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Efficient Data Processing and Consensus Algorithms for Resource-Constrained Wireless Sensor Networks in Environmental Monitoring: Survey

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Abstract: This research paper focuses on the applications and challenges of wireless sensor networks (WSNs). WSNs consist of small, low-cost sensors that can collect and process data in various fields such as military, environmental monitoring, health, home appliances, and other commercial applications. The paper discusses the benefits of structured deployments over ad hoc deployments and highlights the resource constraints of sensor nodes, including limited energy, communication range, and processing capabilities. It emphasizes the importance of clustering sensor nodes and utilizing sophisticated routing protocols for data transfer to fusion centers. The research also explores consensus algorithms for achieving global statistics in WSNs while sharing data with close neighbors. Various applications of WSNs are discussed, including military operations, environmental monitoring, health monitoring, home automation, and commercial uses. The paper presents a literature review on topics such as distributed consensus algorithms, multi-agent systems, and coordination control in WSNs. It covers topics like average consensus, event-triggered consensus control, nonlinear multi-agent networks, and consensus in stochastic networks. The research highlights the challenges and potential solutions for achieving consensus in WSNs, considering factors such as switching topology, communication delays, and uncertain nonlinear dynamics. Overall, this paper provides insights into the applications, challenges, and consensus algorithms in wireless sensor networks.

Keywords *Wireless sensor networks, Consensus algorithms, Environmental monitoring*.

1. Introduction

In recent years, advancements in wireless communications and digital electronics have paved the way for the development of small, low-cost, low-power sensors capable of connecting over short distances. Sensor networks, based on the principle of collective effort, rely on a large number of sensors working together. These sensor nodes consist of various components, including sensors, data processing units, and communication modules [1], [2].

Sensor networks have the ability to perform local computations and transmit only relevant and processed data. They find applications in diverse fields such as climate monitoring, humidity measurement, tracking vehicular movement, monitoring lightning situations, measuring pressure and noise levels, and assessing physical stress levels on objects [3], [4].

Compared to unstructured networks, structured networks offer advantages such as deploying fewer nodes and lower maintenance costs. By strategically positioning networks in specific locations, areas can be adequately covered, unlike ad hoc deployments that may leave certain regions unprotected. Scheduled deployments are particularly beneficial in hard-to-reach areas with limited human accessibility. Additionally, environmental obstructions can hinder communication between nodes, affecting the stability of the network topology.

Sensor networks and ad hoc networks typically involve a significantly larger number of nodes compared to routing networks. Despite their dense deployment, sensor nodes are prone to failures, have limited power and computational capabilities, and experience constantly changing topographies. In ad hoc networks, nodes communicate in a point-to-point fashion, while sensor networks rely on broadcast mode communication. These sensors have limited resources in terms of processing, energy, communication range, and memory bandwidth, leading them to collect, measure, and interpret data based on their surrounding environment. Sensor networks often lack infrastructure and rely on thousands of sensors within the network to monitor and collect environmental data [5].

Due to their limited energy capacity, short communication distance, low bandwidth, and restricted processing speed, wireless networks enter sleep mode when there is no communication. As a result, sensor nodes are deployed in

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uneven terrains and inhospitable conditions. The cooperative nature of sensor networks sets them apart, as nodes transmit only necessary or partially processed data to fusion nodes or nodes with greater capabilities. The fusion center acts as the core network, collecting data from different sensor nodes and combining it to produce the final result. Clustered sensor nodes and sophisticated routing protocols are crucial for the application of mathematical algorithms in fusion processes. The increasing costs of fusion centers, which require substantial energy and computing power, contribute to the overall expense of large-scale wireless sensor networks. Various fusion approaches and fuzzy concept consensus models have been studied to address these challenges [6], [7].

A base station serves as a gateway for connecting sensor networks to other networks, such as the internet. Sensor node data is transmitted to other sensor nodes through the base station. Users can access updated information from base stations via the internet, leveraging the base station's data processing capabilities. Data transmission using a single-hop network architecture allows for faster and more efficient relay of data to data base stations. However, in multi-hop systems, cluster heads consume a significant amount of energy when transmitting data over long distances [8]– [10]. Consensus methods typically involve sharing statistical data only among direct neighbors. The convergence rates of consensus techniques are determined by the Laplacian eigenvalues in graphs [11].

Developing consensus algorithms that can compute desired global statistics while sharing data only with close neighbors has garnered significant attention in the past two decades. Consensus algorithms find application in numerous multi-agent systems. Notably, DeGroot's contribution to the consensus problem has been influential [12]-[15]. Nodes in sensor networks collaborate with their immediate neighbors for computations, rather than relying on a fusion center. This approach is useful for determining global topology and dynamically adjusting topology due to frequent node failures. Graph theory concepts offer a wide range of applications in distributed consensus algorithms [16].

Given their versatility, distributed consensus algorithms have gained popularity across various fields. These algorithms involve neighboring nodes collaborating locally to compute the average of initial measurements. Due to the limited energy resources in wireless sensor networks, the convergence of consensus methods is an important research area that focuses on determining the number of iterations required to achieve steady-state values [17]-[22].

1.1. Application of WSNs

Wireless Sensor Networks (WSNs) have a wide range of applications across various fields. Here are some common applications of WSNs:

1. Environmental Monitoring: WSNs are extensively used for environmental monitoring purposes such as climate monitoring, air quality monitoring, water quality monitoring, forest fire detection, and natural disaster detection. Sensor nodes can collect data on temperature, humidity, air pollution levels, water quality parameters, and other environmental variables to provide real-time information for environmental management and research [23].

2. Industrial Automation: WSNs play a crucial role in industrial automation by enabling remote monitoring and control of industrial processes. They can be used to monitor parameters like temperature, pressure, vibration, and energy consumption in factories and production facilities. WSNs help optimize operations, improve efficiency, detect faults, and ensure worker safety [24].

3. Smart Agriculture: WSNs are utilized in precision agriculture to monitor soil conditions, crop growth, irrigation systems, and weather patterns. Sensor nodes collect data on soil moisture, temperature, humidity, and light intensity to optimize irrigation schedules, detect diseases, and enhance crop yield. WSNs enable farmers to make data-driven decisions and minimize resource wastage [25].

4. Healthcare and Biomedical Applications: WSNs are employed in healthcare for remote patient monitoring, telemedicine, and assisted living applications. Sensor nodes can monitor vital signs, detect falls or emergencies, and provide real-time health information to healthcare providers. WSNs enable personalized healthcare, early disease detection, and continuous monitoring of patients in their homes or healthcare facilities [26].

5. Smart Cities: WSNs are a key component of smart city infrastructure, enabling efficient management of resources and improving the quality of life for residents. They are used for smart parking systems, traffic monitoring, waste management, energy monitoring, and environmental sensing in urban areas. WSNs help optimize resource usage, reduce traffic congestion, and enhance sustainability in cities [27].

6. Disaster Management: WSNs play a crucial role in disaster management by providing early warning systems, monitoring natural phenomena, and coordinating emergency response efforts. They can detect earthquakes, tsunamis, floods, and other disasters, allowing for timely evacuation and response. WSNs facilitate efficient communication and data collection in disaster-prone areas [28].

7. Home Automation: WSNs are used in home automation

systems to monitor and control household appliances, security systems, lighting, and energy consumption. Sensor nodes enable remote access and control, energy optimization, and enhanced convenience and security in smart homes [29].

8. Military and Defense: WSNs find applications in military operations for surveillance, reconnaissance, battlefield monitoring, and communication in challenging environments. Sensor nodes can detect enemy movements, monitor critical areas, and provide situational awareness to military personnel [30].

These are just a few examples of the wide range of applications for Wireless Sensor Networks. The versatility and scalability of WSNs make them valuable tools for data collection, monitoring, and decision-making in various domains.

2. Literature Review

The literature review highlights the importance of engaging children in museum visits to enhance their understanding of artifacts. Live cause-and-effect activities provide opportunities to explore science and the environment. ATLAS utilizes a network of sensors to remotely detect and report risks, thereby ensuring the safety of the museum [31].

Warehouse sensors play a crucial role in locating items and counting quantities within specific categories. The collected data from sensor nodes is transmitted to a base station for calculating vehicle location.

Underwater sensor networks are utilized to monitor reefs and fisheries throughout their life cycles. These networks consist of both static and mobile sensor nodes connected through high-speed links. The coverage includes temperature and pressure sensors, as well as cameras for relocation and recovery purposes.

Wireless sensor networks (WSN) bring cost reductions and increased efficiency to petroleum facilities. The interactive elements of the show are designed to meet the plant's specific data rate and latency requirements.

The network configuration consists of four sensor nodes and one actuation node. Radio packets are sent from an e-mote sky device to a base station, which then transmits them to a crossbow stair gate gateway.

In an industrial setting, the functionality of a WSN is significantly affected by delay and environmental noise. The task of finding unoccupied parking spaces is typically assigned to a traffic control person.

Consensus problems, both local and global, arise in directed networks with highly nonlinear aspects. Various strategies such as the manifold approach and Lyapunov methods are employed to determine the necessary consensus requirements for complex systems. The Laplacian matrix plays a crucial role in determining these requirements. The paper also discusses networks with heterogeneous autonomous agents and switching topologies, highlighting applications in unmanned aerial vehicle regulation, military observation, computing, pharmaceutics, and environmental control structures [32].

Nonlinear techniques have been applied to solve the problem of average consensus. Computer simulations demonstrate the effectiveness of these ideas in dynamic scenarios. Previous studies addressing consensus convergence have consistently employed specific sufficient conditions [33]. Distributed consensus problems in multi-agent systems utilize adaptive laws for neighboring agents, both in linear and nonlinear dynamics [34]. Event-triggered consensus control for a class of discrete-time stochastic multi-agent systems has been discussed, where matrix inequalities derived from topology information are employed to achieve consensus [35].

The consensus monitoring problem in nonlinear multi-agent networks with time-varying states is challenging. The paper proposes a strategy using fixed and switched communication topologies, demonstrating convergence under suitable conditions. The theoretical approaches employed include graph theory, matrix theory, and Lyapunov theory [8]. The paper also explores six techniques for achieving time-varying formations in unmanned aircraft (UAV) swarms and addresses control challenges for UAVs using various consensus approaches. The efficacy of theoretical results is demonstrated through simulations involving five quadrotors. The authors provide necessary and sufficient conditions for UAV swarm systems to achieve time-varying formations, including an explicit expression for the formation core function and a procedure for generating gain matrices [36]-[38].

The consensus problem in stochastic networks of nonlinear agents with switching topology and the utilization of noisy and delayed agent information is investigated. The study employs the average models’ technique and conducts large-scale simulations and tests on a stochastic computer network [39].

The paper discusses ad hoc sensor networks and utilizes a Markov Chain model to analyze error probabilities. The convergence of consensus in these networks is a time-consuming process [40].

The work focuses on consensus issues in multi-agent cooperative control, exploring the applications of consensus protocols for future research on multi-agent cooperation. In a time-invariant setting, the system under investigation eventually reaches an exponential agreement, illustrating the dynamic flow of knowledge among individuals for consensus [41]. The agents achieve agreement through cooperation [42]-[44].

Complex-valued Laplacians (CVLs) play a crucial role in coordinating distributed multi-agent systems. They are commonly employed in solving control consensus problems in complex-weighted graphs. The properties of digraphs are evaluated and analyzed using the intricate Laplacian. Under appropriate conditions, complex consensus convergence is achieved, allowing for the resolution of coordination challenges in multi-agent systems. The application of complex Laplacians also benefits other multi-agent coordination issues [45]– [47].

Second-order neighbor information is utilized in consensus among second-order multi-agent systems. This study calculates the convergence rates of both the second-order neighbour protocol and the general protocol. The research aims to enhance the consensus speed in multi-agent systems, surpassing the delay margins of the second-order protocol [48], [49].

Consensus problems are prevalent in dispersed multi-agent systems, where designing a distributed control policy is necessary to achieve agreement on specific parameters among agents negotiating with their neighbours. In the context of continuous-time uncertain nonlinear multi-agent networks, distributed cooperative stabilization presents a challenge, making them suitable for utilizing unpredictable neural networks [50].

The paper introduces stochastic switching topology to examine its impact on the consensus of a system, which is affected not only by topological networks and communication delay but also by other factors [51].

The complexity in consensus often arises from the nature of interactions and topologies, which are frequently stochastic. The authors utilize a global integer time approach, where clocks are installed on edges described by independent Poisson random variables. Various statistical modal dialogs are employed to calculate sample probabilities [52]-[54].

In the context of situation researchers, numerous autonomous local agents interact with each other. Each situational agent possesses a state associated with a measurable quantity of interest, such as opinions, beliefs, positions, values, and speeds. The study examines fishing and bird schools, as well as agents moving at the same speed and their spatial arrangements. In particle physics, constant velocity is assumed at each step [55]-[57].

Consensus difficulties are prevalent in robotics and control systems, particularly in the communication among robotic and sensor network agents [58].

The DeGroot Model, a linear consensus problem with a stochastic matrix, is employed to control consensus issues. The linear model dialogues are constructed based on vector columns with initial values representing DeGroot Model beliefs [59]. It achieves consensus more rapidly than the DeGroot Model, particularly in periodic and reducible networks where the DeGroot Model exhibits limitations in achieving agreement [60], [61].

Mass spectrometry is a scientific method used for analyzing clinical samples in disease diagnosis. It involves the examination of spectrums composed of multiple values and utilizes pattern expression for analysis. Various tools have been developed for spectral viewing, pattern recognition, protein database searching, protein measurement, and identification, as well as for storing biological samples [62].

Stability algebraic graphs serve as models for communication network topology. The eigenvectors of the graph Laplacian matrix are utilized to analyze communication topologies [63]– [66].

The paper explores directed networks with fixed and switching topologies, as well as undirected networks with fixed topologies, focusing on average consensus problems using diagraphs. Network integrators with time delays affect linear consensus as they are inversely proportional to the greatest eigenvalues. The convergence disagreement measures (Lyapunov function) are applied to directed networks with switching topology. Various methodologies from algebraic graph theory, matrix theory, and control theory are employed [67].

This paper analyses a linear distributed protocol with first-order and second-order integrals in multi-agent networks affected by communication noise. Additionally, the author discusses stress consensus in multi-agent systems with dynamically changing asymmetric communication networks [68].

Linear iteration using a transition matrix (stochastic matrix) with positive diagonals enables the achievement of linear consensus. Positive diagonals are associated with updating states and transmitting positive values [69].

Consensus problems in engineering physical models possess unique challenges due to the unrestricted values and behavior. Linear consensus has limitations in physical systems where unbounded values cannot modify performance. To address second-order multi-agent systems with unclear nonlinearity, a disturbed adaptive consensus control strategy is proposed, satisfying the robustness of the Lyapunov function based on simulation findings [70].

Nonlinear protocols enhance the speed and accuracy of both dynamic and linear consensus mechanisms. The Lyapunov theory is applied to achieve agreement, and a dynamic consensus algorithm is implemented to improve reliability. Nonlinear protocols are widely adopted for achieving consensus in multi-agent systems, benefiting synchronization, flocking, swarming, and distributed decision-making [70].

This study enhances cooperative and coordinated control in multi-agent systems with fixed topologies by improving consensus through nonlinear protocols based on the Lyapunov theory. The authors' findings demonstrate that the proposed nonlinear method is more effective than linear methods in controlling agent generation, offering improved performance and robustness [71].

In the context of fixed network topologies, a nonlinear protocol is utilized for controlling a multi-agent system. Nonlinear protocols, compared to linear protocols, exhibit greater power and outperform linear methods in terms of performance and robustness. The paper proposes a nonlinear protocol with connected undirected communication topology for full and partial access. Distributed estimators are used as references, and stability simulations are conducted in Matlab, resulting in reduced energy costs and more reliable assessments [72].

Two types of consensus problems exist in Multi-Agent Networks: linear and nonlinear consensus. Consensus concepts can be applied in the development of central robots and unmanned aerial vehicles (UAVs). While most research has focused on linear and complex nonlinear systems, this study aims to explore low-complexity nonlinear consensus models to address the challenges of nonlinear dynamics in multi-agent systems. Multi-Agent Systems find various applications in artificial intelligence, including consensus and agreement problems, which have been historically challenging [73].

Nonlinear consensus protocols are commonly used to solve agreement challenges in Multi-Agent Systems. The authors employ a nonlinear system based on the Lyapunov function to achieve consensus convergence in multi-agent systems. Many researchers consider nonlinear protocols for stability in the consensus problem, where autonomous agents interact locally to reach an agreement. The concept of "common agreement" implies self-communication among all autonomous agents, ensuring equal information exchange and synchronization of agent states [74].

The theory of nonlinear control is applied to address consensus problems in multi-agent systems. There are two main consensus topologies: directed and switched topologies, which can involve communication delays. Graph theory, matrix inequalities, and the Lyapunov function are employed to achieve consensus using a graphical method (diagraph) and a matrix inequality method with sufficient conditions. Agents reach consensus exponentially fast with the lowest convergence rate. The Lyapunov function is applied when the theory is formulated in the form of matrix inequalities [75].

The consensus problem for second-order multi-agent systems with inherent nonlinear dynamics under directed topologies is discussed. The Lipchitz condition is used for nonlinear models, and consensus states are reached with time-varying and inherent nonlinear terms [76].

This study compares linear and nonlinear consensus protocols in multiconnected systems. A nonlinear technique is employed to achieve consensus, which is a simple and more powerful approach without sacrificing the original status. Nonlinear protocols require fewer iterations to reach consensus. These applications find use in various fields such as game theory, sensor networks, flocking, population genetics, economics, management science, sociology, and robotics. A specific nonlinear model, MDSQO, is designed, and stochastic matrices are found to be faster than the linear DeGroot model. The MDSQO technology is more efficient than DSQO for stability, and agents using MDSQO and DSQO interact with each other [77].

Doubly stochastic quadratic operators (EDSQO) and Markov chains are utilized for multi-agent distributed applications. These operators are implemented using finite-dimensional stochastic matrices. The modified nonlinear EDSQO model, which converges faster, is employed, and agents interact and communicate by confining the extreme EDSQO to a finite-dimensional simplex. The solution to the consensus problem in multi-agent systems is represented by this model [78].

Nonlinear models are highly efficient in processing and are deployed in software and engineering applications to restrict symmetry behaviour. The Exchange Quadratic Stochastic Operators (EQSO) model, specifically the Extremely Doubly Stochastic Quadratic Operator (EDSQO), is used. This paper focuses on the limitations of EDSQOs on a two-dimensional simplex (2DS) and provides results for finite-dimensional simplexes. The behavior of trajectories impacts the nonlinear limit control of EDSQOs on finite-dimensional simplexes, resulting in convergent, fixed, and periodic limit behaviors. EDSQOs exhibit sinusoidal and periodic point behavior, converging towards the central point if certain conditions are met [79].

The dynamics of doubly stochastic quadratic operators (DSQO) on a finite-dimensional simplex, particularly the two-dimensional simplex (2D), are investigated. Convergence to the center of the simplex is observed for 198 extreme and 6 permutation operators. While there are no periodic points inside the simplex in lower dimensions, infinitely periodic points exist in higher dimensions. The dynamics on unlimited simplexes are studied due to the absence of fixed points in unlimited dimensions [80].

The behavior of nonlinear models of complementary stochastic quadratic operators is examined, focusing on systems that are nonlinear yet have a simpler structure

[81], [82].

This study presents a nonlinear mathematical model for consensus problems in multi-agent systems, which is used to calculate the probability distribution of transition matrices for EDSQOs on 2DS. The majorization theory is employed to meet the sufficient requirement, and Matlab is used for assessing the number of EDSQOs on 2DS. Throughout the article, 222 EDSQOs on 2DS are considered, with 6 permutations for each EDSQO [83].

The DeGroot linear model, developed in 1974, represents a linear approach to consensus problems [84]. Stochastic matrices, specifically transition matrices, are used for feasible models that update the Markov chain opinions. A stochastic matrix ensures that the sum of any row or column equals one for consensus to be reached. This model encompasses all individual possibilities. While the linear consensus model is easy to calculate, it is slow to converge, whereas the nonlinear consensus model is difficult to calculate but quicker to reach a consensus. The DeGroot model relies on the concept of a "central individual" in the network, representing a group's beliefs in achieving a consensus through a pool of opinions (common agreement). In the DeGroot model, consensus is reached when the group is connected and periodic, with new viewpoints depending on the previous time period [85]-[87].

Consensus has numerous applications in artificial intelligence, biological sciences, robotics, control systems for autonomous vehicles, economics, and management sciences. The paper focuses on EDSQOs with an exponent degree and compares them to the DeGroot linear model. The proposed process achieves optimal consensus with fast convergence, flexible computations, and precision in approximate optimal solutions. The study compares consensus models of fractional degrees (DeGroot, CSQO, and DSQO) to general consensus models (DeGroot, DSQO, and EDSQO). Simulations are conducted using MATLAB software to evaluate the performance of consensus models. The study shows that the nonlinear consensus model of EDSQOs outperforms the DeGroot linear and DSQO nonlinear models, demonstrating superior convergence and efficiency [88]-[98].

3. Conclusion

This research paper has provided a comprehensive overview of the applications and challenges associated with wireless sensor networks (WSNs). The study highlighted the benefits of structured deployments over ad hoc deployments and emphasized the resource constraints of sensor nodes, including limited energy, communication range, and processing capabilities. Clustering sensor nodes and utilizing sophisticated routing protocols were identified as crucial factors in data transfer to fusion centers.

The research explored consensus algorithms for achieving global statistics in WSNs while sharing data with close neighbors. Various applications of WSNs were discussed, including military operations, environmental monitoring, health monitoring, home automation, and commercial uses. The paper presented a literature review on topics such as distributed consensus algorithms, multi-agent systems, and coordination control in WSNs, covering areas like average consensus, event-triggered consensus control, nonlinear multi-agent networks, and consensus in stochastic networks.

The challenges and potential solutions for achieving consensus in WSNs were addressed, considering factors such as switching topology, communication delays, and uncertain nonlinear dynamics. The research highlighted the importance of graph theory concepts and Laplacian eigenvalues in determining convergence rates and consensus requirements in WSNs.

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Author contributions

Rawad Abdulghafor, Sherzod Turaev, and Mohammed A. H. Ali: Conceptualization, Methodology, Software, Field study **Rawad Abdulghafor, Sherzod Turaev, Mohammed A. H. Ali and Abdullah Said AL-Aamri:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Rawad Abdulghafor, Abdullah Said AL-Aamri, Yousuf Al Husaini, and Mohammed Abdulla Salim Al Husaini:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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