

LITERATURE REVIEW: ENERGY EFFICIENCY MECHANISMS USING DATA REDUCTION IN WIRELESS SENSOR NETWORKS (WSNs) APPLICATIONS

Abdurrohman Haidar Nashiruddin, Lusia Rakhmawati

Department of Electrical Engineering, Faculty of Engineering, Universitas Negeri Surabaya
abdurrohmann@mhs.unesa.ac.id
lusiarakhmawati@unesa.ac.id

Abstract - It has been stated that the implementation of Wireless Sensor Networks (WSN) has major problems that can affect its performance. One of the problems he faced was the limited energy source (battery-powered). Therefore, in an attempt to use energy as best as possible, several mechanisms have been proposed. Energy efficiency in WSN is a very interesting issue to discuss. This problem is a challenge for researchers. This paper focuses on the discussion of how research has developed in energy efficiency efforts in the WSNs over the past 10 years. One of the proposed mechanisms is data reduction. This paper discusses data reduction divided into 4 Parts; 1) aggregation, 2) adaptive sampling, 3) compression, and 4) network coding. Data reduction is intended to reduce the amount of data sent to the sink. Data reduction approaches can affect the accuracy of the information collected. Data reduction is used to improve latency, QoS (Quality of Service), good scalability, and reduced waiting times. This paper discusses more adaptive sampling techniques and network coding. It was concluded that using data reduction mechanisms in target detection applications proved efficient compared to without using data reduction mechanisms. To save energy, data reduction (especially with adaptive sampling algorithms) can save up to 79.33% energy.

Keywords: Data Reduction, Wireless Sensor Networks (WSNs), Energy Efficiency

I. INTRODUCTION

In an international conference in 2013, it was stated that the main challenges and problems that could affect the performance of the WSN itself include things, among them; limited energy resources, self-management, hardware, software, Operating System (OS), Medium Access Control (MAC) layer, Quality of Service (QoS), security, architecture, data collection, data transmission, calibration, limited space memory, limited storage space, physical attack and security, network processing, decentralized management, fault tolerance, robustness, interpreting data, heterogeneity, multimedia communications, real-time operations, synchronization, and safe localization [34].

WSN itself can be used for several areas, including health, environment, agriculture, underground and underwater sensor networks, public safety, military systems, industry, and transportation systems [42]. In the paper written by [30] divide the WSN into 5 (five) types; a.) WSN land, b.) WSN Underground, c.) Underwater WSN, d.) WSN multimedia, and e.) Mobile WSN. WSN

itself refers to the Low Rate Wireless Personal Area Network (LR-WPANs) standard IEEE 802.15.4.

It has been noted that WSN applications take advantage of a limited source of energy, that is, in the form of batteries. Several mechanisms in the effort to save (efficiency) energy have been proposed. The energy efficiency mechanism itself is divided into several classifications, including radio optimization, data reduction, sleep-wake scheme, energy-efficient routing, and battery addition. The data reduction approach may affect the accuracy of the information collected. Data reduction is used to improve latency, QoS (Quality of Service), good scalability, and reduced delays. The reduction of data is further divided into 4 parts; including 1) aggregation, 2) adaptive sampling, 3) compression, and 4) network encoding [42].

Data aggregation or better known as Fusion Data is a process that processes some data/information and combines it to be more effective and more appropriate to the needs [35]. Combine data from several sensors on

intermediate nodes then send the aggregate data to the base station (sink) as shown in Figure 1 [53].

The objective of the adaptive sampling algorithm is to reduce the overall power consumption of each wireless sensor node, by reducing its sensing and communication activity [43].

Data Compression is coding information in such a way that the bit size becomes smaller, which is a form of energy efficiency as it can reduce transmission time due to smaller packet size [42]. Several compression algorithms have been designed specifically for WSN, including; encoding by order, compressing the typed network, low complexity video compression, and distributed compression [25].

Network Encoding is an area of information, coding theory, and a method to maximize the flow of information on a network [16]. Network encoding makes each link only used once, so it can balance the network load, reduce network latency, and increase network processing power [18].

Since the use of energy resources is a serious problem in WSN, it is necessary to have a mechanism for using energy to be more efficient. It is one of the reasons why the writing of this paper should be held. In this paper, we will focus more on how research has been developed in energy efficiency efforts in WSN over the past 10 years. To how to effectively extend the limited battery life (extend life). It is hoped that this paper can be used as a reference or reference to assist in the writing of papers or further studies.

It should be noted that discussions on Data Aggregation and Data Compression have been submitted in writing by [31]. So that further discussion in this paper-, focused on adaptive sampling methods and network coding

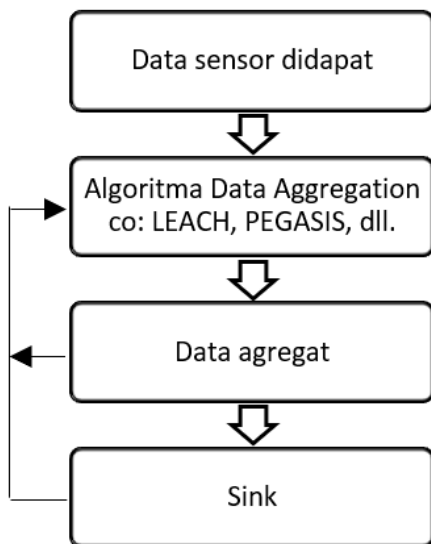


Figure 1. Flowchart data aggregation [53]

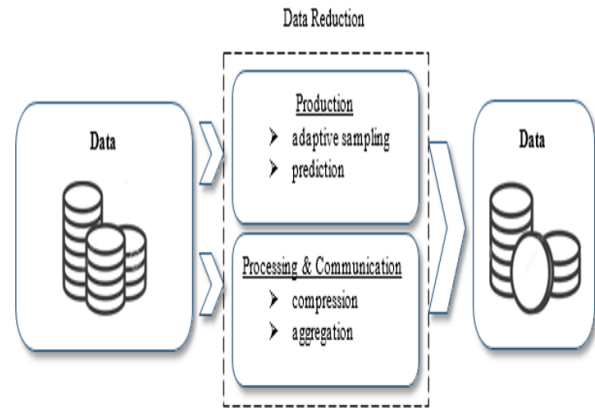


Figure 2. Illustration data reduction

II. DATA REDUCTION

Data reduction is one of the solutions provided, aiming to reduce the amount of data sent to the sink [42]. A paper by [40] says that for energy efficiency, wireless sensor networks classify it into 5 (five) classes, namely data reduction, control reduction, energy-efficient routing, task cycle, and topological control. Regarding the data reduction technique proposed in the literature, it is classified into 3 (three) categories according to the steps of data handling i.e. production steps, processing, and communication measures. As can be seen in Figure 2, it displays a general illustration in the form of illustrations related to the reduction of the data itself.

Aggregation

Data aggregation can be categorized based on network topology, network flow, service quality (QoS), and more. Based on Network Topology, it is divided into 2 parts; structurally based and structurally independent. The structure is further divided into 4 (four) sections, namely flat nets, clusters, trees, and grids as shown in Figure 3 [47]. For example, research applied by [11] uses flat topology without clusters in the body's sensor network (health care).

Data aggregation involves 3 phases, 1) aggregation selection, 2) data transmission from sensors to an aggregator (Intra routing), 3) data transmission from the aggregator to the roller (inter routing). Data aggregation does not work on underwater sensor networks [28].

Several studies have been conducted to compare or create new algorithms or schemes, including by [38] regarding Data Cube Aggregation, an aggregation technique using the data grouping approach used to store the values of node parameters and the location of clusters (base stations). Datacube supports multiple phases in an easy-to-understand and accessible graph format. Data cube aggregation: is a multidimensional approach to data aggregation. Values are stored in separate cells of the data

cube, each phase of the cube is divided into rows and columns and the values of each value are divided into usage, bandwidth, MRIC, RSSI, etc. represented at the beginning of the line. For security solutions use soft computing according to [7] in his writing.

While [10] in his study compared data collection techniques. Using 2 layers of an algorithm, node level, and CH level (Cluster-Head), aimed at optimizing the volume of data on the transmission thereby saving energy consumption and reducing bandwidth at the network level, node-level: collecting data periodically to prevent each node from sending its raw data to the sink, the second method: finding the difference in various conditions between the data set based on the one-way ANOVA model and the Bartlett test, Third method: calculate between sets based on distance functions, such as Euclidean, and Cosine, energy consumption, latency, and accuracy of data.

In another study [46] using a new scheme called somDA (SOM-based Data Aggregation) scheme, SOM (Self-Organized-Map) aims to reduce excess data and eliminate outliers. And research by [11] using the EDAGD (Entropy-driven Data Aggregation with Gradient Distribution) method with 3 algorithms usage strategies: 1) Multihop Tree-based Algorithm Data Aggregation (MTDA), 2) Entropy-driven aggregation-based Tree routing Algorithm (ETA), and 3) Gradient Deployment Algorithm (GDA) aimed at energy-saving (energy-efficient) WSN.

Adaptive Sampling

In his writing, [8] states that adaptive sampling techniques are highly efficient if the correlation of the data obtained is high and the irregularity is low. On the other hand, if the correlation is low and irregularity is high, the performance of this technique is weak due to obstructed sampling.

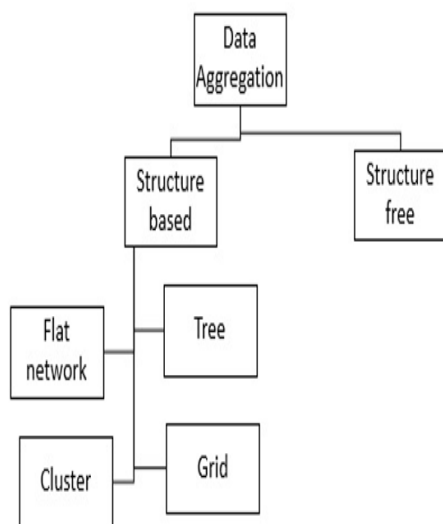


Figure 3. Taxonomy of Data Aggregation [47]

As shown in Figure 4, [6] divides into 3 (three) classes of algorithms aimed at addressing the flow of sensor data from data sources (sensor nodes) in the Internet of Things (IoT), i.e. adaptive sampling algorithms, adaptive filtering algorithms, and hybrid algorithms. Adaptive sampling algorithms are further divided into two subclasses, adaptive rate, and Adaptive Compression. Within the adaptive filtering class, there are two subclasses which are adaptive threshold and model-based filtering. A hybrid algorithm is a combination of adaptive sampling/filtering algorithms with other approaches. And also say that adaptive sampling has three advantages over fixed-rate sampling. First, adaptive sampling takes fewer sensor readings, which has an effect on energy savings in sensor nodes. Second, it sends less value to the central analysis engine, which saves network traffic. And thirdly, the phenomenon reconstructed from the adaptation technique is closer to the original.

Meanwhile, [5] in his writings concludes from the many available works of literature. Generally, adaptive sampling mechanisms can be divided into two categories: adaptive spatial sampling algorithms (ASS) and adaptive temporal sampling algorithms (ATS). The ASS algorithm ensures the accuracy of sampling using self-adjustment based on space area, wake-up/sleep schedule, and so on. And the ATS algorithm ensures the accuracy of sampling using self-sampling frequency adjustment, estimated online signal flow direction, and so on.

Here is a brief explanation of some of the research journals that have been obtained, such as a research journal by [49] that uses a method, called AdaSense, which is intended for the body's sensor network (BSN), as a form of application in the field of healthcare. The research conducted by [20] designed a new adaptive sampling technique, called Exponential Double Smoothing-based Adaptive Sampling (EDSAS) for wireless air pollution sensor networks and compared it to e-Sense techniques (H. Liu et al., 2006).) to evaluate the performance of both techniques, and use similar traffic pollution data. Later, research from [32] on the target detector sensor network, using two adaptive sampling algorithms, Evolutionary Strategy (ES) and Strengthening Learning (RL) can last long with changes in target movement patterns, but the Learning Automata (LA) method of (K.S. Narendra and MAL Thathachar, 1989) proved to be the best and more efficient among others.

Researchers [51] conducted the study using an adaptive sampling scheme on urban air quality designed in the Chinese version. The research was conducted at the School of Electronic Information, Wuhan University. Then, research by [17] research on Mobile Robotic Wireless Sensor Networks (MRWSNs).

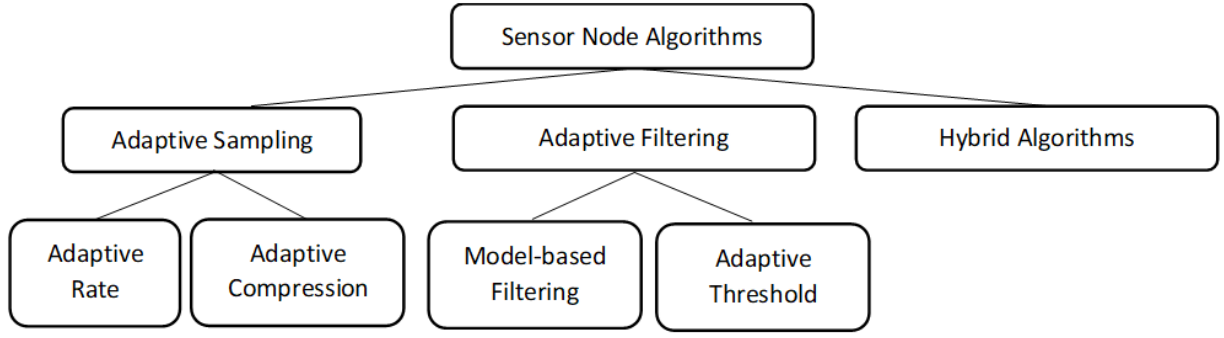


Figure 4. Taxonomy of sensor node algorithms [6]

Research by [19] research on DPCAS (Dual Prediction with Cubic Adaptive Sampling) combines predictive modes with exponential time series and adaptive sampling methods, based on TCP CUBIC's congestion control algorithm for environmental physical variables in WSN, compared to EDSAS and ASTCP, presenting results between good data quality and energy consumption in sensors having a good balance. The research by [4] used power wear sensors (ultrasonic wind sensors and gas sensors) with two application domains, namely SHM (Structural Health Monitoring) and beehive monitoring.

Research by [8] conducted a study that combined adaptive sampling techniques and dual predictive mechanisms. Also describes the statistical model of Kruskall-Wallis. And a study from [14] on air monitoring, measuring pollution levels in the city of Uppsala, Sweden. Simulate on MatLab and implement GreenIoT projects.

Table 1 shows several studies that have been carried out, using the symbol mark (✓) which means the study only uses adaptive sampling algorithms without any separate naming. For example, in a journal investigation by Linh V. Nguyen et al. 2016 [17].

Data Compression

Data compression is the process of converting input data flows (raw/original data) to other data streams (compressed streams) that have fewer bits. Delete unnecessary data by using more efficient encoding [21].

Here are some studies that use data compression algorithms. The research by [44] used a compression technique called Aggregated Deflate-RLE (ADR) for a network of body sensors that combined Deflate and RLE (Run Length Encoding) algorithms and compared them to the compression techniques of RLE, Huffman Encoding, and Deflate. Get the conclusion that the ADR algorithm is better than Deflate, Huffman, and RLE.

And research by [13] compares performance between the design of an algorithm called mLEC (Modified Lossless Entropy Compression) with LEC algorithms in general for environmental monitoring (environmental monitoring). Then [48] about a thesis study on the design of a lightweight Huffman coding algorithm. In a study [33], comparing Huffman coding techniques with LZW techniques. It was concluded that Huffman was better than LZW. Later [36] using the LTC (Lightweight Temporal Compression) algorithm in-state studies, reducing data before it is transmitted through compression can significantly reduce resource consumption and increase network life. And, research by [11] using the S-LZW algorithm on solar WSN. The difficulty is that when at night, solar energy is not enough, then the transmission ceases. When the workload reaches its peak at night, in the morning the delivery resumes. And the nodes are starved of energy, some data may be lost.

Network Coding (NC)

Network coding was first introduced by (Yeung and Zhang, 1999), which proposed to improve the flow of data that can be used in several different layers and classes of networks [3]. Generally, the Network Encoding method can be classified into between sessions or intra-session. The network encoding method can be used in unicast, multicast, or broadcast applications. In addition, some network encodings are made only for one-hop, two-hop, or multi-hop networks [29]. Network encoding is described in Figure 5, which uses 5 nodes as an example. Node 1 is responsible for transmitting information to nodes 2 and 3, then proceeding to the next node (nodes 4 and 5).

Some studies related to Network Encoding are shown in Table 2. Research by [3] on fog computing uses the programming language Python intending to minimize latency, save bandwidth, increase QoS, and overcome limitations inaccurate content distribution, using 4 different topologies (Square, Tree, Random, and Mist).

Table 1. Energy Efficiency using Adaptive Sampling techniques

PAPER	TAHUN	PARAMETER	ADAPTIVE SAMPLING	DESKRIPSI ALGORITMA	APLIKASI
Xin Qi dkk. [49]	2013	Lying down, sitting, standing & walking	AdaSense	Efficient Activity Recognition (EAR), Sampling Rate Optimization (SRO)	Body Sensor Network (BSN)
Manik Gupta dkk.	2011	Maximum step size (Smax) dan tolerance error	EDSAS (Exponential Double Smoothing-based Adaptive Sampling)	- Berdasar ESD, merupakan metode prediksi menggunakan ekstensi Wright ke metode ESD Holt digabungkan dengan deteksi perubahan EWMA - Membandingkan dengan e-Sense (H. Liu dkk., 2006)	Jaringan sensor polusi udara nirkabel
Mohammad Rahimi & Reza Safabakhsh	2010	fixed and adaptive	(Evolutionary Strategy) ES & Reinforcement Learning (RL)	Membandingkan dengan Learning Automata (LA) (1989)	Pelacakan target
Yuanyuan Zeng & Kai Xiang	2017	AQI level Efisiensi sampling (%)	AS-air	Membandingkan dengan skema berbasis Q-learning dasar	Kualitas udara perkotaan melalui penginderaan partisipatif
Linh V. Nguyen dkk.	2016	RMSE (Root-Mean-Square Error)	✓	Untuk mendapatkan sampel lokasi paling informatif	Robotik mobile
Leonardo C. Monteiro dkk.	2017	MAE (Mean Absolute Error)	DPCAS (Dual Prediction with Cubic Adaptive Sampling)	- Mengkombinasikan adaptive sampling dengan data prediction model - Membandingkan dengan EDSAS & ASTCP	-
Bruno Srbinovski dkk.	2016	-	EASA (Energy-aware Adaptive Sampling Algorithm)	Sumber energi, solar & angin	-
Gaby B. Tayeh dkk.	2018	MAE, MAPE (Mean Absolute Percentage Error), MSE (Mean Square Error) & RMSE	✓	- Mengkombinasikan teknik adaptive sampling dengan mekanisme prediksi ganda - Membandingkan AS+TR dengan DPCAS	Diuji dalam ruangan lab dengan environmental features
Timothy Kurp dkk. [43]	2010	Signal to Noise Ratios (SNR) & MSE	New adaptive sampling	-	Peningkatan pemanfaatan energi
Y.E.M. Hamouda & C. Philips	2011	Konsumsi energi total dengan waktu simulasi	✓	Diusulkan DMMT (Distributed Multi-sensor Multi-target Tracking) membandingkan dengan skema tracking Uniform, Lin & Xiao	Multi-target tracking
Sovannarith Heng dkk. [41]	2020	- Sampling rate - Block size - PSNR (Peak Signal-to-Noise Ratio)	FABCS (Fuzzy Adaptive Block Compressed Sensing)	- Mengkombinasikan FSL dan algoritma BCS - Membandingkan dengan metode lain (BCS, STD-BCS, SABCS, SACS-MC)	Wireless Multimedia Sensor Networks
Yongjae Jon	2016	- NO ₂ , Ozone & CO - perbandingan pengukuran sekarang dengan sebelumnya	✓	- Mengukur polusi udara di Uppsala (NO ₂) - Menggunakan Kalman filter	Sistem monitoring udara
Alireza Masoum dkk. [1]	2013	Biaya transmisi, kualitas data & konsumsi energi	New adaptive sampling	Membandingkan dengan ASAP & Hybrid	-
Tongxin Shu dkk. [45]	2017	DO (Dissolved Oxygen) & kekeruhan	DDASA (Data-Driven Adaptive Sampling Algorithm)	Membandingkan dengan adaptive sampling algorithm (ASA)	Pemantauan kualitas air otomatis
Najam us Saqib dkk. [23]	2017	- Tekanan & vibrasi - Dengan & tanpa adaptive sampling	Hierarchical adaptive sampling	Mendeteksi kebocoran pada pipa air berbasis WSN	Pipa air berbasis WSN
Yanlong Sun dkk.	2018	- Tracking position error - Tracking step - Konsumsi energi	ASIA (Adaptive Sampling Interval Adjustment)	- Metode 2-input 1-output fuzzy logic controller - Membandingkan dengan algoritma adaptive sampling yang ada (MINS. EEDAS, FLAS-FT, FLAS-DT & MAXS)	Pelacakan target di jaringan sensor nirkabel bawah air

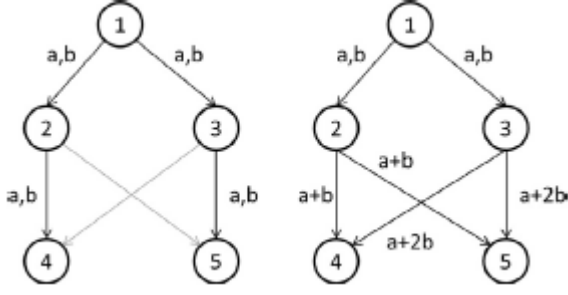


Figure 5. Example of network coding [42]

Later, research by [2] research on the application of network coding techniques for sensor networks based on IEEE 802.15.4/6LoWPAN (IPv6 via Low Power Wireless Private Area Network) was one of the standards intended for IoT architecture. Research by [26] on CodeDrip tested more than 350 physical sensor nodes. Then, the investigation continued on CodeDrip. CodeDrip: is a data dissemination protocol for WSN, research comparing with the Protocols of Drip, DIP (Dissemination Protocol), and DHV. And get faster results, lighter, and fewer send messages [27].

Then, research on network coding applications for bridge monitoring by [37]. The research compared network coding on wired and wireless networks by [22]. And, research by [39] research on NCBPR (Back Pressure Routing Network Encoding) which compares with InFRA (Information-Fusion-Based Role Assignment) and DRINA (Aggregation in Data Routing Networks).

III. RESULT AND DISCUSSION

In this section, we discuss the analysis and discussion on energy efficiency mechanisms from several sources that have been obtained. It is summarized in Table 1 on adaptive sampling and in Table 2 of the discussion on network coding.

Aggregation

Based on the article [31] states that the performance of the data aggregation algorithm depends on the number of parameter variations in the network. And whether homogeneous or heterogeneous nodes are used also plays an important role in influencing the performance of the algorithm itself. Also submitted by [42] the data reduction approach can increase latency by reducing the number of packets to be delivered, thus reducing the waiting time (delay) in the queue. This method-, can improve QoS by setting a higher priority for a particular data class when performing the aggregation function or when sampling parameters. This technique demonstrates the nature of good scalability by reducing the workload in traffic.

Compression

The paper [31] also states that data compression algorithms are categorized into two main categories: Lossless and Lossy compression algorithms. The level of compression achieved in the loss-free compression algorithm is limited by resource entropy. Any compression beyond that leads to lossy compression. And most of the algorithms used in the network, use a tree-based network.

Adaptive Sampling

Various adaptive sampling techniques have been developed and can be combined or compared with other adaptive sampling techniques, shown in Table 1 to obtain results on the performance of the proposed techniques with existing techniques. Can be applied in everyday life to get real results. Widely used to monitor the environment (environmental monitoring) such as air quality (pollution) [20], [51], water monitoring [14], and more.

Target Tracking

In the last 10 years, many studies have been carried out mainly on target detection using adaptive sampling techniques. As [52], [50], [51], [51], [48], and [9] have done.

Shown in Graph 1, on energy consumption as a percentage (%) of each research result (source) obtained, the research [52] states that using adaptive sampling consumes energy of 25.16 mJ compared to without adaptive sampling of 88.28 mJ, it can be concluded. that adaptive sampling can save 71.50% of energy. Using 20 sensors is randomly placed on a field of 100m x 100m.

Research by [10] states that using an adaptive scheme uses 0.3J of energy while the uniform scheme is 1.2J, at sampling intervals, $\Delta t(k) = 0.1$ with an average of more than 20 simulations. It is concluded that the adaptive scheme can save 75% of the energy used. Using 800 wireless sensor nodes scattered randomly on an area measuring 300m x 300m.

In 2011, researchers [9] conducted a study on multi-target tracking using multiple sensors that had problems when sensors tracked more than one target. Have a solution by defining a prioritized target and comparing it with a schema (Lin et al., 2009) and (Xiao et al., 2010). It was concluded that the proposed scheme achieved the success that experiencing increased energy efficiency compared to other schemes. For all targets, using adaptive sampling intervals $T_{min} = 0.1s$ and $T_{max} = 0.5s$ with a target speed of 10 M/s. By distributing 1500 wireless sensor nodes scattered randomly over a 300m x 300m field.

Table 2. Energy Efficiency Comparative Analysis using Network Coding

PAPER	TAHUN	PARAMETER	NETWORK CODING	DESKRIPSI	APLIKASI
Bruno Marques dkk.	2019	- Topology square, tree, random dan fog - NC & tanpa NC	✓	Untuk meminimalkan latensi, menghemat bandwidth, meningkatkan QoS dan mengatasi keterbatasan dalam distribusi konten yang akurat	Komputasi kabut dengan sensor nirkabel
Marek Amanowicz & Jaroslaw Krygier	2018	- Packet loss ratio - end-to-end packet delay	NC6LoWPAN	Untuk mengurangi beban jaringan secara keseluruhan	Jaringan multihop sensor berbasis 6LoWPAN
Nildo dos Santos R. J. dkk.	2014	- Jumlah pesan terkirim - Waktu penyebaran	CodeDrip	- Menggunakan pengatur waktu (trickle timer) - Membandingkan dengan protokol Drip, DIP & DHV	-
Nildo dos Santos R. J. dkk.	2016	- Waktu penyebaran - Jumlah pesan terkirim - Kesuksesan penerimaan pesan	CodeDrip	- Membandingkan dengan protokol Drip, DIP & DHV - Mengevaluasi dengan >350 node sensor fisik	-
Jelena Skulic & Kin K. Leung	2012	- Single-line layout & double-line layout - 1-hop, 2-hop, & 3-hop	✓	Menggunakan 2 layout berbeda: single-line & double-line layout	Monitoring jembatan
B. Muniswamy & N. Geethanjali	2014	-	✓	- Broadcasting di wireless networks - Aplikasi di jaringan peer-to-peer - Aplikasi terhadap toleransi delay	Jaringan kabel & nirkabel
S. Malathy dkk.	2020	-	✓	-	Internet of Things (IoT)

For the distance between the sensor nodes, each one is designed with a distance of 100m and 50m. The total energy used is 0.76 J for the proposed scheme, while the uniform scheme is 3.58 J, (Lin et al., 2009) of 1.14 J, and (Xiao et al., 2010) by 2.67 J. The total energy here is the energy required for sensing, communication and processing activities with each, an average of 20 simulations. In percentage terms, the proposed scheme is capable of saving 79.33% of energy while 72% for other schemes.

Research by [51] on target detection in underwater WSN. For sampling intervals, $T = \{0,1s, 0,2s, 0,3s, 0,4s, 0,5s\}$ which then gets the average energy consumption result with adaptive sampling of 100mJ while non-adaptive sampling is 260mJ, so inferred can save 62.23% of energy. With the monitored area measuring 100m x 100m x 100m and 7 m for the distance between the sensors.

Meanwhile, research by [50] conducted research on adaptive sampling in an area measuring 1000m x 1000m x 1000m with 125 wireless sensor nodes scattered randomly. Comparing between five algorithms, namely MINS algorithms, EEDAS algorithms, FLAS(FT) algorithms, FLAS(DT) algorithms, and MAXS algorithms. The average sampling interval for each step of the five algorithms is 0.50s, 1.08s, 1.69s, 1.69s, and 4.00s. The larger the sampling interval, the smaller the number of samples obtained and the less energy used. For energy consumption 664.56J, 302.21J, 191.06J, 191.18J, and 82.53J of each algorithm. Both FLAS(DT) and FLAS(FT)

algorithms can save about 36% of energy compared to EEDAS algorithms, and save about 71% of energy; when compared to the MINS algorithm. Although the MAXS algorithm uses the least energy, the approximate position error is too large.

By comparing the performance of five algorithms, in estimating error positioning and energy consumption, it can be proven that the ASIA method of the proposed algorithm can significantly reduce energy consumption while delivering good approximate performance. And the results show that the proposed algorithm not only saves about 36% of energy but also reduces energy consumption imbalances in various parts of the tracking area.

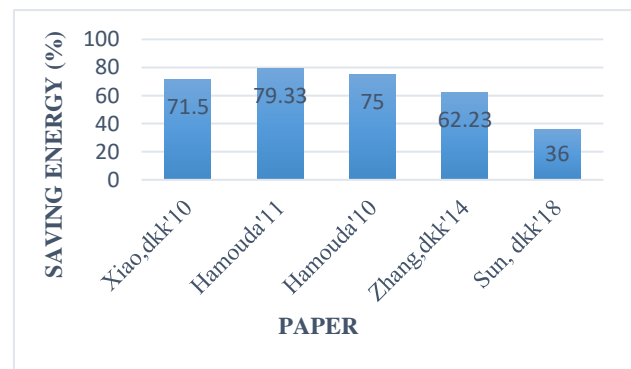


Figure 6. Graph of Energy Saving Per Paper in Percentage (%)

In [50] in his research has proven that adaptive sampling provides a good estimate, as opposed to taking

the target set. It can be concluded that research by [9] is better at energy saving compared to other studies. As can be seen in Graph 1, of the highest percentage, it can save energy up to 79.33%. However, the source of the literature obtained has a different area, number of sensor nodes, and parameters. In principle, it should be noted that all literature has an effect in reducing energy consumption.

Network Coding

Several new methods have been proposed and compared with existing methods, which are shown in Table 2 to find out which performance is more impactful to the increase in energy efficiency (limited). Also described in the International Conference Future Network and Communication (FNC) article 2016 by [23] which has compared the advantages and disadvantages of current network coding techniques, including COPR, SenseCode, CodeDrip, GBR-NC, and MORE.

IV.CONCLUSION

Based on the references that have been obtained, it can be concluded that many studies have been carried out, discussing efforts to improve the limited energy efficiency (battery) in the last 10 years. Several new mechanisms were proposed and then compared with existing mechanisms. Or compare using the data reduction method without using it. To get performance results that are more efficient in energy saving. It can be concluded that using data reduction mechanisms including data aggregation, data compression, adaptive sampling, and network coding proved efficient in energy saving (efficiency) in WSN. To save energy, data reduction (especially with adaptive sampling algorithms) proved to save energy by 79.33%.

In the future, it is hoped that this article will benefit other academics, to assist in the writing of references. Data reduction applications in energy-saving efforts are not only used for environmental monitoring, but can also be used for the health sector, manufacturing industry, smart grids, transportation systems, and public & military security systems.

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