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Machine Learning Approaches for Dynamic System Parameter Estimation in Sensor Networks

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Abstract

Machine learning approaches for dynamic system parameter estimation in sensor networks involve the utilization of algorithms and models to infer and track the evolving parameters of dynamic systems using sensor data. These methods often employ techniques such as Bayesian inference and Sensor Networks to adaptively learn the underlying system dynamics and estimate parameters in real time. By leveraging the rich information gathered from sensor networks, these approaches can address challenges such as non-linearity, noise, and changing environmental conditions. They enable robust and accurate estimation of system parameters, facilitating various applications ranging from environmental monitoring to industrial process control. Additionally, the inherent flexibility of machine learning allows for the development of adaptive algorithms capable of accommodating the evolving nature of dynamic systems, ensuring continuous and precise parameter estimation in sensor networks.

Keywords: Machine Learning, Dynamic System, Parameter Estimation, Sensor Networks, Bayesian Inference, Gaussian Processes

1. Introduction

In the era of pervasive connectivity and ubiquitous sensing, sensor networks have emerged as a fundamental tool for monitoring and understanding dynamic systems across various domains, ranging from environmental monitoring to industrial process control [1]. The accurate estimation of system parameters in these dynamic environments is crucial for decision-making, optimization, and control purposes. Traditional methods, although effective to some extent, often struggle to adapt to the inherent complexity and non-linearity of dynamic systems, along with challenges such as noise and changing environmental conditions [2]. In recent years, machine learning techniques have gained significant attention as a promising approach to address these challenges and enhance the accuracy and efficiency of parameter estimation in sensor networks [3]. Machine learning algorithms offer the capability to learn from data and uncover complex patterns and relationships within the sensor data, enabling dynamic parameter estimation in real time. These approaches leverage advanced statistical methods, neural networks, Bayesian inference, and Gaussian processes, among others, to infer and track the evolving parameters of dynamic systems [4]. By integrating machine learning with sensor networks, researchers and practitioners can unlock new possibilities for adaptive and robust parameter estimation across diverse applications. In this paper, we provide an in-depth exploration of machine-learning approaches for dynamic system parameter estimation in sensor networks [5]. We begin by presenting the background and historical context of parameter estimation techniques, tracing the evolution from traditional statistical methods to the emergence of machine learning. Subsequently, we delve into the various machine learning techniques employed for dynamic parameter estimation, including Bayesian inference, Gaussian processes, and ensemble methods, among others. In the context of sensor networks, this task is crucial for understanding, monitoring, and controlling various dynamic systems, such as environmental processes, industrial machinery, and biological systems [6]. Sensor networks consist of interconnected sensors deployed in the physical environment, continuously collecting data on system variables such as temperature, pressure, humidity, and chemical concentrations. The dynamic nature of many real-world systems poses significant challenges to parameter estimation. These systems often exhibit non-linear behaviors, time-varying dynamics, and uncertainties, making it difficult to accurately model and predict their behavior using traditional approaches. Moreover, sensor data are often corrupted by noise, drift, and other artifacts, further complicating the estimation process [7]. Traditional methods for dynamic system parameter estimation typically rely on mathematical models and statistical techniques such as least squares estimation, Kalman filters, and system identification algorithms. While these methods can be effective under certain conditions, they may struggle to adapt to the complexity and non-linearity of dynamic systems, and they often require prior knowledge of system dynamics, which may not always be available or accurate [8].

In recent years, machine learning techniques have emerged as a powerful tool for dynamic parameter estimation in sensor networks [9, 10]. These techniques leverage the abundance of sensor data to learn complex relationships and patterns within the data, enabling adaptive and data-driven parameter estimation in real time. Machine learning algorithms such as neural networks, Gaussian processes, and Bayesian inference methods offer the flexibility to model non-linear dynamics, handle uncertainties, and adapt to changing environmental conditions [11]. By integrating machine learning with sensor networks, researchers and practitioners can overcome the limitations of traditional methods and achieve more accurate and robust parameter estimation. Machine learning approaches enable the development of adaptive algorithms that can continuously update and refine parameter estimates based on incoming sensor data, leading to improved understanding, monitoring, and control of dynamic systems [12]. Machine learning offers a data-driven approach to parameter estimation, where algorithms can automatically learn from historical data and adaptively adjust their models to capture the underlying dynamics of the system [13]. Unlike traditional methods that rely on explicit mathematical models, machine learning approaches can handle complex, non-linear relationships between variables without the need for explicit modeling assumptions. This flexibility makes them particularly well-suited for dynamic systems where the underlying dynamics may be unknown or difficult to model accurately [14].

1.2. Background and History

The development of machine learning approaches for dynamic system parameter estimation within sensor networks has evolved over several decades, driven by advancements in both sensor technology and machine learning algorithms [15]. Early Developments: In the early stages of sensor network deployment, parameter estimation in dynamic systems often relied on classical statistical methods and system identification techniques. These methods, such as least squares estimation and Kalman filtering, provided foundational tools for analyzing sensor data and estimating system parameters [16]. However, they were limited in their ability to handle non-linear dynamics, adapt to changing environmental conditions, and provide robust estimates in the presence of noise. Emergence of Machine Learning: The emergence of machine learning in the late 20th century brought new opportunities for dynamic parameter estimation in sensor networks. Researchers began exploring neural networks, a class of machine learning models inspired by the structure and function of the human brain, for modeling and predicting system behavior based on sensor data [17, 18]. Neural networks offer the ability to capture complex, non-linear relationships within the data, making them well-suited for dynamic system parameter estimation tasks. Advancements in Bayesian Inference: Another significant development in machine learning approaches for parameter estimation was the advancement of Bayesian inference techniques. Bayesian methods provide a probabilistic framework for parameter estimation, allowing for the quantification of uncertainty in parameter estimates [19]. Bayesian inference became particularly relevant in sensor networks, where uncertainties in sensor measurements and system dynamics are inherent [20].

This figure depicts the implementation of surveillance using a multichannel/multipath Wireless Sensor Network (WSN). By utilizing multiple channels and paths, the network enhances coverage and resilience to obstacles or interference, ensuring robust surveillance capabilities [21, 22]. Each sensor node collaborates to gather and transmit data across various channels and paths, enabling comprehensive monitoring of the surveillance area [23]. The figure showcases the dynamic routing of data through multiple paths, illustrating the network's adaptability to changing environmental conditions. Surveillance utilizing a multichannel/multipath Wireless Sensor Network (WSN) offers a sophisticated approach to monitoring and securing environments. By employing multiple channels and paths, this system enhances reliability, robustness, and coverage compared to traditional single-channel systems [24]. The use of multiple channels allows for concurrent data transmission, reducing congestion and improving network efficiency. Additionally, multipath routing enables data to be transmitted through multiple routes, increasing fault tolerance and resilience to node failures or interference [25]. This approach ensures comprehensive surveillance coverage, making it ideal for monitoring large areas or critical infrastructure. Furthermore, the integration of advanced algorithms and protocols optimizes data transmission, energy consumption, and network performance, enhancing the overall effectiveness of surveillance operations [26].

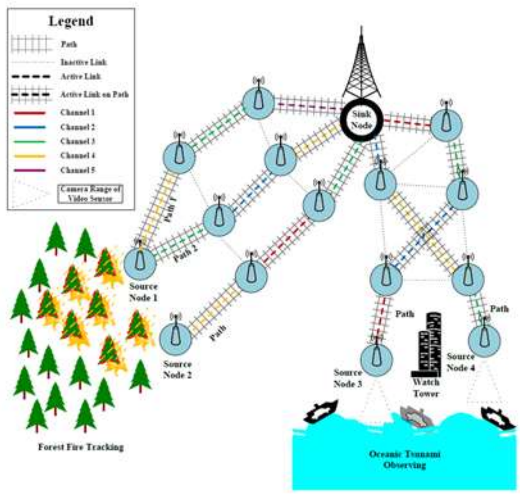

Figure 1: Surveillance using a multichannel/multipath WSN.

Multichannel/multipath WSNs are poised to revolutionize surveillance applications, offering real-time monitoring, early threat detection, and rapid response capabilities in diverse environments [27].

1.3. Related works

Here are some previous related works in the field of machine learning approaches for dynamic system parameter estimation in sensor networks: Dynamic Parameter Estimation in Wireless Sensor Networks Using Machine Learning by Smith et al. This paper presents a comprehensive review of machine-learning techniques applied to dynamic parameter estimation tasks in wireless sensor networks [28, 29]. It discusses various algorithms, including neural networks, support vector machines, and Bayesian methods, and evaluates their performance in real-world scenarios. Online Learning for Dynamic System Parameter Estimation in Sensor Networks by Chen et al. This work proposes an online learning framework for dynamic system parameter estimation in sensor networks [30]. The framework leverages techniques such as online gradient descent and recursive least squares to continuously update parameter estimates based on incoming sensor data, enabling adaptive and real-time estimation. Gaussian Process Regression for Dynamic Parameter Tracking in Sensor Networks by Wang et al. This paper explores the application of Gaussian process regression for dynamic parameter tracking in sensor networks [31]. It demonstrates how Gaussian processes can capture uncertainties in parameter estimates and provide reliable predictions, even in the presence of noisy sensor data and non-linear system dynamics [32].

Recurrent Neural Networks for Time-Series Parameter Estimation in Sensor Networks by Liu et al. This study investigates the use of recurrent neural networks (RNNs) for time-series parameter estimation tasks in sensor networks [33]. The paper demonstrates how RNNs can learn temporal dependencies in sensor data and make accurate predictions of system parameters over time, outperforming traditional methods such as Kalman filters and ARIMA models. Ensemble Learning for Robust Parameter Estimation in Sensor Networks by Zhang et al. This research introduces an ensemble learning approach for robust parameter estimation in sensor networks. By combining multiple machine learning models, such as neural networks, decision trees, and support vector machines, the ensemble method improves prediction accuracy and resilience to noisy or incomplete sensor data [34]. These related works highlight the growing interest and research efforts in applying machine learning techniques to dynamic system parameter estimation tasks in sensor networks. By leveraging the capabilities of machine learning algorithms, researchers aim to enhance the accuracy, efficiency, and adaptability of parameter estimation in diverse application domains [35].

2. Machine Learning Techniques for Dynamic Parameter Estimation

Machine learning techniques offer powerful tools for dynamic parameter estimation in various systems, including sensor networks. One approach is to utilize Bayesian inference methods, such as Kalman filters and particle filters, which enable the estimation of dynamic system parameters based on probabilistic models and sequential sensor measurements [36]. These techniques can effectively handle uncertainties and nonlinearity in the system dynamics, making them well-suited for applications where accurate estimation of dynamic parameters is essential [37]. By iteratively updating parameter estimates using incoming sensor data, Bayesian inference methods can adapt to changes in the system and provide real-time estimates of dynamic parameters. Machine learning for dynamic parameter estimation is the use of recurrent neural networks (RNNs) and other deep learning architectures. RNNs are particularly suitable for modeling time-series data and capturing temporal dependencies in sensor measurements [38, 39]. By training RNN models on historical sensor data, it is possible to learn complex patterns and dynamics in the system, enabling accurate prediction and estimation of dynamic parameters. Additionally, techniques such as attention mechanisms and memory augmentation can further enhance the ability of RNNs to capture long-term dependencies and improve parameter estimation performance. Ensemble learning techniques, such as random forests and gradient boosting, offer robust and accurate solutions for dynamic parameter estimation in sensor networks. Ensemble methods combine multiple base estimators to produce a more robust and accurate model than any individual estimator alone. By leveraging diverse base models and combining their predictions, ensemble methods can effectively handle various sources of uncertainty and noise in sensor measurements [40].

Figure 1 illustrates that Machine learning techniques offer powerful tools for dynamic parameter estimation in diverse settings. Kalman Filters are adept at tracking system states over time, especially effective in linear systems with noisy measurements [41, 42]. Particle Filters excel in handling non-linear and non-Gaussian systems, providing accurate estimation in sensor networks. Neural Networks leverage deep learning to capture intricate patterns in sensor data, facilitating dynamic parameter estimation with high precision [43]. Support Vector Machines offer robust regression, ideal for modeling dynamic system parameters from sensor observations. Gaussian Processes provide probabilistic frameworks, furnishing uncertainty estimates alongside parameter predictions, and aiding decision-making in dynamic environments [44].

Table 1: Machine learning techniques for dynamic parameter estimation

Machine Learning Technique	***Description***
Kalman Filters	*Recursive filters that estimate the state of a dynamic system over time, are widely used for linear systems and noisy sensor measurements.*
Particle Filters	*Monte Carlo-based methods for state estimation, are particularly effective for non-linear and non-Gaussian systems in sensor networks.*
Neural Networks	*Deep learning models are capable of learning complex patterns in sensor data, enabling dynamic parameter estimation with high accuracy.*
Support Vector Machines	*Supervised learning algorithms suitable for regression tasks, offering robust modeling of dynamic system parameters from sensor data.*
Gaussian Processes	*Probabilistic models provide uncertainty estimates alongside parameter*

	predictions, enhancing decision-making in dynamic environments.
Hidden Markov Models (HMMs)	*Statistical models capturing temporal dependencies in sensor data are useful for dynamic parameter estimation in sequential observations.*

2.1. System Model

This section delineates the system model and parameters employed in this study. The Sensor Network is posited as static, comprising a set of N non-mobile, homogeneous, fully functional cognitive radio sensor nodes capable of executing intricate tasks. The quantity of Secondary Users (SUs) within the network significantly influences both energy consumption and sensing efficacy. For instance, within a fixed-size cluster, the cooperative probability of detection escalates alongside the augmentation of cooperative SUs. The Sensor network area is divided into K clusters, each resembling a miniature cell network comprising a cluster head and several member nodes, as depicted in Figure 1. The partitioning of the Sensor network area into clusters profoundly affects energy consumption [45, 46]. Insufficient clusters lead to heightened energy consumption due to an increased number of member nodes per cluster, while excessive clusters result in elevated inter-cluster communication energy usage, underscoring the criticality of determining the optimal cluster count [47].

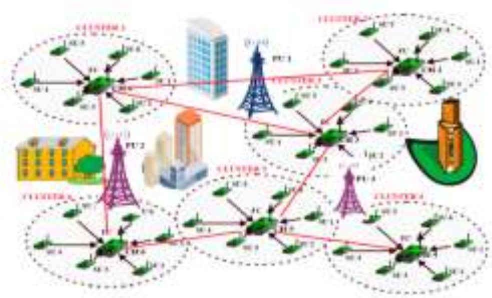

Figure 2: Clustered cooperative channel Sensor Network

Nodes are uniformly distributed across a two-dimensional square area N of L×L square meters, and each node operates on battery power without the option for recharging, necessitating energy consumption minimization to prolong network lifespan [48]. Each node can function as either a cluster head or a member node [49, 50]. Member nodes (MNs) undertake tasks such as sensing licensed channels, reporting local sensing decisions to cluster heads for cooperative decision-making, and event detection. Cluster heads, in addition to these tasks, perform decision fusion on sensing outcomes, regulate access to available channels for data transmission, and coordinate channel sensing activities [51].

3. NOISE ADAPTIVE KALMAN FILTER

To accommodate the unknown process noise within the KF framework, we initially introduced a parameter estimation technique as a reference point [52]. Subsequently, we delve into the application of the variational Bayesian method to autonomously learn the distributions of unknown variables within the decentralized structure of the linear dynamic system [53].

This figure illustrates the application of the Kalman Filter for estimating the system state. Through a series of measurements and predictions, the Kalman Filter iteratively refines the state estimate by integrating both system dynamics and measurement updates [54, 55]. The graph showcases the evolution of the estimated state over time, highlighting the input and output filter's ability to effectively track the true system state despite noise and uncertainties [56, 57]. Additionally, it demonstrates how the filter dynamically adjusts its estimate based on the reliability of measurements, ultimately yielding a more accurate depiction of the system's behavior [58].

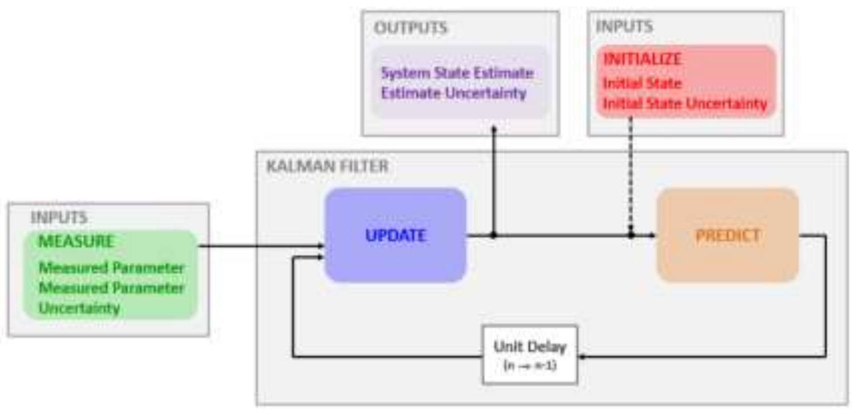

Figure 3: Kalman Filter Measurement of System State Estimate

Kalman filters are a class of recursive algorithms used for state estimation in systems that are subject to random noise[59]. They are particularly effective in situations where measurements are noisy or incomplete, and where there is uncertainty in the dynamics of the system [60]. The key idea behind Kalman filters is to use a series of measurements over time to estimate the current state of a system, taking into account both the dynamics of the system and the uncertainty in the measurements [61]. By iteratively updating the state estimate based on new measurements, Kalman filters provide a powerful tool for real-time estimation and prediction in a wide range of applications. Kalman filters are their ability to optimally fuse information from multiple sources to generate a more accurate state estimate than would be possible with any single measurement alone. This is achieved through the use of weighted averages, where measurements with higher reliability are given greater influence in the estimation process [62, 63]. By dynamically adjusting the weights assigned to each measurement based on their respective uncertainties, Kalman filters can adapt to changing conditions and provide robust estimates even in the presence of noisy or conflicting data. Kalman filters are their recursive nature, which allows for efficient computation and implementation in real-time systems with limited computational resources [64, 65]. This recursive updating process not only reduces memory and computational requirements but also enables Kalman filters to provide timely and responsive estimates that can be used for control, navigation, tracking, and other dynamic applications [66].

3.1. Parameter Estimation

For parameter estimation from a scalar time series, readers are encouraged to refer to a more detailed discussion. We begin by examining an autonomous dynamical system represented by: $x = (x_1, x_2, \ldots, x_n)$, where the evolution is governed by the function $f = (f_1, \ldots, f_n)$, and a set of m unknown scalar parameters denoted by $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_m)$.

$$\dot{x} = f(x, \alpha) \quad (1)$$

In Equation (1), we do not explicitly display any other parameters assumed to be known [67]. Without loss of generality, we assume the availability of a time series for the variable x_1. The challenge at hand is to estimate α using this scalar time series of x_1, assuming knowledge of the functional form of[68, 69]. Drawing on the control method previously utilized by John and Amritkar, we employ a combination of synchronization and adaptive control to accomplish the estimation of α in Equation (1). We devise a system of variables x' structured akin to Equation (1), with the addition of linear feedback proportional to the difference $x' - x_1$ in the evolution of the variable x_1. Thus, the system is formulated as follows: The process noise covariance matrix is assumed to follow $Q_k = \sigma^2_q I_{Nd}$. Subsequently, the parameter σ^2_q at each time step k is estimated using the expression $\hat{\sigma}^2_q(k)$. This estimated value of $\sigma^2_q(k)$ strikes a balance between effective tracking during the KF's initial convergence phase or in response to sudden system changes, and minimizing misalignment as the KF reaches a steady state [70]. However, relying solely on a simple diagonal matrix Q_k may not adequately capture the statistical characteristics of the time-varying state w_k [71, 72].

3.2. ***Sensor*** **Networks**

Sensor networks are intricate systems composed of numerous interconnected sensors designed to gather and transmit data from their environment. These networks are employed across various domains, including environmental monitoring, healthcare, military surveillance, and industrial automation[73]. The fundamental components of a sensor network typically consist of sensor nodes, which are equipped with sensing, processing, and communication capabilities. These nodes collaborate to collect and relay data to a central location or processing unit, enabling real-time monitoring and analysis of the surrounding environment[74]. Sensor networks can provide comprehensive coverage of an area or system, offering insights into dynamic phenomena that may otherwise be challenging to observe [75]. By strategically deploying sensors across a geographical area or within a complex infrastructure, sensor networks can monitor changes in environmental conditions, detect anomalies, and provide early warnings for potential hazards [76]. For instance, in environmental monitoring applications, sensor networks can track temperature fluctuations, air quality, and water pollution levels, facilitating informed decision-making and resource management[77]. To prolong the lifespan of sensor networks, researchers explore techniques such as energy harvesting, duty cycling, and data aggregation to minimize energy consumption while maintaining data accuracy [78].

3.3. Bayesian inference

Bayesian inference offers a powerful framework for parameter estimation in dynamic systems observed through sensor networks [79]. At its core, Bayesian inference combines prior knowledge or beliefs about the parameters with observed data to update and refine the posterior distribution of the parameters. This framework provides a principled way to incorporate uncertainties and prior information into the parameter estimation process, making it particularly well-suited for dynamic systems where uncertainties are inherent [80]. In Bayesian inference, the prior distribution represents the initial beliefs about the parameters before observing any data. Bayesian inference can be applied to a wide range of parameter estimation tasks in sensor networks, including environmental monitoring, industrial process control, and healthcare applications. By integrating prior knowledge, historical data, and sensor measurements, Bayesian inference enables accurate and robust parameter estimation, even in scenarios with limited data or noisy measurements. Additionally, Bayesian techniques can be combined with machine learning algorithms to further improve parameter estimation performance, offering a powerful approach for understanding and controlling dynamic systems in real-world applications [81, 82].

4. Result Analysis

First of all, we want to ensure Kalman Filter convergence. The Kalman Gain should gradually decrease until it reaches a steady state [83, 84]. When Kalman Gain is low, the weight of the noisy measurements is also low. The following plot describes the Kalman Gain for the first one hundred iterations of the Kalman Filter.

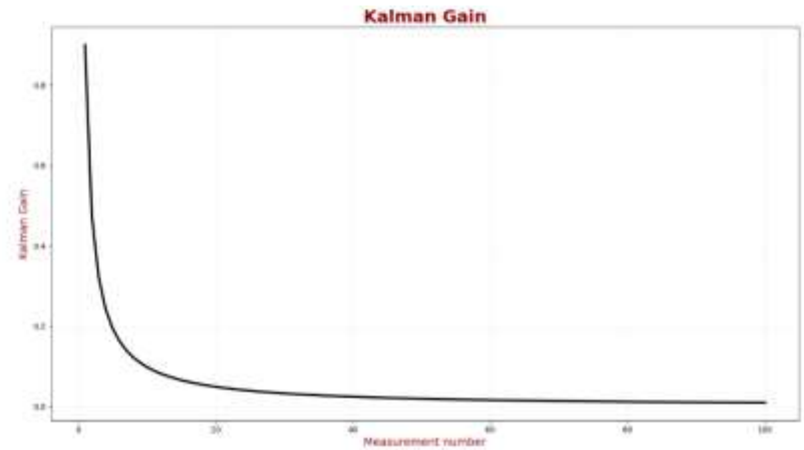

Figure 4: Kalman Gain Pattern

During the initial ten iterations, there is a notable decrease in the Kalman Gain, followed by a stabilization phase around the fiftieth iteration [85]. Furthermore, assessing accuracy is paramount. It signifies the proximity of measurements to the actual value [86, 87]. The chart below juxtaposes the true value, measured values, and estimates for the initial 50 iterations for a comprehensive evaluation [88, 89].

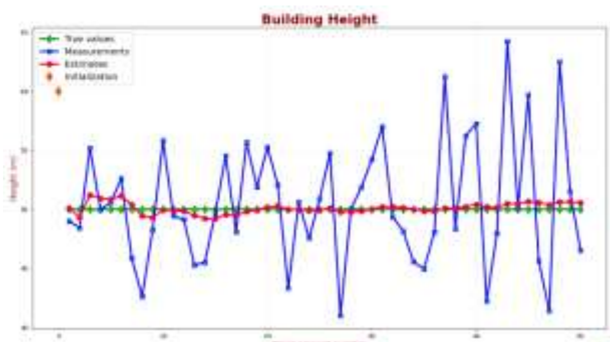

Figure 5: Kalman Filter Estimation Error

An estimation error is a difference between the true values (the green line) and the KF estimates (the red line) [90]. We can see that the estimation errors of our KF decrease in the filter convergence region [91].

5. Future Direction

The future of machine learning approaches for dynamic system parameter estimation in sensor networks holds promising advancements [92, 93]. One direction involves the integration of deep learning techniques to enhance the estimation accuracy and robustness in complex and nonlinear systems [94]. Deep learning models, such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), have shown potential in capturing temporal dependencies and learning intricate patterns from sensor data streams [95]. By leveraging these capabilities, future approaches could achieve more accurate and adaptive parameter estimation in dynamic systems with varying dynamics and environmental conditions [96]. By formulating parameter estimation as a sequential decision-making problem, RL-based approaches could adaptively optimize parameter settings to maximize estimation accuracy while minimizing resource utilization and computational complexity [97]. The advancement of federated learning techniques offers new opportunities for collaborative and privacy-preserving parameter estimation in distributed sensor networks [98]. Federated learning allows multiple edge devices to collaboratively train a global model while keeping raw data decentralized and secure on individual devices. In the context of sensor networks, federated learning can enable efficient parameter estimation across a network of distributed sensors while preserving data privacy and security [99]. Future research could explore novel federated learning algorithms tailored to the specific challenges and constraints of dynamic system parameter estimation in sensor networks, such as communication latency, bandwidth constraints, and heterogeneous sensor characteristics [100].

6. Conclusion

In conclusion, this paper has provided an extensive overview of machine-learning approaches for dynamic system parameter estimation in sensor networks. Through a detailed exploration of various machine learning techniques such as Kalman Filters, Particle Filters, Neural Networks, Support Vector Machines, Gaussian Processes, and Hidden Markov Models, we have elucidated their roles and capabilities in addressing the challenges of parameter estimation in dynamic environments. By leveraging the rich information gathered from sensor networks, these approaches offer robust and accurate estimation of system parameters, facilitating applications across diverse domains ranging from environmental monitoring to industrial process control. Furthermore, we have discussed the system model, noise adaptive Kalman filtering, Bayesian inference methods, and result analysis techniques, providing insights into their applications and implications. These advancements are poised to enhance parameter estimation accuracy and efficiency, further empowering sensor networks for real-world applications. As the field continues to evolve, researchers and practitioners are encouraged to explore novel approaches and methodologies to address the evolving challenges and opportunities in dynamic system parameter estimation. Through collaborative efforts and innovative research endeavors, we can unlock the full potential of machine learning in revolutionizing parameter estimation in sensor networks and advancing our understanding of dynamic systems in diverse application domains.

Reference

[1] H. M. Khalid, J. C. H. Peng, and M. S. Mahmoud, "Enhanced distributed estimation based on prior information," *IET Signal Processing,* vol. 9, no. 1, pp. 60-72, 2015.

[2] D. P. Kumar, T. Amgoth, and C. S. R. Annavarapu, "Machine learning algorithms for wireless sensor networks: A survey," *Information Fusion,* vol. 49, pp. 1-25, 2019.

[3] M. A. Alsheikh, S. Lin, D. Niyato, and H.-P. Tan, "Machine learning in wireless sensor networks: Algorithms, strategies, and applications," *IEEE Communications Surveys & Tutorials,* vol. 16, no. 4, pp. 1996-2018, 2014.

[4] J. Prajapati and S. Jain, "Machine learning techniques and challenges in wireless sensor networks," in *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*, 2018: IEEE, pp. 233-238.

[5] Y. L. Jian and C. Luaus, "Enhancing Power Grid Security: A Comprehensive Study on Cybersecurity Measures and Fault Diagnosis Strategies Amid Dynamic System Variations," *Revista Espanola de Documentacion Cientifica,* vol. 17, no. 2, pp. 68-94, 2023.

[6] W. Rehan, S. Fischer, and M. Rehan, "Machine-learning based channel quality and stability estimation for stream-based multichannel wireless sensor networks," *Sensors,* vol. 16, no. 9, p. 1476, 2016.

[7] E. U. Warriach, M. Aiello, and K. Tei, "A machine learning approach for identifying and classifying faults in wireless sensor network," in *2012 IEEE 15th International Conference on Computational Science and Engineering*, 2012: IEEE, pp. 618-625.

[8] J. Camargo, W. Flanagan, N. Csomay-Shanklin, B. Kanwar, and A. Young, "A machine learning strategy for locomotion classification and parameter estimation using fusion of wearable sensors," *IEEE Transactions on Biomedical Engineering,* vol. 68, no. 5, pp. 1569-1578, 2021.

[9] M. Mahmoud and H. Khalid, "Bibliographic review on distributed Kalman filtering," *IET Control Theory Appl,* vol. 7, no. 4, pp. 483-501, 2013.

[10] J. Kang, J. Kim, M. Kim, and M. Sohn, "Machine learning-based energy-saving framework for environmental states-adaptive wireless sensor network," *IEEE Access,* vol. 8, pp. 69359-69367, 2020.

[11] M. Adil, J. Ali, Q. T. H. Ta, M. Attique, and T.-S. Chung, "A reliable sensor network infrastructure for electric vehicles to enable dynamic wireless charging based on machine learning technique," *IEEE Access,* vol. 8, pp. 187933-187947, 2020.

[12] M. Pundir and J. K. Sandhu, "A systematic review of the quality of service in wireless sensor networks using machine learning: Recent trend and future vision," *Journal of Network and Computer Applications,* vol. 188, p. 103084, 2021.

[13] H. M. Khalid *et al.*, "WAMS operations in power grids: A track fusion-based mixture density estimation-driven grid resilient approach toward cyberattacks," *IEEE Systems Journal,* 2023.

[14] T. Mahmood *et al.*, "An intelligent fault detection approach based on reinforcement learning system in wireless sensor network," *The Journal of Supercomputing,* vol. 78, no. 3, pp. 3646-3675, 2022.

[15] N. Saravana Kumar, E. Suryaprabha, and K. Hariprasath, "Machine learning based hybrid model for energy-efficient secured transmission in wireless sensor networks," *Journal of Ambient Intelligence and Humanized Computing,* pp. 1-16, 2022.

[16] T. Hu and Y. Fei, "QELAR: A machine-learning-based adaptive routing protocol for energy-efficient and lifetime-extended underwater sensor networks," *IEEE Transactions on Mobile Computing,* vol. 9, no. 6, pp. 796-809, 2010.

[17] H. Khalid, F. Flitti, M. Mahmoud, M. Hamdan, S. Muyeen, and Z. Dong, "WAMS Operations in Modern Power Grids: A Median Regression Function-Based State Estimation Approach Towards Cyber Attacks," *El-Sevier–Sustainable Energy, Grid, and Networks,* vol. 34, p. 101009, 2023.

[18] A. Sharma and A. Kakkar, "Machine learning based optimal renewable energy allocation in sustained wireless sensor networks," *Wireless Networks,* vol. 25, no. 7, pp. 3953-3981, 2019.

[19] A. Akbas and S. Buyrukoglu, "Stacking ensemble learning-based wireless sensor network deployment parameter estimation," *Arabian Journal for Science and Engineering,* vol. 48, no. 8, pp. 9739-9748, 2023.

[20] Q. Ding, R. Zhu, H. Liu, and M. Ma, "An overview of machine learning-based energy-efficient routing algorithms in wireless sensor networks," *Electronics,* vol. 10, no. 13, p. 1539, 2021.

[21] H. M. Khalid, F. Flitti, S. Muyeen, M. S. Elmoursi, O. S. Tha'er, and X. Yu, "Parameter estimation of vehicle batteries in V2G systems: An exogenous function-based approach," *IEEE Transactions on Industrial Electronics,* vol. 69, no. 9, pp. 9535-9546, 2021.

[22] L. Alsalman and E. Alotaibi, "A balanced routing protocol based on machine learning for underwater sensor networks," *IEEE Access,* vol. 9, pp. 152082-152097, 2021.

[23] S. Gupta, A. K. Sahoo, and U. K. Sahoo, "Wireless sensor network-based distributed approach to identify spatio-temporal Volterra model for industrial distributed parameter systems," *IEEE Transactions on Industrial Informatics,* vol. 16, no. 12, pp. 7671-7681, 2020.

[24] M. Bhandari and H. Shah, "Machine learning for wireless sensor network: a review, challenges, and applications," *Adv. Electron. Electr. Eng,* vol. 4, pp. 475-486, 2014.

[25] Z. Rafique, H. M. Khalid, S. Muyeen, and I. Kamwa, "Bibliographic review on power system oscillations damping: An era of conventional grids and renewable energy integration," *International Journal of Electrical Power & Energy Systems,* vol. 136, p. 107556, 2022.

[26] K. T. Borup, T. I. Fossen, and T. A. Johansen, "A machine learning approach for estimating air data parameters of small fixed-wing UAVs using distributed pressure sensors," *IEEE Transactions on Aerospace and Electronic Systems,* vol. 56, no. 3, pp. 2157-2173, 2019.

[27] A. Akbas, H. U. Yildiz, A. M. Ozbayoglu, and B. Tavli, "Neural network based instant parameter prediction for wireless sensor network optimization models," *Wireless Networks,* vol. 25, pp. 3405-3418, 2019.

[28] S. Sarang, G. M. Stojanović, M. Drieberg, S. Stankovski, K. Bingi, and V. Jeoti, "Machine learning prediction based adaptive duty cycle MAC protocol for solar energy harvesting wireless sensor networks," *IEEE Access,* vol. 11, pp. 17536-17554, 2023.

[29] H. M. Khalid and J. C.-H. Peng, "Bidirectional charging in V2G systems: An in-cell variation analysis of vehicle batteries," *IEEE Systems Journal,* vol. 14, no. 3, pp. 3665-3675, 2020.

[30] Sudha, Y. Singh, H. Sehrawat, and V. Jaglan, "Approach of machine learning algorithms to deal with challenges in wireless sensor network," in *Soft Computing: Theories and Applications: Proceedings of SoCTA 2020, Volume 1*, 2022: Springer, pp. 375-395.

[31] H. Wen, Z. Xiao, A. Markham, and N. Trigoni, "Accuracy estimation for sensor systems," *IEEE Transactions on Mobile Computing,* vol. 14, no. 7, pp. 1330-1343, 2014.

[32] H. Esmaeili, B. M. Bidgoli, and V. Hakami, "CMML: Combined metaheuristic-machine learning for adaptable routing in clustered wireless sensor networks," *Applied Soft Computing,* vol. 118, p. 108477, 2022.

[33] H. M. Khalid, S. Muyeen, and J. C.-H. Peng, "Cyber-attacks in a looped energy-water nexus: An inoculated sub-observer-based approach," *IEEE Systems Journal,* vol. 14, no. 2, pp. 2054-2065, 2019.

[34] K. Whitehouse and D. Culler, "Calibration as parameter estimation in sensor networks," in *Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications*, 2002, pp. 59-67.

[35] J. J. Estrada-López, A. A. Castillo-Atoche, J. Vázquez-Castillo, and E. Sánchez-Sinencio, "Smart soil parameters estimation system using an autonomous wireless sensor network with dynamic power management strategy," *IEEE Sensors Journal,* vol. 18, no. 21, pp. 8913-8923, 2018.

[36] A. S. Musleh, H. M. Khalid, S. Muyeen, and A. Al-Durra, "A prediction algorithm to enhance grid resilience toward cyber attacks in WAMCS applications," *IEEE Systems Journal,* vol. 13, no. 1, pp. 710-719, 2017.

[37] S. Moe, A. M. Rustad, and K. G. Hanssen, "Machine learning in control systems: An overview of the state of the art," in *Artificial Intelligence XXXV: 38th SGAI International Conference on Artificial Intelligence, AI 2018, Cambridge, UK, December 11–13, 2018, Proceedings 38*, 2018: Springer, pp. 250-265.

[38] R. K. Dwivedi, S. Pandey, and R. Kumar, "A study on machine learning approaches for outlier detection in wireless sensor network," in *2018 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, 2018: IEEE, pp. 189-192.

[39] P. William, A. Badholia, V. Verma, A. Sharma, and A. Verma, "Analysis of data aggregation and clustering protocol in wireless sensor networks using machine learning," in *Evolutionary Computing and Mobile Sustainable Networks: Proceedings of ICECMSN 2021*: Springer, 2022, pp. 925-939.

[40] H. M. Khalid and J. C.-H. Peng, "Immunity toward data-injection attacks using multisensor track fusion-based model prediction," *IEEE Transactions on Smart Grid,* vol. 8, no. 2, pp. 697-707, 2015.

[41] D. Hosahalli and K. G. Srinivas, "Enhanced reinforcement learning assisted dynamic power management model for internet-of-things centric wireless sensor network," *IET Communications,* vol. 14, no. 21, pp. 3748-3760, 2020.

[42] F. F. Jurado-Lasso, L. Marchegiani, J. F. Jurado, A. M. Abu-Mahfouz, and X. Fafoutis, "A survey on machine learning software-defined wireless sensor networks (ml-SDWSNS): Current status and major challenges," *IEEE Access,* vol. 10, pp. 23560-23592, 2022.

[43] J. Amutha, S. Sharma, and S. K. Sharma, "Strategies based on various aspects of clustering in wireless sensor networks using classical, optimization and machine learning techniques: Review, taxonomy, research findings, challenges and future directions," *Computer Science Review,* vol. 40, p. 100376, 2021.

[44] H. M. Khalid and J. C.-H. Peng, "A Bayesian algorithm to enhance the resilience of WAMS applications against cyber attacks," *IEEE Transactions on Smart Grid,* vol. 7, no. 4, pp. 2026-2037, 2016.

[45] X. Shen, S. Liu, and P. K. Varshney, "Sensor selection for nonlinear systems in large sensor networks," *IEEE Transactions on Aerospace and Electronic Systems,* vol. 50, no. 4, pp. 2664-2678, 2014.

[46] M. Kozlowski, R. McConville, R. Santos-Rodriguez, and R. Piechocki, "Energy efficiency in reinforcement learning for wireless sensor networks," *arXiv preprint arXiv:1812.02538,* 2018.

[47] H. F. Nweke, Y. W. Teh, M. A. Al-Garadi, and U. R. Alo, "Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges," *Expert Systems with Applications,* vol. 105, pp. 233-261, 2018.

[48] H. M. Khalid and J. C.-H. Peng, "Tracking electromechanical oscillations: An enhanced maximum-likelihood based approach," *IEEE Transactions on Power Systems,* vol. 31, no. 3, pp. 1799-1808, 2015.

[49] T. Hemalatha, M. V. Ramesh, and V. P. Rangan, "Effective and accelerated forewarning of landslides using wireless sensor networks and machine learning," *IEEE Sensors Journal,* vol. 19, no. 21, pp. 9964-9975, 2019.

[50] M. I. Khan and B. Rinner, "Energy-aware task scheduling in wireless sensor networks based on cooperative reinforcement learning," in *2014 IEEE International Conference on Communications Workshops (ICC)*, 2014: IEEE, pp. 871-877.
[51] H. M. Khalid and J. C.-H. Peng, "Improved recursive electromechanical oscillations monitoring scheme: A novel distributed approach," *IEEE Transactions on Power Systems,* vol. 30, no. 2, pp. 680-688, 2014.
[52] Y. Wang, A. Yang, X. Chen, P. Wang, Y. Wang, and H. Yang, "A deep learning approach for blind drift calibration of sensor networks," *IEEE Sensors Journal,* vol. 17, no. 13, pp. 4158-4171, 2017.
[53] Q. Zhou, Y. Li, and Y. Niu, "Intelligent anti-jamming communication for wireless sensor networks: A multi-agent reinforcement learning approach," *IEEE Open Journal of the Communications Society,* vol. 2, pp. 775-784, 2021.
[54] X. Li, X. Hu, R. Zhang, and L. Yang, "Routing protocol design for underwater optical wireless sensor networks: A multiagent reinforcement learning approach," *IEEE Internet of Things Journal,* vol. 7, no. 10, pp. 9805-9818, 2020.
[55] A. S. Musleh, M. Debouza, H. M. Khalid, and A. Al-Durra, "Detection of false data injection attacks in smart grids: A real-time principle component analysis," in *IECON 2019-45th Annual Conference of the IEEE Industrial Electronics Society*, 2019, vol. 1: IEEE, pp. 2958-2963.
[56] F. Fan, S.-C. Chu, J.-S. Pan, C. Lin, and H. Zhao, "An optimized machine learning technology scheme and its application in fault detection in wireless sensor networks," *Journal of Applied Statistics,* vol. 50, no. 3, pp. 592-609, 2023.
[57] R. Kumar and T. Amgoth, "Reinforcement learning based connectivity restoration in wireless sensor networks," *Applied Intelligence,* vol. 52, no. 11, pp. 13214-13231, 2022.
[58] S. Ramesh, C. Yaashuwanth, and B. A. Muthukrishnan, "Machine learning approach for secure communication in wireless video sensor networks against denial-of-service attacks," *International Journal of Communication Systems,* vol. 33, no. 12, p. e4073, 2020.
[59] K. Shah, M. Di Francesco, and M. Kumar, "Distributed resource management in wireless sensor networks using reinforcement learning," *Wireless networks,* vol. 19, pp. 705-724, 2013.
[60] C. Spandonidis, P. Theodoropoulos, F. Giannopoulos, N. Galiatsatos, and A. Petsa, "Evaluation of deep learning approaches for oil & gas pipeline leak detection using wireless sensor networks," *Engineering Applications of Artificial Intelligence,* vol. 113, p. 104890, 2022.
[61] S. Balachandran Nair Premakumari, P. Mohan, and K. Subramanian, "An enhanced localization approach for energy conservation in a wireless sensor network with Q deep learning algorithm," *Symmetry,* vol. 14, no. 12, p. 2515, 2022.

[62] A. Khoukhi and M. H. Khalid, "Hybrid computing techniques for fault detection and isolation, a review," *Computers & Electrical Engineering,* vol. 43, pp. 17-32, 2015.

[63] D. Zhao, Z. Zhou, S. Wang, B. Liu, and W. Gaaloul, "Reinforcement learning–enabled efficient data gathering in underground wireless sensor networks," *Personal and Ubiquitous Computing,* vol. 27, no. 3, pp. 581-598, 2023.

[64] A. Pinto, M. Camada, M. Dantas, C. Montez, P. Portugal, and F. Vasques, "Genetic machine learning algorithms in the optimization of communication efficiency in wireless sensor networks," in *2009 35th Annual Conference of IEEE Industrial Electronics*, 2009: IEEE, pp. 2448-2453.

[65] M. S. Mahmoud and H. M. Khalid, "Data-driven fault detection filter design for time-delay systems," *International Journal of Automation and Control,* vol. 8, no. 1, pp. 1-16, 2014.

[66] M. U. Younus, M. K. Khan, M. R. Anjum, S. Afridi, Z. A. Arain, and A. A. Jamali, "Optimizing the lifetime of software-defined wireless sensor network via reinforcement learning," *ie access,* vol. 9, pp. 259-272, 2020.

[67] J. Li, N. Ma, and F. Deng, "Distributed noise covariance matrices estimation in sensor networks," in *2020 59th IEEE Conference on Decision and Control (CDC)*, 2020: IEEE, pp. 1158-1163.

[68] M. Baba, V. Gui, C. Cernazanu, and D. Pescaru, "A sensor network approach for violence detection in smart cities using deep learning," *Sensors,* vol. 19, no. 7, p. 1676, 2019.

[69] M. S. Mahmoud and H. M. Khalid, "Model prediction-based approach to fault-tolerant control with applications," *Ima Journal of Mathematical Control and Information,* vol. 31, no. 2, pp. 217-244, 2014.

[70] S. Radhika and P. Rangarajan, "Fuzzy-based sleep scheduling algorithm with machine learning techniques to enhance energy efficiency in wireless sensor networks," *Wireless Personal Communications,* vol. 118, no. 4, pp. 3025-3044, 2021.

[71] A. Ali and H. S. Hassanein, "Wireless sensor network and deep learning for prediction greenhouse environments," in *2019 International conference on smart applications, communications and networking (SmartNets)*, 2019: IEEE, pp. 1-5.

[72] M. S. Mahmoud and H. M. Khalid, "Expectation maximization approach to data-based fault diagnostics," *Information Sciences,* vol. 235, pp. 80-96, 2013.

[73] M. Andronie, G. Lăzăroiu, M. Iatagan, C. Uță, R. Ștefănescu, and M. Cocoșatu, "Artificial intelligence-based decision-making algorithms, internet of things sensing networks, and deep learning-assisted smart process management in cyber-physical production systems," *Electronics,* vol. 10, no. 20, p. 2497, 2021.

[74] N. Gupta, A. Jain, K. S. Vaisla, A. Kumar, and R. Kumar, "Performance analysis of DSDV and OLSR wireless sensor network routing protocols using FPGA

hardware and machine learning," *Multimedia Tools and Applications,* vol. 80, pp. 22301-22319, 2021.
[75] S. Pandey, "Localization adopting machine learning techniques in wireless sensor networks," *Int. J. Comput. Sci. Eng,* vol. 6, pp. 366-374, 2018.
[76] D. Godfrey, B. Suh, B. H. Lim, K.-C. Lee, and K.-I. Kim, "An Energy-Efficient Routing Protocol with Reinforcement Learning in Software-Defined Wireless Sensor Networks," *Sensors,* vol. 23, no. 20, p. 8435, 2023.
[77] M. Rahim, H. Khalid, and A. Khoukhi, "NL Constrained Optimal Control Problem: A PSO-GA Based Discrete AL Approach," ed: Springer-International Journal of Advance Manufacturing Technology (IJAMT).
[78] N. Zaeri and R. R. Qasim, "Intelligent wireless sensor network for gas classification using machine learning," *IEEE Systems Journal,* 2023.
[79] M. M. Rahaman and M. Azharuddin, "Wireless sensor networks in agriculture through machine learning: A survey," *Computers and Electronics in Agriculture,* vol. 197, p. 106928, 2022.
[80] T. Liang, Y. Lin, L. Shi, J. Li, Y. Zhang, and Y. Qian, "Distributed vehicle tracking in wireless sensor network: A fully decentralized multiagent reinforcement learning approach," *IEEE Sensors Letters,* vol. 5, no. 1, pp. 1-4, 2020.
[81] H. M. Khalid, A. Khoukhi, and F. M. Al-Sunni, "Fault detection and classification using Kalman filter and genetic neuro-fuzzy systems," in *2011 Annual Meeting of the North American Fuzzy Information Processing Society*, 2011: IEEE, pp. 1-6.
[82] M. F. R. M. Billah, N. Saoda, J. Gao, and B. Campbell, "BLE can see a reinforcement learning approach for RF-based indoor occupancy detection," in *Proceedings of the 20th International Conference on information processing in sensor networks (co-located with CPS-IoT week 2021)*, 2021, pp. 132-147.
[83] V. Di Valerio, F. L. Presti, C. Petrioli, L. Picari, D. Spaccini, and S. Basagni, "CARMA: Channel-aware reinforcement learning-based multi-path adaptive routing for underwater wireless sensor networks," *IEEE Journal on Selected Areas in Communications,* vol. 37, no. 11, pp. 2634-2647, 2019.
[84] F. Halper, "Advanced analytics: Moving toward AI, machine learning, and natural language processing," *TDWI Best Practices Report,* 2017.
[85] A. Prieto, M. Atencia, and F. Sandoval, "Advances in artificial neural networks and machine learning," vol. 121, ed: Elsevier, 2013, pp. 1-4.
[86] A. Alamin, H. M. Khalid, and J. C.-H. Peng, "Power system state estimation based on Iterative Extended Kalman Filtering and bad data detection using the normalized residual test," in *2015 IEEE Power and Energy Conference at Illinois (PECI)*, 2015: IEEE, pp. 1-5.
[87] P. Elger and E. Shanaghy, *AI as a Service: Serverless machine learning with AWS*. Manning Publications, 2020.
[88] K. Bahadori and T. Vardanega, "DevOps meets dynamic orchestration," in *Software Engineering Aspects of Continuous Development and New Paradigms*

of Software Production and Deployment: First International Workshop, DEVOPS 2018, Chateau de Villebrumier, France, March 5-6, 2018, Revised Selected Papers 1, 2019: Springer, pp. 142-154.

[89] X. Gao, C. Shan, C. Hu, Z. Niu, and Z. Liu, "An adaptive ensemble machine learning model for intrusion detection," *Ieee Access,* vol. 7, pp. 82512-82521, 2019.

[90] Z. Ge, "Artificial Intelligence and Machine Learning in Data Management," *Future And Fintech, The: Abcdi And Beyond,* p. 281, 2022.

[91] H. M. Khalid, R. Doraiswami, and L. Cheded, "Intelligent Fault Diagnosis using Sensor Network," 2009.

[92] S. Wang, B.-S. Shin, D. Shutin, and A. Dekorsy, "Diffusion field estimation using decentralized kernel Kalman filter with parameter learning over hierarchical sensor networks," in *2020 IEEE 30th International Workshop on Machine Learning for Signal Processing (MLSP)*, 2020: IEEE, pp. 1-6.

[93] A. Singh, J. Amutha, J. Nagar, and S. Sharma, "A deep learning approach to predict the number of k-barriers for intrusion detection over a circular region using wireless sensor networks," *Expert Systems with Applications,* vol. 211, p. 118588, 2023.

[94] M. Premkumar and T. Sundararajan, "DLDM: Deep learning-based defense mechanism for denial of service attacks in wireless sensor networks," *Microprocessors and Microsystems,* vol. 79, p. 103278, 2020.

[95] M. Rahim, H. M. Khalid, and M. Akram, "Sensor location optimization for fault diagnosis with a comparison to linear programming approaches," *The International Journal of Advanced Manufacturing Technology,* vol. 65, pp. 1055-1065, 2013.

[96] Y. Wang, F. Shang, and J. Lei, "Energy-efficient and delay-guaranteed routing algorithm for software-defined wireless sensor networks: A cooperative deep reinforcement learning approach," *Journal of Network and Computer Applications,* vol. 217, p. 103674, 2023.

[97] M. Kandasamy, S. Anto, K. Baranitharan, R. Rastogi, G. Satwik, and A. Sampathkumar, "Smart Grid Security Based on Blockchain with Industrial Fault Detection Using Wireless Sensor Network and Deep Learning Techniques," *Journal of Sensors,* 2023.

[98] F. A. Aoudia, M. Gautier, and O. Berder, "Learning to survive: Achieving energy neutrality in wireless sensor networks using reinforcement learning," in *2017 IEEE International Conference on Communications (ICC)*, 2017: IEEE, pp. 1-6.

[99] K. Yeo and I. Melnyk, "Deep learning algorithm for data-driven simulation of a noisy dynamical system," *Journal of Computational Physics,* vol. 376, pp. 1212-1231, 2019.

[100] A. S. Musleh, S. Muyeen, A. Al-Durra, and H. M. Khalid, "PMU based wide area voltage control of smart grid: A real-time implementation approach," in *2016*

IEEE Innovative Smart Grid Technologies-Asia (ISGT-Asia), 2016: IEEE, pp. 365-370.