Nonlinear Consensus for Wireless Sensor Networks: Enhancing Convergence in Neighbor-Influenced Models

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***Abstract*—Wireless sensor networks (WSNs) are a modern technology that has revolutionized many industries thanks to their ability to collect and analyze information from surrounding environments and improve the performance of complex systems through the cooperation of a group of independent sensors to achieve common goals. Sensor clustering and agreement have wide applications in daily life, ranging from environmental monitoring and industrial control to healthcare and smart cities. However, the WSN system faces many challenges, one of the most prominent is achieving agreement between different sensors on a common state. This challenge is essential to enable successful cooperation between sensors in complex systems. Many previous research and models have been developed to address the problem of sensor agreement, such as the Neighbor-Influenced Timestep Consensus Model (NITCM), which was presented as a framework to achieve agreement effectively. In this paper, we propose a new technique to improve this model by using fractional force in the updating process. This leads to developing the Neighbor-Influenced Fractional Timestep Consensus Model (NIFTCM). This technique achieves faster convergence between sensors, which leads to improved efficiency in reaching agreement over previous techniques. This development aims to enhance the speed and stability of consensus processes in wireless sensor networks and make them more suitable for time-sensitive applications.**

Keywords—Fractional power; consensus; WSNs; NIAM; NIFFAM

I. Introduction

Wireless sensor networks (WSNs) are a modern technology that has greatly influenced many industrial and technological fields. These networks consist of small sensors that communicate via wireless communications to collect data from the surrounding environment, analyze it, and transmit it to a central processing center or to other relevant devices. Wireless sensor networks are a powerful tool in improving the efficiency of operations and providing smart solutions, and they have been employed in many applications such as healthcare, smart agriculture, environmental monitoring, smart cities, and security systems [1]. This technology allows communities to improve resource management and enhance the overall quality of life.

Wireless sensor networks have revolutionized various industries thanks to the ability to monitor and collect data continuously and present it in real time. By applying this technology, it has become possible to improve the efficiency of operational processes, reduce costs, and increase the reliability of systems, making wireless sensor networks a key focus for the development of future technologies [2].

Multi-agent systems are advanced models that rely on independent agents working simultaneously to achieve common goals. Agents can represent independent devices or intelligent programs like sensors, and they work collaboratively to solve complex problems [3]. Multi-agent systems have been used in applications such as robot coordination, e-commerce, and network management, including wireless sensor networks. In this context, MAS is an effective tool for managing and organizing work between different sensors in a single network, which improves the overall efficiency of the network [4]. Despite the significant advantages of wireless sensor networks, they face several critical challenges, the most prominent of which is the problem of consensus between different sensors to achieve collective agreement on the collected data or actions taken. Consensus between sensors is vital to ensure the accuracy and reliability of data; hence, the importance of achieving a common agreement between all agents in the system [5]. Other challenges include reducing energy consumption, improving data security, and increasing fault tolerance.

The consensus problem in multi-agent systems is defined as the ability to achieve common agreement among a group of independent agents on a particular state or value, through their repeated interactions with each other [6]. In wireless sensor networks, the consensus problem is fundamental, as it contributes to improving the efficiency of the network and ensuring that all sensors reach uniform results regarding the collected data. Challenges facing consensus in these networks include communication delays, unstable wireless links, and the negative impact of environmental noise [7].

Several consensus models have been suggested in past works, and the human-friendly Neighbor-Influenced Timestep Consensus Model (NITCM) is one of them. However, due to its simplicity, NITCM takes comparatively longer to resolve in complex environments. Alternatively, nonlinear models have shown quicker and more straightforward convergence than linear models; however, they are not as widely used in wireless sensor networks.

In this paper, we propose a new model called the Neighbor-Influenced Fractional Timestep Consensus Model (NIFTCM). This model is based on and builds on the well-known linear Neighbor-Influenced Timestep Consensus Model (NITCM) [8].

NIFTCM accomplishes this by adding a fractional power method to the update steps, thus changing the original linear system into a nonlinear system. NIFTCM aims to quicken the convergence process and improve the efficiency of reaching consensus while maintaining the system's simplicity.

Due to its nonlinear nature, the model is likely to provide higher efficiency and a quicker rate of convergence than regular linear models, mainly in dynamic WSNs. We will review academic works to show the quality of our suggested strategy, reveal any current open issues, and verify its relevance.

We then explain how NIFTCM is obtained using fractional powers, carry out comparison tests, and report the differences in their performance. We will explore how the NIFTCM model helps achieve greater agreement speed and less overhead, therefore making the model a better option for timely WSN uses.

The organization of the paper goes as explained below.

- Section II discusses existing research on the topic and points out weaknesses in existing approaches.
- Section III outlines the methodology and shows where the fractional power has been put into the model.
- Section IV presents the results of tests and compares NIFTCM to NITCM.
- Section V covers the findings and suggests possible future work.

II. Related Work

Wireless sensor networks (WSNs) and Internet of Things (IoT) systems have witnessed rapid developments in the last decade, making them a mainstay for modern applications including agriculture, health, industry, and military fields. Many researchers have addressed the challenges associated with these technologies and sought to provide innovative solutions to improve their performance and efficiency. Gulati et al. [9] pointed out the problem of energy consumption in wireless networks where small nodes that rely on batteries suffer from short lifespan, and presented energy-efficient data collection techniques to improve the network lifetime. However, their techniques faced challenges in dynamic environments.

In a different context, Al-Hamami and Nasser Al-Din [10] focused on the use of wireless networks to manage irrigation systems, which contributed to improving water use efficiency and reducing the global water crisis, despite challenges related to costs and infrastructure. Other research has focused on improving the compatibility speed in wireless networks, such as the study by Jiang and Li [11] who presented asymmetric mixing matrices to accelerate compatibility and reduce computational complexity using spectrum standards.

On the other hand, Wang et al. [12] proposed the MECTS algorithm to improve the convergence speed in industrial networks while reducing the communication overhead by 22.7%. In the same context, Yu [13] addressed the improvement of distributed consensus protocols using the Reliability Gain metric to analyze the relationship between reliability and latency, while presenting an adaptive protocol that ensures continuous decision-making even in the event of failure.

Research has also focused on improving the efficiency of wireless networks. Patel and Parveen [14] presented the CSCS framework to enhance security and efficiency in wireless networks, while Chen et al. [15] developed the HSL strategy to improve information aggregation and speed up the consensus process. In industrial applications, Xu et al. [16] studied distributed consensus protocols such as Raft to improve the reliability of autonomous systems. Also, Ishii et al. [17] reviewed the security algorithms of cyber systems against data injection attacks and denial of service attacks.

In the field of hybrid protocols, Pranathi et al. [18] proposed a routing protocol that combines energy efficiency and network resilience against node failure, while Li et al. [19] focused on the DIFIR algorithm that enhances target tracking accuracy in MAS. On the other hand, Mahato et al. [20] presented an algorithm to improve task allocation in unstable network environments using synchronous transfer protocols.

In terms of time synchronization, Fan et al. [21] developed the NTSP protocol to reduce the impact of asynchronous nodes and speed up synchronization by three times compared to traditional protocols. In a different context, Feng et al. [22] discussed improving autonomous driving using a distributed consensus framework in V2V networks, with protocols designed to meet the requirements of complex maneuvers.

Liao et al. [23] presented an algorithm to improve energy efficiency using network utility maximization technique, while Jin and Sun [24] presented a DOP algorithm to improve the stability and accuracy of estimations in sensor networks. In the field of distributed state estimation, Zhang et al. [25] introduced RCIF and DRCIF algorithms that improved the stability of networks and the estimation accuracy, while Chen et al. [26] focused on developing a new estimator for distributed state estimation in energy harvesting capable networks, providing innovative solutions to energy-related challenges.

Other research has addressed the consensus challenges in UAV networks. Cheng et al. [27] developed the UCP protocol to improve consensus in dynamic and complex UAV environments. Prabhu et al. [28] focused on secure routing mechanisms in sensor networks to improve security against attacks.

In advanced consensus applications, Guyeux et al. [29] discussed improving the consensus process using parallel atomic transactions to speed up consensus time and reduce communication and energy costs.

Security solutions have multiplied in wireless networks, as Chen et al. [30] focused on implementing federated learning in distributed networks through the DACFL framework, which increased the consistency and accuracy of models by up to 50% compared to traditional methods. Fan and Kim [31] designed the VTSP protocol to improve time synchronization in wireless networks, which reduced the convergence time by three times compared to traditional protocols.

In terms of MAS, Amirkhani and Parshvi [32] presented a comprehensive review of consensus algorithms and their applications in collective control and configuration formation.

In terms of improving energy consumption, Lu et al. [33] proposed a method to optimize topology and reduce data redundancy using an iterative algorithm to determine common parameters. While Benkhadra et al. [34] focused on the use of Blockchain technology to improve the security of wireless networks in the healthcare sector, which led to enhanced data protection and security assurance.

Abdulghafor et al. [35]-[49] presented novel nonlinear models such as SSQO and MDSQO, which have proven effective in accelerating consensus and improving efficiency. In additionally, Abdulghafor and Shahidi et al. [50]-[55] addressed the dynamics of random quadratic motors, providing deep insights into compatibility optimization using Lyapunov theorems, and demonstrated that these models effectively solve compatibility problems in wireless networks.

Over the past few years, researchers have developed some advanced consensus methods to make WSNs work more efficiently in 2025. They have also looked into distributed consensus in WSNs to make the data more accurate and reliable in different situations. Kenyeres et al. [56] studied seven fusion algorithms based on gossip to mitigate Gaussian - noise-induced errors in measured values. The results clearly stated that Push-Sum is preferred for densely connected nets while Geographic Gossip improves results in more dispersed networks, making both methods result in at least 24 dB less MSE. Yuan and Ishii [57] applied the MSR method to multi-hop networks and found that including more relay stations can ensure resilience to adversaries. By using a state-dependent approach, Zhao et al. [58] designed a high-gain protocol that guarantees that multi-agent systems move towards consensus even when the communication graph is dynamic. Xu et al. [59] gave a clear explanation of how wireless consensus works, looking at both standard fault-tolerant and Byzantine-tolerant protocols, and also talked about how blockchain tech can be used with wireless networks to help build trust between devices. Giridi et al. [60] explained how WSNs with blockchain can weed out unreliable information and help with optimal routing. All these innovations point to how gossip, multi-hop systems, state-based protocols, good spectrum use, and blockchain trust help achieve reliable and fast consensus in wireless networks without many resources.

Most suggested methods for getting agreement in wireless sensor networks are classic and fail to perform well in complex or challenging environments. Although nonlinear models perform better in some situations, they are not used as commonly or appropriately tailored to the special features of WSNs. The linear NITCM model is simple but takes a long time to adjust. It is unsuitable for applications that require constant adaptation due to topology or environmental changes. By comparison, fractional power models offer a different path since their nonlinear behavior allows them to escape these limitations. We added fractional power to the model to help convergence and maintain adequate stability in a way that does not increase computational difficulty. Also, there is not enough research on using methods such as fractional power, which might improve the speed and efficiency with which nodes come to a consensus.

So, it is necessary to develop a model that addresses these weaknesses using linear models' simplicity and retaining nonlinear methods' increased performance. To achieve this, the authors suggest using their model NIFTCM, with fractional power techniques, which enables faster consensus and is still helpful in wireless sensor networks.

These studies demonstrate that the continuous development of wireless network technologies provides practical solutions to compatibility, energy, and security challenges, enhancing their adaptability to more demanding future applications.

III. Research Methodology

Wireless sensor networks (WSNs) and Internet of Things (IoT) systems have rapidly developed in the last decade, making them a mainstay for modern applications, including agriculture, health, industry, and military. Many researchers have addressed the challenges associated with these technologies and sought to provide innovative solutions to improve their performance and efficiency. Gulati et al. [9] pointed out the problem of energy consumption in wireless networks where small nodes that rely on batteries suffer from short lifespans and presented energy-efficient data collection techniques to improve the network lifetime. However, their techniques faced challenges in dynamic environments.

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The research methodology in this paper is to develop the traditional consensus equation system into an improved system using fractional power $1/n$, with the mechanism of this development being systematically defined as follows:

1) Understanding classical model of NITCM

- The classic equations represent a simple mathematical system that uses time steps dt to calculate the future values of each element P_i based on the effects of neighbours.
- The weight used to update the values is determined based on parameters such as $(1 - dt)$ and dt, which allows the combined effect of neighboring elements to be calculated.

The basic formula for equations in NITCM is:

$$\begin{gathered} P_1^{i+1} = (1 - dt)P_1^i + dtP_2^i \\ P_2^{i+1} = (1 - 1.5 * dt)P_2^i + 1.5 * dtP_3^i \\ P_3^{i+1} = (1 - 2 * dt)P_3^i + 2 * dtP_1^i \end{gathered} \tag{1}$$

- These equations aim to achieve consistency between values through the influence of neighbours, where the update rate is controlled by dt.

2) Identifying limitations and challenges

- Limited speed of convergence: The model relies on small time steps dt, which results in slow convergence in complex systems.
- Linear response: The linear model makes dealing with nonlinear or variable environments difficult.
- Reliance on absolute values: This may have a limited impact on improving efficiency in complex scenarios such as wireless sensor networks.

3) Fractional power technique proposal of NIFTCM

- The traditional equations are modified to include the fractional power $1/n$, where this technique is applied to the weighted values after updating at each time step.
- This modification allows dynamic control of the convergence speed and accuracy of the results by changing the value of n, where $n = 2$, $n = 3$, …, n, and so on.
- Improved equations of NIFTCM:

$$P_1^{i+1} = \left((1 - dt)P_1^i + dtP_2^i\right)^{\frac{1}{n}}$$

$$P_2^{i+1} = \left((1 - 1.5 * dt)P_2^i + 1.5 * dtP_3^i\right)^{\frac{1}{n}} \quad (2)$$

$$P_3^{i+1} = \left((1 - 2 * dt)P_3^i + 2 * dtP_1^i\right)^{\frac{1}{n}}$$

4) Comparison between the classical model of NITCM and improved model of NIFTCM

A comprehensive comparison is made between the two models in terms of:

- Consensus speed: the extent to which each model can achieve consensus in a given number of iterations.
- Flexibility: the model's ability to adapt to nonlinear environments.
- Efficiency: reducing resource consumption such as energy and computing time.

5) Practical application

The two models are applied to scenarios in wireless sensor networks (WSNs) to determine:

- The efficiency of the improved model in improving energy consumption.
- Consensus speed compared to the simple model.

This research represents a significant development of the simple model using the fractional power technique $1/n$, where performance is greatly improved by adding the nonlinear response. This development can lead to faster and more efficient consensus, making it suitable for applications in complex environments such as wireless sensor networks.

B. *Flowchart of the Research*

Following the diagram seen in Section I, here is how the research methodology and model development process are described:

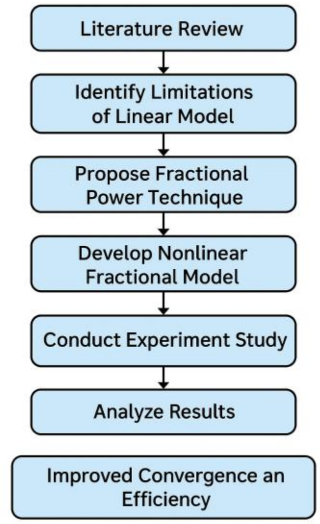

Diagram 1. Research flowchart.

It describes the research problem as the slow way traditional agreement methods, such as NITCM, function in wireless sensor networks (WSNs). The literature review reviews existing methods and tools, pointing out their weaknesses and shortcomings. Trying to improve on it, a new version called the Neighbor-Influenced Fractional Timestep Consensus Model (NIFTCM) is introduced. It combines a fractional power into the standard update formulas, which turns it into a nonlinear system that performs better. The second step is to make and test the proposed algorithm, then run experiments in simulation to observe the differences between old and new methods when supplied with different fractional power ratings. Plots are used to compare the results and show that the NIFTCM model strongly speeds up the rate of reaching consensus. Ultimately, the team summarizes the work and discusses how best to move forward, such as using it in practice or further experiments.

IV. Results

A. *Experimental settings*

- Initial values:

$$P_1 = 1, P_2 = 2, P_3 = 3$$

- $dt = 0.01$
- tolerance= 1×10^{-5}

B. *Examples*

1) Original Model (NITCM):

a) Iteration 1:

- Initial Values:

$$P_1 = 1, P_2 = 2, P_3 = 3$$

- Update P_1 using the equation (1):

$$P_1^{1+i} = (1 - dt) * P_1^i + dt * P_2^i$$

Substitution:

$$P_1^1 = (1 - 0.01) * 1 + 0.01 * 2$$
$$= 0.99 + 0.02 = 1.01$$

- Update P_2:

$$P_2^{1+i} = (1 - 1.5 * dt) * P_2^i + 1.5 * dt * P_3^i$$

Substitution:

$$P_2^1 = (1 - 0.015) * 2 + 0.015 * 3$$
$$= 1.985 + 0.045 = 2.03$$

- Update P_3:

$$P_3^{1+i} = (1 - 2 * dt) * P_3^i + 2 * dt * P_1^i$$

Substitution:

$$P_3^1 = (1 - 0.02) * 3 + 0.02 * 1$$
$$= 2.94 + 0.02 = 2.96$$

b) Final result:

- The process is repeated until the differences between the values are less than tolerance.
- Eventually, the values reach:

$$P_1 = P_2 = P_3 = 1.76$$

- Number of iterations ~ 500.

2) Develop Model with fractional power ($\frac{1}{2}$) (NIFTCM):

a) Iteration 1:

- Initial Values:

$$P_1 = 1, P_2 = 2, P_3 = 3$$

- Update P_1 using the equation (2):

$$P_1^{1+i} = \left((1 - dt) * P_1^i + dt * P_2^i\right)^{\frac{1}{2}}$$

Substitution:

$$P_1^1 = \left((1 - 0.01) * 1 + 0.01 * 2\right)^{\frac{1}{2}}$$
$$P_1^1 = (0.99 * 1 + 0.01 * 2)^{1/2} = (0.99 + 0.02)^{\frac{1}{2}}$$
$$P_1^1 = \sqrt{1.01} = 1.004987$$

- Update P_2:

$$P_2^{1+i} = \left((1 - 1.5 * dt) * P_2^i + 1.5 * dt * P_3^i\right)^{\frac{1}{2}}$$

Substitution:

$$P_2^1 = \left((1 - 1.5 * 0.01) * 2 + 1.5 * 0.01 * 3\right)^{\frac{1}{2}}$$
$$P_2^1 = (0.985 * 2 + 0.015 * 3)^{1/2} = (1.97 + 0.045)^{\frac{1}{2}}$$
$$P_2^1 = \sqrt{2.015} = 1.418332$$

- Update P_3:

$$P_3^{1+i} = \left((1 - 2 * dt) * P_3^i + 2 * dt * P_1^i\right)^{\frac{1}{2}}$$

Substitution:

$$P_3^1 = \left((1 - 2 * 0.01) * 3 + 2 * 0.01 * 1\right)^{\frac{1}{2}}$$
$$P_3^1 = (0.98 * 3 + 0.02 * 1)^{1/2} = (2.94 + 0.02)^{\frac{1}{2}}$$
$$P_3^1 = \sqrt{2.96} = 1.720465$$

b) Iteration 2:

- Update $\boldsymbol{P_1}$:

$$P_1^2 = \left((1 - 0.01) * 1.004987 + 0.01 * 1.418332\right)^{\frac{1}{2}}$$
$$P_1^2 = (0.99 * 1.004987 + 0.01 * 1.418332)^{1/2}$$
$$= (0.994937 + 0.014183)^{\frac{1}{2}}$$
$$P_1^2 = \sqrt{1.00912} = 1.004548$$

- Update $\boldsymbol{P_2}$:

$$P_2^2 = \left((1 - 1.5 * 0.01) * 1.418332 + 1.5 * 0.01 * 1.720465\right)^{\frac{1}{2}}$$
$$P_2^2 = (0.985 * 1.418332 + 0.015 * 1.720465)^{\frac{1}{2}}$$
$$= (1.396067 + 0.025807)^{\frac{1}{2}}$$
$$P_2^2 = \sqrt{1.421874} = 1.192712$$

- Update $\boldsymbol{P_3}$:

$$P_3^2 = \left((1 - 2 \cdot 0.01) \cdot 1.720465 + 2 \cdot 0.01 \cdot 1.004987\right)^{\frac{1}{2}}$$
$$P_3^2 = (0.98 * 1.720465 + 0.02 * 1.004987)^{\frac{1}{2}}$$
$$= (1.686056 + 0.0201)^{\frac{1}{2}}$$
$$P_3^2 = \sqrt{1.706156} = 1.306157$$

c) Final result:

- The model reaches consensus in only ~ 16 iterations.
- Final values:

$$P_1 = P_2 = P_3 = 1$$

3) Explanation of the graphs

a) For 3 WSNs:

i) Fig. 1 (NITCM vs NIFPCM at $n = 2$):

- Left part (NITCM):
  - Shows the convergence of the three values (P_1, P_2, P_3) towards the mean (1.76) over 500 iterations.

- The curves represent the gradual change of each value until consensus is achieved.

- Right part (NIFPCM at $n = 2$):
  - Shows that the values reach consensus quickly ($\sim$16 iterations).
  - Fractional power makes updates faster compared to the simple model.

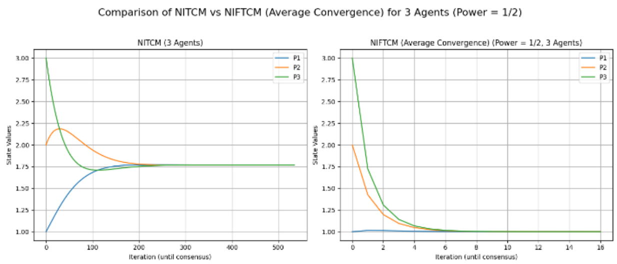

Fig. 1. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{2}$ for 3 WSNs.

ii) Fig. 2 ($n = 10$):

- Left part: Similar to the simple model (NITCM) in Fig. 1.
- Right part: Shows faster convergence ($\sim$4 iterations only).

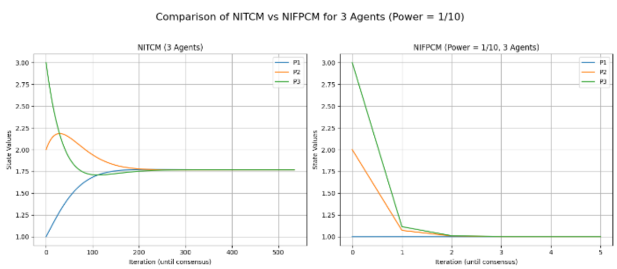

Fig. 2. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{10}$ for 3 WSNs.

iii) Fig. 3 ($n = 100$):

- Left part: Similar to the simple model (NITCM) in Fig. 1.
- Right: Shows the effect of large n, where convergence becomes faster ($\sim 2\ iterations$).

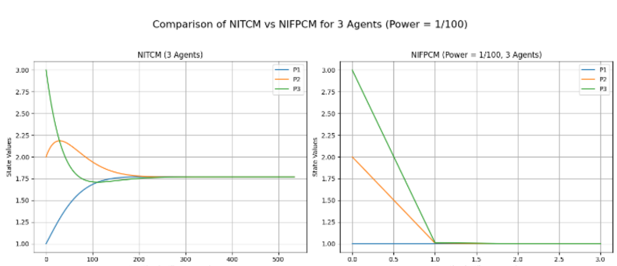

Fig. 3. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{100}$ for 3 WSNs.

iv) Fig. 4 ($n = 1000$):

- Left part: Similar to the simple model (NITCM) in Fig.1.
- Right: Almost instantaneous convergence, showing that large n makes the model very close to linear (only one iteration).

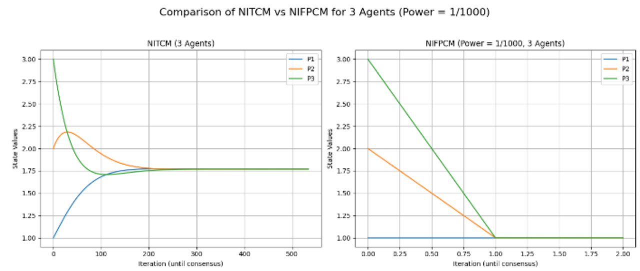

Fig. 4. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{1000}$ for 3 WSNs.

b) For 5 WSNs:

i) Fig. 5: NITCM and NIFTCM for 5 WSNs at $n = 2$

NITCM: The first figure on the left shows how five sensors interact using the linear model (NITCM). As can be seen, the initial values $P_1 = 1, P_2 = 2, P_3 = 3, P_4 = 4, P_5 = 5$ gradually converge towards an average value of around 3 . The convergence process takes around 1400 iterations to reach consensus, indicating a relatively slow convergence speed.

NIFTCM ($n = 2$): The second figure on the right shows the results of the improved model (NIFTCM) with a fractional power of $\frac{1}{2}$. The convergence speed is significantly higher, with the values reaching consensus to 1 in only around 17 iterations. This indicates that the fractional force contributes to the acceleration of the convergence process effectively.

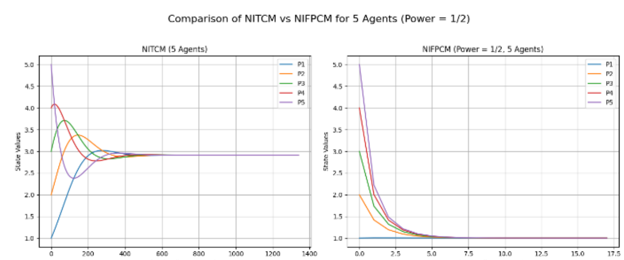

Fig. 5. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{2}$ for 5 WSNs.

ii) Fig. 6: NITCM and NIFTCM for 5 WSNs at $n = 10$

NITCM: The linear model continues with almost the same performance as before, reaching consensus after about 1400 iterations.

NIFTCM ($n = 10$): The second figure shows a greater improvement in convergence speed. When applying a fractional power of $\frac{1}{10}$, the values reach consensus in only about 6 iterations, reflecting the high efficiency of the improved model at this value.

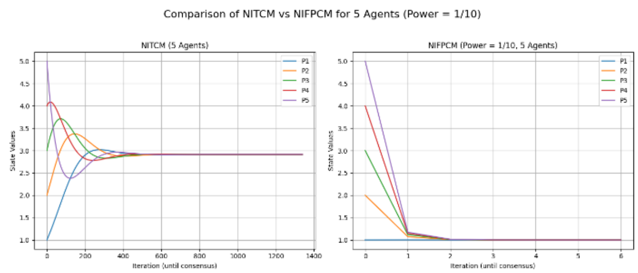

Fig. 6. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{10}$ for 5 WSNs.

iii) Fig. 7: NITCM and NIFTCM for 5 WSNs at $n = 100$

NITCM: It is no different from the linear model in the previous figures, reaching consensus after the same number of iterations.

NIFPCM (n=100): The graph shows significantly faster convergence, with the values reaching consensus to 1 after only 3 iterations. The higher the value of n, the faster the improved model can converge.

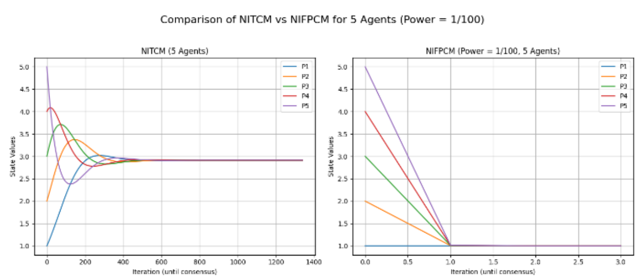

Fig. 7. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{100}$ for 5 WSNs.

iv) Fig. 8: NITCM and NIFTCM for 5 WSNs at n=1000

NITCM: continues to perform the same without any noticeable change.

NIFPCM (n=1000): With such a large value of n, it appears that the values reach consensus in less than 2 iterations, reflecting the very high efficiency of the model as n increases.

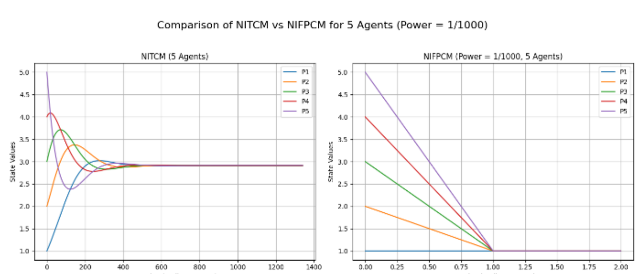

Fig. 8. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{1000}$ for 5 WSNs.

c) For 10 WSNs:

i) Fig. 9: Comparison of NITCM and NIFPCM at $n = 2$ for 10 WSNs

Left figure (NITCM): The figure shows the evolution of the state of each of the ten sensors over time (iterations). The states start with different values (1, 2, 3, ..., 10). It is clear that the traditional model (NITCM) needs a very large number of iterations to reach the consensus state (more than 5000 iterations). The oscillations between the states are evident at the beginning, which shows that the system needs more time to achieve stable values.

Right figure (NIFTCM, $n = 2$): Shows the effect of adding the fractional power $\left(\frac{1}{2}\right)$ on the improved model (NIFTCM). The iterations required to reach the consensus state are significantly reduced (only about 15 iterations). The figure enhances the efficiency of the improved model as the states show a rapid and steady decline towards the mean value.

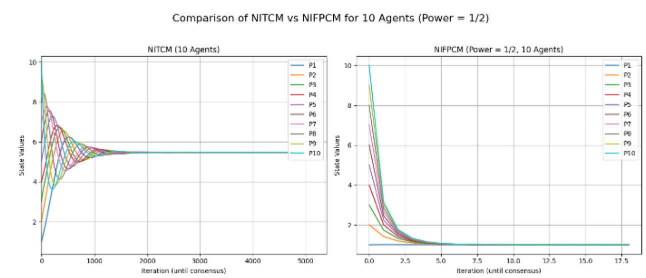

Fig. 9. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{2}$ for 10 WSNs.

ii) Fig. 10: Comparison of NITCM and NIFTCM at $n = 10$ for 10 WSNs

Left figure (NITCM): The figure shows that the ten sensors still show similar behavior as in the first figure with large oscillations and a huge number of iterations required to achieve consensus. The initial values react slowly to reach the final consensus.

Right figure (NIFTCM, $n = 10$): With the application of fractional power $\left(\frac{1}{10}\right)$, a very large decrease in the number of iterations required to achieve consensus is seen (only about 6 iterations). The lines show a smooth and regular convergence, reflecting the significant improvement in the speed of reaching consensus.

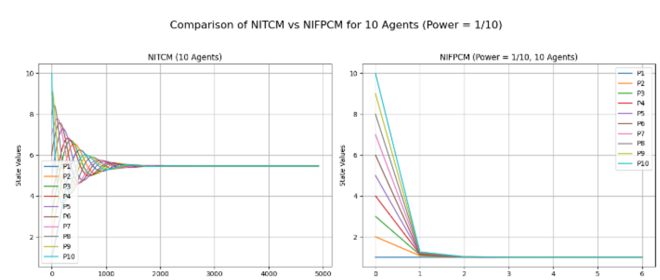

Fig. 10. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{10}$ for 10 WSNs.

iii) Fig. 11: Comparison of NITCM and NIFTCM at $n = 100$ for 10 WSNs

Left figure (NITCM): The pattern is similar to the previous two figures. The time required to achieve consensus is still very long due to the linear nature of the traditional model.

Right figure (NIFPCM, $n = 100$): The figure shows that the number of iterations required to achieve consensus has become much smaller (only about 3 iterations). The lines indicate a fast and direct convergence towards the mean value without any significant oscillations.

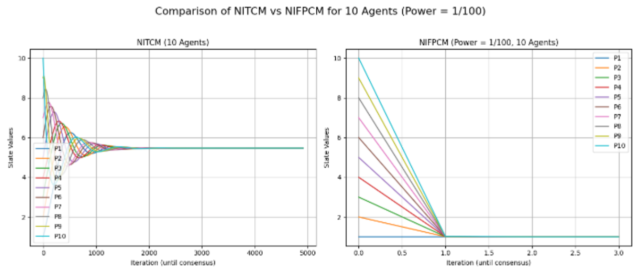

Fig. 11. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{100}$ for 10 WSNs.

iv) Fig. 12: Comparison of NITCM and NIFTCM at $n = 1000$ for 10 WSNs

Left figure (NITCM): Same observations as before with continued slow oscillations and a very large number of iterations required to reach consensus.

Right figure (NIFTCM, $n = 1000$): The improvement becomes more pronounced. Only less than two iterations are required to achieve consensus across all sensors. The figure reflects the maximum efficiency of the improved model using large fractional power, where the mean value is reached in record time.

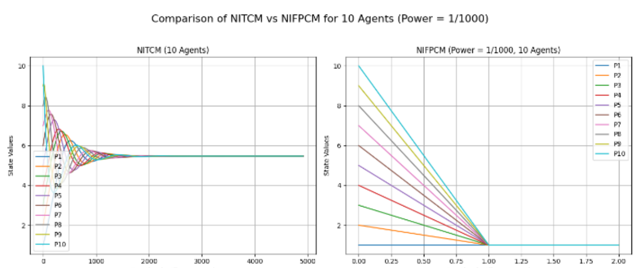

Fig. 12. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{1000}$ for 10 WSNs.

d) For 100 WSNs:

i) Fig. 13: Comparison of NITCM and NIFPCM at $n = 2$ for 100 WSNs

Left figure (NITCM): The traditional NITCM model is very slow in reaching consensus values between 100 nodes. The large fluctuations in node values are clearly visible with the number of iterations exceeding hundreds of thousands before reaching consensus.

Right figure (NIFTCM): The improved NIFTCM model with fractional power $n = \frac{1}{2}$ shows very fast convergence, where consensus is achieved after only about 17 iterations. This result shows a significant improvement in efficiency compared to NITCM.

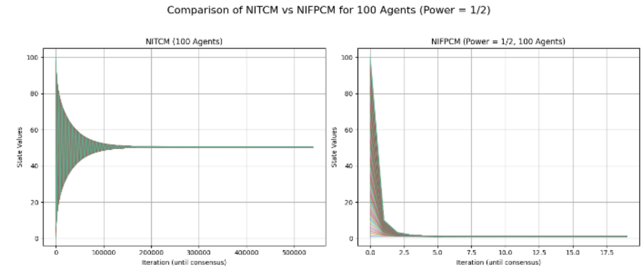

Fig. 13. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{2}$ for 100 WSNs.

ii) Fig. 14: Comparison of NITCM and NIFPCM at $n = 10$ for 100 WSNs.

Left plot (NITCM): High oscillations remain evident with the traditional NITCM model, taking over half a million iterations to reach convergence.

Right plot (NIFTCM): At the fractional power $n = \frac{1}{10}$, the improved model achieves convergence much faster, with only 6 iterations needed to reach stability.

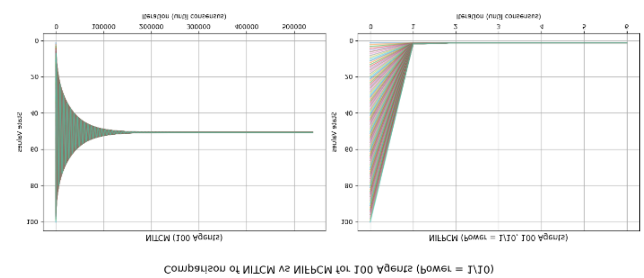

Fig. 14. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{10}$ for 100 WSNs.

iii) Fig. 15: Comparison of NITCM and NIFPCM at $n = 100$ for 100 WSNs.

Left plot (NITCM): The same slow pattern continues in the traditional model, with a failure to improve the time to convergence.

Right plot (NIFTCM): As the fractional power increases to $n = \frac{1}{100}$, convergence becomes faster, with only 3 iterations needed to achieve convergence between nodes.

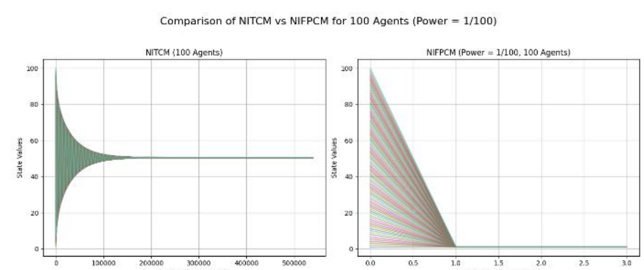

Fig. 15. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{100}$ for 100 WSNs.

iv) Fig. 16: Comparison of NITCM and NIFPCM at $n = 1000$ for 1000 WSNs.

Left plot (NITCM): Large oscillations and pronounced slowdown persist, demonstrating the limitations of the conventional model's efficiency.

Right plot (NIFPCM): Using the fractional power $n = \frac{1}{1000}$, convergence becomes almost instantaneous, with agreement achieved after less than 2 iterations.

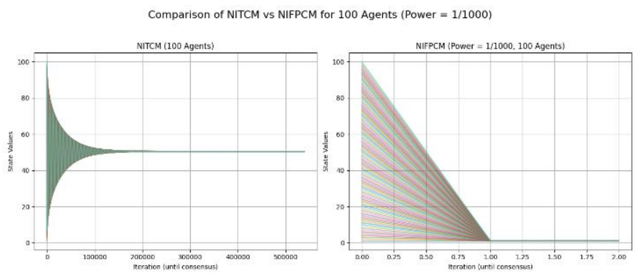

Fig. 16. Comparison of the consensus NITCM vs NIFTCM with fraction $\frac{1}{1000}$ for 100 WSNs.

The results confirm that the improved NIFTCM model using fractional power shows a clear superiority in convergence speed compared to the traditional NITCM model. When using small values of fractional power n, consensus is achieved faster, reducing the number of iterations needed to reach the steady state. The graphs highlight the importance of the improved NIFTCM model in achieving higher efficiency and faster convergence speed, making it ideal for practical applications that require high accuracy and response speed. The improved model shows its efficiency especially in WSNs, where complex environments require innovative and fast solutions.

V. Conclusion

The study clearly shows that the improved model (NIFTCM) based on fractional power offers significant improvements compared to the traditional model (NITCM) in achieving consensus speed in wireless sensor networks. The results extracted from the graphs show that using fractional power contributes to reducing the number of iterations required to reach consensus, which reflects the high efficiency of the improved model. The higher the value of fractional power $\frac{1}{n}$, the faster the convergence between nodes increases, while reducing the computational effort required, which makes the improved model ideal for practical applications that require fast responses and high accuracy, especially in time-sensitive systems. The developed model (NIFTCM) emerges as an ideal tool for improving the performance of wireless sensor networks, which opens up broad horizons for its application in our daily lives. Potential applications of the model include improving environmental monitoring systems such as tracking climate change and monitoring forests, in addition to healthcare applications that rely on accurate and fast-responding sensors to monitor patients' health. It can also be applied in smart cities to improve the efficiency of resource management, such as electricity and water, and in intelligent transportation systems to coordinate the movement of self-driving vehicles, in addition to its role in enhancing the performance of industrial systems based on artificial intelligence and the Internet of Things. This development makes the NIFPCM model an ideal solution to the challenges associated with complex and changing systems. It enhances their efficiency and suitability for applications that require high speed and accuracy in various vital fields.

While the simulation study showed favorable performances for NIFPCM, we believe testing the model in practical conditions is valuable. The model will be tested in practical settings such as monitoring the environment or controlling industrial machines to test its ability to work under delays, dropped packets, and various hardware limitations. Real-world tests are needed to ensure the model can handle changing situations.

Future work will cover creating mixes of existing algorithms, adding more optimization tricks to run better, and studying the links between shape changes and the time taken for convergence or accuracy.

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Conflicts of Interest

The authors declare no conflicts of interest.

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