.7 Similarity sets, delta=0.1

C. Data Accuracy

Data accuracy is also calculated by checking the percentage of data loss not sent at all to the sink taking into consideration the delta variation. As shown in figureVI.9 and figureVI.8 the percentage of loss measurements after aggregation can be neglected. This means that applying K-means on the prefix set will lead to same data integrity as applying it on the whole set.

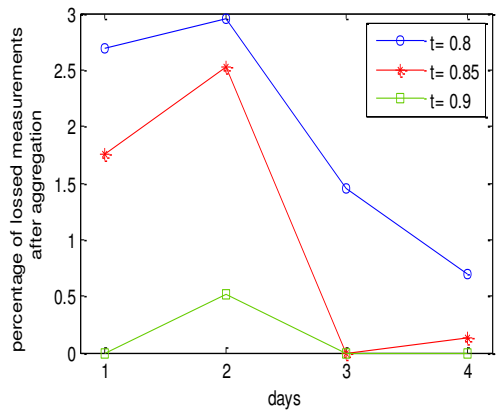


Figure VI.8 Data accuracy, delta=0.07

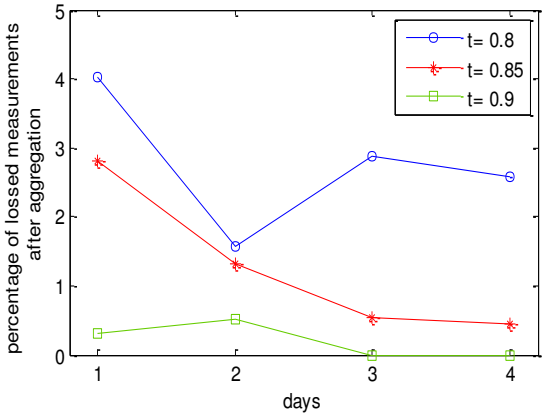


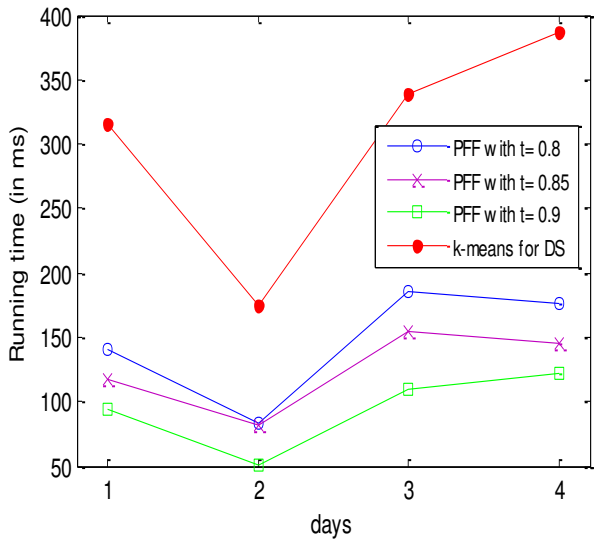
Figure VI.9 Data accuracy, delta=0.1

D. Performance of the prefix K-means

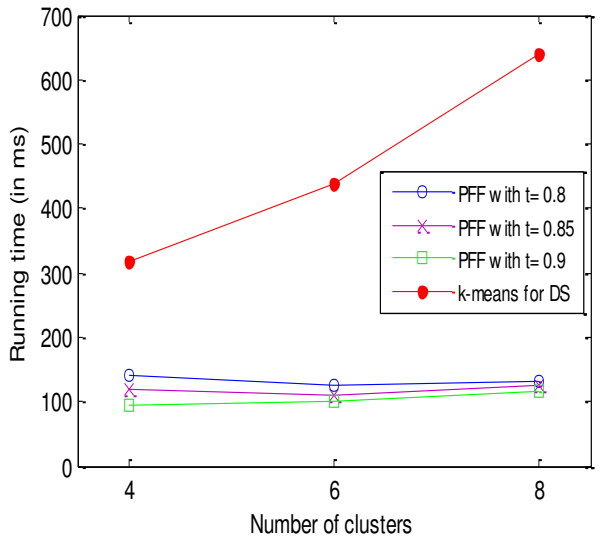
The performance of K-means is measured based on two factors: Running Time and Number of iterations.

1. Running time

Running time is also calculated and it showed us that K-means applied on the preprocessed data is highly performing thus running time is decreased by 30% as per figureVI.10 and figureVI.11. In effect, it is very normal to obtain such results since the data source is minimized in terms of size.



FigureVI.10 Running time, k= 4, delta=0.07



FigureVI.11 Running time, day= 1, delta=0.07

2. Number of iterations

The performance of the mining algorithm is also increased when applying k-means on the prefix sets only since the number of iterations is decreased by at least 40% as shown in figureVI.12 till figureVI.17 taking into consideration the different variation of the number of delta on the level of different days. By varying delta between 0.07 and 0.1 and the threshold of similarity between 0.75 and 0.9, we checked the number of iterations needed by k-means algorithm in order to reach the optimal end. We noticed

that the number of iterations increases when the threshold of similarity decreases. The number of iteration is also reduced by 30% when applying K-means on prefix set instead of applying it on the whole data source.

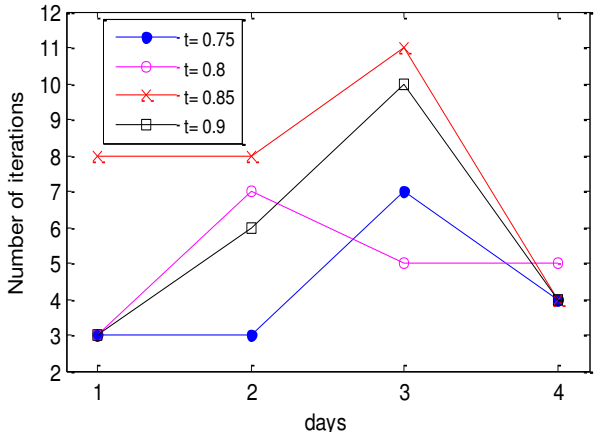


Figure VI.12 K-means after PFF, iterations number, k= 4, delta=0.07

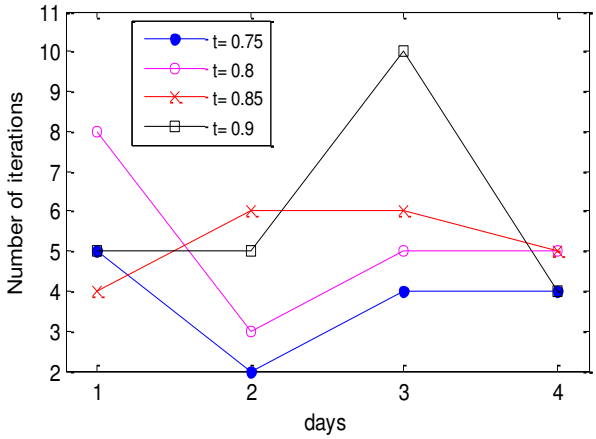


Figure VI.13 K-means after PFF, Iterations number, k= 4, delta=0.1

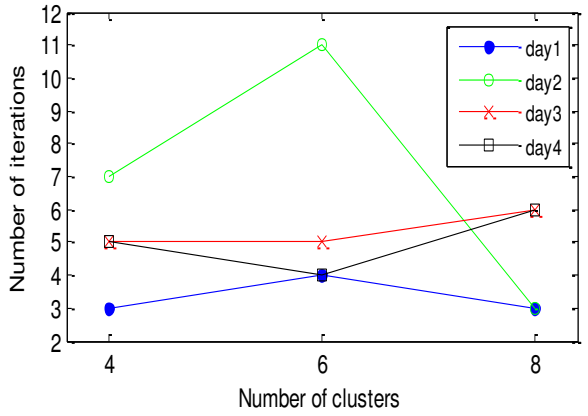


Figure VI.14 K-means after PFF, iterations number, t= 0.8, delta=0.07

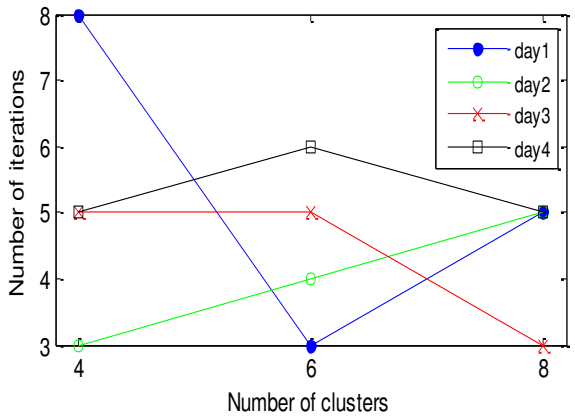


Figure VI.15 K-means after PFF, iterations number, t= 0.8, delta=0.1

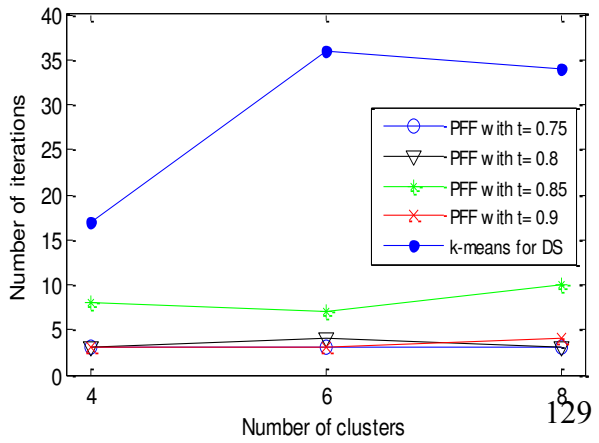


Figure VI.16 Iterations number, day=1

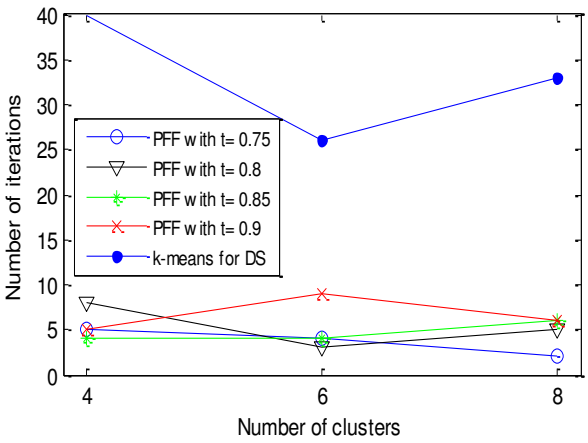


Figure VI.17 Iterations number, day=1

V. CONCLUSION

Extracting knowledge from big data generated by periodic sensor networks is crucial for decision maker. Data mining techniques can serve this purpose. However, they impose high computational cost that challenges their application in sensor networks. In this chapter, we tackled an interesting problem on the level of mining data in sensor network with low energy consumption. We applied the k-means algorithm on prefix sets of the data generated by the sensors and showed that we can have same result as the one received by applying k-means on the whole set of data. Our approach reduces the energy consumption and increase the performance of the mining algorithm. Moreover, our simulation results show that k-means is optimized in terms of running time and number of iterations. Other data mining algorithm on prefix set generated by sensor network can be also studied since this will be a good venture in overcoming the challenge of data mining facing big data generated by sensor networks.

Chapter VII Conclusion and Future Work

I. CONCLUSION

This thesis presents novel algorithms for data management in periodic wireless sensor networks. Energy efficiency in wireless sensor networks and mining data generated are at the core of this thesis. Our work highlighted the researches in this field to date and identifies new directions in periodic wireless sensor network big data management.

The main goal of this research is to overcome the challenges imposed by periodic WSN through data management while preserving the quality of the data. In fact, battery power is a main limitation imposed by a wireless sensor network. As a result, saving resource expensive transmission becomes a must. It is commonly understood that newest current applications require data processing with temporal constraints in their tasks. In chapterII, we gave an overview of periodic sensor networks, characteristics, challenges. Periodic applications require querying processed data and real-time storage thus adding new challenge to WSN. Data Management on the node level will ensure the usefulness of every reading, thus reducing packet transmission size which consequently optimizes the energy consumption. In such periodic networks, data collection, data aggregation and data mining constitute the main components of data management. The listed phases in periodic sensor data management are the pillars of interest in this thesis which analyzes the existing and suggests efficient and improved algorithms.

In chapterIII we studied the data collection approach. We presented an efficient adaptive sampling approach based on the dependence of conditional variance on measurements that varies over time. Then, we propose a multiple levels activity model that uses behavior functions modeled by modified Bezier curves to define application classes and allow for sampling adaptive rate. The proposed method was successfully tested in a real sensor data set. We showed that it can be effectively used to increase the sensor network lifetime, while still preserving the high quality of the collected data.

In chapters IV and V we presented two data aggregation techniques for periodic sensor networks. In the first technique presented in chapter IV, we introduced a tree-based bi-level periodic data aggregation approach implemented on both the source node and the aggregator levels. Our contribution in this component is two folds. First we look on a periodic basis at each data measured. Secondly we, periodically, clean it while preserving the number of occurrences of each measure captured. Then, data aggregation is performed between groups of nodes on the level of the aggregator. The quality of the information is preserved during the in-network transmission through the number of occurrence of each measure called weight. The experimental results show the effectiveness of this technique in terms of energy efficiency and quality of the information.

ChapterV presented the second technique of data aggregation. By using it a new method based on sets similarity functions and prefix filtering technique is proposed. The objective of our aggregation approach is to reduce the number of redundant data sent to the end user while preserving the data integrity. We have developed a new frequency based prefix filtering technique that avoids computing similarity values for all possible pairs of sets. We used the Jaccard similarity function to estimate the similarity between sets of data measures. It was shown through simulations that the proposed method reduces drastically the redundant sensor measures while preserving information integrity. Therefore, it saves energy and improves the overall network lifetime.

Last but not least, in chapterVI we customized an existing datamining algorithm on the tides of data captured by sensors networks and aggregated it using our prefix filtering algorithm. The idea was to load balance between the high computational cost imposed by data mining techniques and the limitation existing in sensor networks in terms of energy and power consumption. We developed a new multilevel optimized version of a data mining algorithm named « k-means » to work on the prefix sets. Periodic preprocessing algorithm based on prefix filtering technique is applied on big data generated by sensor networks. Then a distributed K-means optimization in terms of comparison and number of iterations is applied by exploiting prefix subsets of data. The main idea of this technique is to optimize the clustering of observations generated by sensor networks into groups of related readings without any prior knowledge of the

relationships between the prefixes sets. Simulations results are presented to validate the performance of the proposed approach.

II. DISCUSSIONS AND FUTURE WORKS

Novel methods for data management in periodic sensor networks have been proposed in this thesis. The contribution of our work lies not only in the new data management's algorithms and techniques proposed, but also in the new research horizons we established through these findings. Future works can be conducted upon our work to realize more efficient data management techniques for wireless sensor network and for data mining areas. In this section I would like to discuss some interesting points to be improved in the presented work, and my opinions on directions that would be interesting for someone addressing similar challenges.

To begin with, adaptive data sampling from sensor nodes in a periodic basis should take into consideration the level of residual energy. As the residual energy at the node is time varying, and is subject to a variety of other factors like the sampling rate, it is challenging to formulate closed form expressions that indicate future energy levels and lifetime of a node. Therefore, in order to save more energy in sensor networks, the adaptive model must be adapted to adjust the sampling rate on the basis of the available energy beside the variation of the Fisher function, while, at the same time minimizing the total uncertainty error. On the other hand, adapting sampling rate may lead sometimes to some missing important data. Therefore, using spatio-temporal correlations between sensor measurements can be used to detect faulty readings and improve the overall information quality.

We have two major directions for future work concerning the prefix-frequency filtering technique. In our data aggregation technique, we consider sensor nodes operating with same sampling rate. This means that the size of the generated data sets is the same for all sensor nodes. Hence, in periodic sensor networks and as seen in chapter III sensor nodes can operate with different sampling rate. Therefore, the first direction seeks to adapt our proposed method to take into account non equal data sets. The second direction is to develop a new suffix frequency filter algorithm. To optimize the number of the generated candidates, new suffix filter algorithm beside the prefix filtering approach

proposed in this thesis can be checked. The goal will be to use additional filtering method that prunes erroneous candidates that survive after applying the prefix and frequency filtering technique. Our approach can also be extended to other commonly used similarity measures, like overlap or cosine similarities and especially" Hamming distance".

A preliminary study and results of periodic data mining was presented in this thesis. The purpose of this study is to apply the k-means algorithm on the prefixes instead of the whole set in order to save energy and especially to accelerate the computing process. The preliminary results confirmed the efficiency of such approach. On the other hand, this method remains a heuristic proposition that needs to be proved theoretically. The idea here is to study the best prefix length that guarantees best data mining results. Moreover, this method can be generalized to integrate more data mining algorithms and not only the k-means.

Publications

I. Articles in journal or book chapters

1. Jacques Bahi,Abdallah Makhoul, and Maguy Medlej. **A Two Tiers Data Aggregation Scheme for Periodic Sensor Networks**.*Ad Hoc & Sensor Wireless Networks*, 21(1-2):77-100 (2014)
2. Jacques Bahi,Abdallah Makhoul, and Maguy Medlej. **Energy Efficient in-Sensor Data Cleaning for Mining Frequent Itemsets**.*Sensors and Transducers journal*, 14(2):64--78, March 2012.

II. Conference articles

1. Jacques Bahi,Abdallah Makhoul, and Maguy Medlej. **An Optimized In-Network Aggregation Scheme for Data Collection in Periodic Sensor Networks**. In *ADHOC-NOW 2012, 11-th Int. Conf. on Ad Hoc Networks and Wireless*, volume 7363 of *LNCS*, Belgrade, Serbia, pages 153--166, July 2012. Springer.
2. Jacques Bahi,Abdallah Makhoul, and Maguy Medlej. **Frequency Filtering Approach for Data Aggregation in Periodic Sensor Networks**. In *NOMS 2012: 570-573, 13-th IEEE/IFIP Network Operations and Management Symposium*, Hawaii, United States, April 2012. IEEE Computer Society Press.
3. Jacques Bahi,Abdallah Makhoul, and Maguy Medlej. **Data Aggregation for Periodic Sensor Networks Using Sets Similarity Functions**. In *IWCMC 2011, 7th IEEE Int. Wireless Communications and Mobile Computing Conference*, Istanbul, Turkey, pages 559--564, July 2011. IEEE Computer Society Press.
4. Jacques Bahi,Abdallah Makhoul, and Maguy Medlej. **Energy Efficient 2-Tiers Weighted in-Sensor Data Cleaning**. In *SENSORCOMM'11, 5-th Int. Conf. on Sensor Technologies and Applications*, Nice, France, pages 197--202, August 2011.

III. Articles in journal submitted

1. Jacques Bahi,Abdallah Makhoul, and Maguy Medlej. **Data Mining in periodic sensor networks: K-Means clustering**

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Résumé

Les recherches présentées dans ce mémoire s'inscrivent dans le cadre des réseaux de capteurs périodiques. Elles portent sur l'étude et la mise en oeuvre d'algorithmes et de protocoles distribués dédiés à la gestion de données volumineuses, en particulier : la collecte, l'agrégation et la fouille de données. L'approche de la collecte de données permet à chaque nœud d'adapter son taux d'échantillonnage à l'évolution dynamique de l'environnement. Par ce modèle le sur-échantillonnage est réduit et par conséquent la quantité d'énergie consommée. Elle est basée sur l'étude de la dépendance de la variance de mesures captées pendant une même période voir pendant plusieurs périodes différentes. Ensuite, pour sauvegarder plus de l'énergie, un modèle d'adpatation de vitesse de collecte de données est étudié. Ce modèle est basé sur les courbes de bézier en tenant compte des exigences des applications. Dans un second lieu, nous étudions une technique pour la réduction de la taille de données massive qui est l'agrégation de données. Le but est d'identifier tous les nœuds voisins qui génèrent des séries de données similaires. Cette méthode est basée sur les fonctions de similarité entre les ensembles de mesures et un modèle de filtrage par fréquence. La troisième partie est consacrée à la fouille de données. Nous proposons une adaptation de l'approche k-means clustering pour classifier les données en clusters similaires, d'une manière à l'appliquer juste sur les préfixes des séries de mesures au lieu de l'appliquer aux séries complètes. Enfin, toutes les approches proposées ont fait l'objet d'études de performances approfondies au travers de simulation (OMNeT++) et comparées aux approches existantes dans la littérature.

Mots-Clés: réseaux de capteurs périodiques, collecte adaptative de données, agrégation de données, filtrage par préfixe, fonction de similarité, fouille de données, K-Means.

Abstract

This thesis proposes novel big data management techniques for periodic sensor networks embracing the limitations imposed by wsn and the nature of sensor data. First, we proposed an adaptive sampling approach for periodic data collection allowing each sensor node to adapt its sampling rates to the physical changing dynamics. It is based on the dependence of conditional variance of measurements over time. Then, we propose a multiple level activity model that uses behavioral functions modeled by modified Bezier curves to define application classes and allow for sampling adaptive rate. Moving forward, we shift gears to address the periodic data aggregation on the level of sensor node data. For this purpose, we introduced two tree-based bi-level periodic data aggregation techniques for periodic sensor networks. The first one look on a periodic basis at each data measured at the first tier then, clean it periodically while conserving the number of occurrences of each measure captured. Secondly, data aggregation is performed between groups of nodes on the level of the aggregator while preserving the quality of the information. We proposed a new data aggregation approach aiming to identify near duplicate nodes that generate similar sets of collected data in periodic applications. We suggested the prefix filtering approach to optimize the computation of similarity values and we defined a new filtering technique based on the quality of information to overcome the data latency challenge. Last but not least, we propose a new data mining method depending on the existing K-means clustering algorithm to mine the aggregated data and overcome the high computational cost. We developed a new multilevel optimized version of « k-means » based on prefix filtering technique. At the end, all the proposed approaches for data management in periodic sensor networks are validated through simulation results based on real data generated by periodic wireless sensor network.

Keywords: periodic sensor networks, adaptive sampling approach, Bezier Curve, tree-based data aggregation, similar sets, prefix frequency filtering, data mining, K-Means.

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