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Channel Estimation Optimization Model in Internet of Things based on MIMO/OFDM with Deep Extended Kalman Filter

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Highlights

- Presenting two NDMRS-assisted algorithms for channel estimation
- LS estimator and the MMSE in the EKF developed with deep learning
- The signal processing of the narrowband IoT connector receiver will be based on OFDM
- Theoretical PAPR analysis for OFDM-based narrowband RC and RRC pulse shaping filters is presented

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Abstract

Channel estimation plays a vital role in the performance of wireless communication systems. However, apart from the usual OFDM modes, there are also orthogonal conditions for modulation-based multi-channel systems which making channel estimation on networks such as the Internet of Things (IoT) more complex. To estimate the IoT channel, its type is considered as narrow or wide band. The purpose of this research is narrowband IoT based on OFDM. There are various classical methods for channel estimation such as Least Squares (LS) and Linear Minimum Mean Square Error (LMMSE). However, due to high computational complexity as well as inaccurate channel estimation and remaining weaknesses such as latency and other quality of service criteria, especially Bit Error Rate (BER), Signal to Noise Ratio (SNR) and Maximum to Average Power Ratio (PAPR), this research Improves these two methods based on the Deep Extended Kalman filter.

1. Introduction

Internet of Things is complex system which suggest extensive communication by using sensor in physical things, radio frequency identification (RFID) tags, vehicles, actuators, sensors, and other electronics embedded on the Internet. The IoT provide objects to connect with their sensors to network and devices can interact with each other through unique addressing schemes. This job can reduce additional deployment costs and also improve accuracy and performance. A lot of wireless devices will be connected to the IoT at future [1]. Nokia INC. predicted that by 2025 about 30 billion connected IoT devices will be deployed based on Machina research which is about 23% of the cellular state of the IoT and low-power modules[2]. In addition, mobile broadband networks infrastructure needs low delay and high throughput with low power, low bandwidth, low network coverage, low cost, low computational complexity, and better scalability efficiency [3–6]

Existing cellular standards including 4G, do not support IoT connectivity. In addition, obtaining channel status information required for effective transmission will be costly, thus provide IoT connections even more challenging. It is noteworthy that IoT network data transmission traffic is usually scattered, meaning that only some devices are busy and some others are idle at any given time. For example, Wireless Sensor Networks (WSNs) designed as sleep/idle nodes/device which can created only with external events to save energy. Using scattering can support simultaneously with efficient schemes to detect

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device activity and channel estimation in the device activity pattern. It is noteworthy that it cannot possible to assign orthogonal signature sequences to all nodes/devices, so, channel estimation concept created in this field to solve these kinds of problems.

There are a lot of wireless communication technologies with short-ranges [7,8] such as Low Power Bluetooth (BLE), Z-Wave, 6LowPan, Wi-Fi, Li-Fi, ZigBee and etc. to enable IoT. Some IoT-equipped technologies operate in a licensed band such as SigFox and LoRa [9,10](i.e. industrial, scientific, and medical band, or ISM). On the other hand, the global mobile communications system and the Third Generation Partnership Project, (3GPP) or Long-Term Evolution (LTE) standard are operating within the range allowed to enable IoT. A new IoT technology which is named IoT narrowband is specifically designed for low-level IoT applications. 3GPP finalized the specification of narrowband IoT in the LTE-13 version [11]. It is safe and reliable for data transmission due to its location in the authorized range of the global mobile communication system or LTE. Narrow-band IoT provides the IoT with a wide variety of applications, including smart metering, smart cities, smart water, smart environment, smart farming, retailing, logistics, security and emergencies, industrial control and home automation. Therefore, the state of the narrowband IoT channel is very complex due to the various application scenarios.

A channel described as every data from the source to the radio signal sink. The channel contains physical environment (waveguides, fiber, free space, and etc.) between the receiver and transmitter through the transmitted signal. The word channel refers to this physical environment during this task. A necessary feature of any physical environment is to transmit signal and receive it at the receiver, broken down in various ways by frequency and phase distortion, interference between the symbol and thermal noise. Channel Mode Information (CSI) refers to the recognized channel characteristics of a communication link in wireless communication. This information explains that how a signal is transmitted from the transmitter to the receiver and indicate a combined effect for example fading, scattering, and power reduction at any distance. CSI enables transmission compatibility during channel conditions which is critical to achieving stable high-speed data communication of antenna systems. CSI must be estimate and predict at the receiver or quantize, then it can be sent to the transmitter.

Channel estimation may or may not use the training sequence. Accordingly, there are two methods for estimation. These two are channel sequence-based/pilot estimation and blind channel estimation. The purpose of channel estimation methods and algorithms is to minimize and optimize the Mean Square Error (MSE). After creating an estimation model, its parameters must be constantly updated (estimated) to minimize the error by changing the channel. If the receiver is aware of the information transmitted through the previous channel, it can use this knowledge to achieve an accurate channel estimation in impact response. This method is simply called channel sequencing estimation. Otherwise the estimate is blind. Channel estimation plays vital role in communicational systems, especially in the long-term evolution of 3GPP, which aims to continue the competition of global mobile communication system technology. OFDM is considered as one of the key 3GPP technologies to improve the quantity and quality of communication and mobile communication system capacity. Because high mobility support is required on 3GPP systems, OFDM receiver signals are likely to change rapidly with a multi-channel channel. Therefore, estimation and good channel parity at the receiver are required before coherent modulation of OFDM symbols. In mobile communications, since the radio channel is modeled by some additional dominant paths and represented by path bumps, channel estimation is consistent and efficient for channel tracking.

In this new information age, the idea of using multiple antennas when transmitting and receiving has made significant progress in the communication system in a network such as the IoT. One of the major advantages of Multi-Input Multi-Output (MIMO) technology is the ability to reduce the Symbol Error Rate (SER) in multi-channel due to increased spatial variability. Variation is the result of a combination of signals at the receiver in end-to-end mode that fade independently, so the signal can be received with minimal error at the receiver end. In MIMO system, increasing bandwidth efficiency and system reliability is achieved without using additional bandwidth or transferring more energy to the channel. MIMO has been shown to have a higher capability than Single-Input-Single-Output (SISO) systems.[12]

Since the narrowband IoT is still in its initial levels, there is still no proper guideline in the current literature for efficiently estimating and equalizing channels. Channel signal based on pilot signal for Orthogonal Frequency Division Multiplexing systems (OFDM) and Single-Carrier Frequency Division Multiple Access (SC-FDMA) has been well studied, for example in [13] and [14] this is explained in details. In the literature, more researches of narrowband IoT surveyed in frame structure design [15], link planning and compatibility [16], random access method [17], and system access [18]. The performance of narrowband IoT positioning has been investigated in [19,20]. In [[21], the performance of three traditional channel estimators is investigated only for the distance below the 15 kHz carrier. [22] The issue of channel parity and the coexistence of narrowband and LTE IoT signals are supported only using the traditional distance below the LTE carrier. To the best of our knowledge, the estimated narrowband IoT connection channel with a 3.75 kHz sub-carrier distance has not yet been studied. Therefore, OFDM-based narrowband IoT channels efficient estimation is a prerequisite for improving coverage, standardization, and decoding signal at the receiver.

The peak-to-average power ratio (PAPR) criteria in a narrowband IoT connection can increase the efficiency of the low-cost power amplifier. Low bandwidth radiation is desired the transmitter connectivity because of very narrow bandwidth. The PAPR challenge is the most troubling problem in the IoT. Power amplifier performance is critical to low-power, narrow-band, low-battery IoT equipment. Therefore, low PAPR is the ultimate requirement in internal narrowband IoT connectors due to low power amplifier. PAPR reduction techniques such as scramble, Discrete Fourier Transform (DFT) and constellation (CP) insertion can be applied to the link junction transmitter. Narrowband IoT supports modulation schemes such as BPSK and QPSK, which are also resistant to PAPR by applying constellation rotation to create a smooth transition between constellation points. However, these techniques have not been fully preserved. Further reduction of PAPR will be in high demand in the connection, because the IoT transmitter is low-cost and low-consumption. In [23], the authors evaluated the PAPR values using the employing Root-Raised Cosine Pulse Shaping (RRC-PS) for single data transmission only. This article is the first one which want to analysis partial PAPR on a narrowband IoT transmitter.[24–26]

Broadband IoT created by 3GPP which is the key technology to face with broadband IoT connectivity demands for 5G wireless communication systems development in the future. It can be run in three different operating modes as specified by 3GPP in version 13 [27,28]: stand-alone band, in-band and shield band. Broadband IoT can be deployed by replacing one or more GHM carriers at 200 kHz, which is called stand-alone mode. Using all the transmission power in the evolved eNB node, also known as the base station, the radio coverage of the IoT narrowband can be significantly increased. In band operation, it can be implemented inside the LTE carrier using one or more Physical Resources Blocks (PRB). The PRB corresponds to a bandwidth of 180 kHz. LTE and narrowband IoT share all transmission power in eNB. By increasing the power in the PRB of the IoT narrowband, large-scale coverage can also be achieved. Spectrum efficiency can also be increased by sharing PRB between LTE and the IoT. The third option can be used in the unused protective band of the LTE carrier. This is only allowed for LTE system bandwidth of 5 MHz or higher. Bandwidth deployments and IoT Bandwidth uses the available radio frequency of the existing LTE base station and baseband numbering with some modifications for use in bandwidth [29]. The coexistence of LTE and the IoT has been investigated through detailed simulations in. Therefore, the cost of additional deployment and operation time will not be borne. Operating modes must be known when working with the IoT and narrowband and searching for the IoT. Narrowband IoT supports 100 kHz channel rasters.

Narrowband IoT channels and signals are based on existing LTE channels. Also signals are based on the required modifications and simplifications commensurate with the 180 kHz 3GPP bandwidth. 3GPP is specified as 180 kHz system bandwidth for sub-link and high-link transmissions. The narrowband IoT only supports Frequency Division Duplexing (FDD) with semi-two-way transmission. Underneath the link, the IoT inherits a subnet link from existing LTE, although there is more limited support, and the IEE, like LTE, uses OFDM at a distance of less than 15 kHz.

To achieve extensive coverage and increase transmission robustness, duplication of the same user data and corresponding control signaling over a long period of time should be consider as an important solution in the 3GPP standard for link transfer. The iteration technique means that the receiver can decode the received signal, even if the noise power is much higher than the signal strength. In particular, the modulation of the SC-FDMA in the narrowband IoT connection band is sensitive to residual channel estimation errors and parity. Hence, SC-FDMA inherently extends errors to all dedicated subcarriers in the decoder phase at the receiver. Therefore, effective channel estimation and standardization are necessarily required in an iteration-based transfer scenario, and a prerequisite is to achieve coverage and transmission reliability. Channel estimation in hybrid narrowband IoT systems can be performed using the Narrowband Demodulation Reference Signal (NDMRS) previously known to the receiver, also known as test symbols. Many experimental layout schemes and channel estimation methods have been proposed and reviewed in previous research for the traditional OFMD system[30–33] . The arrangement of block-type training symbols (e.g., introductory pilot design) in which all pilot carriers occupy a SC-FDMA symbol is specified for narrowband IoT systems [34–36]. There are several methods for pilot-assisted channel estimation in the literature, including Least Squares (LS) at [37,38], Linear Minimum Mean Square Error (LMMSE) at [39,40], Maximum Likelihood (ML) at [41]. And many pilot-assisted channel estimation methods have been reported in [42] for bandwidth applications in the traditional OFDM system. Recently, a semi-blind scattered channel estimation algorithm optimized for MIMO OFDM systems has been investigated [43]. In addition, common and channel phase noise estimation [44] and maximum posterior estimator [45] have shown significant performance improvements in high complexity costs with power consumption. Estimation and compensation in this work is outside the scope of this research.

In this research, a model of narrowband IoT system with respect to OFDM is presented to channel estimation. The reason for this work is the narrowband IoT systems transmission is more complex than the short links transmission. This study considers both types of transmission schemes and sub-carrier distances for estimating the narrowband IoT channel based on OFDM and PAPR analysis. The model of this research is the application of a special Kalman filter that is also being developed. The used Kalman filter, also known as the Extended Kalman filter (EKF) is an algorithm that uses a series of measurements made over time to generate noise (random changes) and the accuracy and estimation of unknown variables which is more accurate than those based on a single measurement. Formally, the EKF works recursively on high-noise input data streams to produce a statistically optimal estimate of the underlying state of the system. The EKF uses a form of return control to estimate the process: The filter estimates the state of the process for a period of time and then obtains feedback as a measure (full noise). Similarly, EKF equations are divided into two groups: time update equations and measurement update equations. The update equations of time have the task of predicting (in time) the current situation and estimating the error covariance to obtain the previous estimates for the next step. Measurement update equations are responsible for feedback. This model has been improved to combine new measurements in the previous estimate to obtain a posterior estimate. Time update equations can be considered predictive equations, while measurement update equations can be considered corrective equations. In fact, the final estimation algorithm is similar to the prediction-correction algorithm for solving numerical problems. The EKF works in a two-step process. In the prediction phase, the EKF generates current state variables estimation with their uncertainties. When the result of the next measurement is observed (necessarily with some error, including random noise), these estimates are updated using a weighted average, and more weight is given to the estimates with more confidence. There are four contributions in this article which listed below:

This study provides a brief overview of OFDM-based narrowband IoT technology including deployment options, physical channels and signals, link frame structure, and resource unit definition. The OFDM-based narrowband IoT signal reception model will be derived as a function of signal channel and channel disturbances. NDMRS and time frequency mapping will also be provided.

This research presents two NDMRS-assisted algorithms for channel estimation which use LS estimator and the MMSE in the EKF developed with deep learning that can objectify the complex channel conditions of narrowband IoT based on OFDM. Through the following simulation, the effect of the proposed algorithm can be investigated and confirmed in comparison with conventional LS and MMSE methods based on BER criteria related to SNR. In this section, a random sorting in the efficient conversion range of LS and MMSE is presented based on the EKF developed with deep learning to reduce the error experienced estimation in traditional LS and MMSE method. This works can deal with error estimation by using different additional operations in estimating the LS without occupying additional frequency band resources and increasing the computational complexity significantly. Next, a low-complexity noise reduction based on the EKF developed with a deep learning specifically to develop a very low-performance SNR considering the effect of energy staining on Channel Impact Response (CIR) at frequency limits. Then, the LMMSE approximation estimator with reduced sub-optimal complexity based on the estimates of the EKF developed with deep learning versus the optimal methods is proposed as the main reference of this research. This ignores the channel relationship between the shutdown modes in the time domain and separately suppresses the MSE per estimated stroke of the filtered channel.

Finally, the signal processing of the narrowband IoT connector receiver will be based on OFDM. In the first step, the channel estimation for the whole-time frequency network is calculated using the dimensional linear interpolation of the channel estimation time in a sub-frame of a source unit. In the second step, by considering the mismatch between the base frequency processing of the radio frequency and the sampling rate between the transmitter of the narrowband IoT device based on OFDM and the receiver of the LTE base station, the frequency domain channel equalization is implemented. A one-stroke equalizer per sub-equal is used to calculate the channel parity coefficients. Performance of the proposed estimators by accurately simulating the connection level in terms of MSE, BLER and fast connection of narrowband IoT-based OFDM versus SNR within the 3GPP-based OFDM-based narrowband connection specification system approved.

In addition, theoretical PAPR analysis for OFDM-based narrowband Raised-Cosine (RC) and Square Root Raised-Cosine (RRC) pulse shaping filters is presented. Also represented a comparison of PAPR values obtained with and without Pulse Forming (PS) filtering through simulations for single-instant and multi-instantaneous transmission. Numerical results should show that the PAPR's RC and RRC method is possible to implement an OFDM-based narrowband connection transmitter.

2. Literature Review

Various articles proposed for IoT channel estimation. In [46], a new model of joint activity identification and IoT networks channel estimation have been performed by considering phase transfer with calculation and evaluation. The convergence rate obtained based on smoothing parameter, signature sequence length and also estimation accuracy, Yield between estimation accuracy and computational cost. In [47] Improved low-complexity channel estimation algorithms based on DFT method for LTE-based narrowband IoT systems. In this paper, low-amplitude channel estimation algorithms with the help of NDMRS called Random Least Squares Sorting (RS-LS) and Low Noise are proposed. Another optimal estimator derived from the filtered channel estimation called Linear Minimum Means Squares Error Approximation (LMMSE-A) has also been studied.

In [48]a new model of channel estimation based on pilot length proposed for wide IoT systems in MIMO model. This paper developed simple algorithms for estimating the optimal pilot length that can support most IoT devices simultaneously. In [49] channel estimation and PAPR analysis of high-bandwidth IoT systems have been performed. In this paper, the authors presented two auxiliary channel estimation algorithms for NDMRS using LS and MMSE estimation methods. The evaluation results confirm that the formation of RRC pulses with low PAPR values is practical for the design of a narrowband IoT link transmitter and increases energy efficiency. In [50] presented a blind-channel estimate of the redistribution of collaborative communications in IoT systems. The authors proposd a batch-channel estimation method for IoT relay collaboration that can model a fitness function a modify RCA error function term and adopts the IRLS algorithm to solve the optimization problem.

In [51] the estimation and evolving of the link channel in the narrowband IoT system has been done. In this paper, channel estimation and equality as well as noise variance estimation in narrowband IoT system are specialized. Various narrowband IoT techniques such as LS and LMMSE for channel estimation and Zero Forcing (ZF) and MMSE for equalization have been studied. It has been shown that the low complexity of MMSE-based methods in the narrowband IoT is possible with the use of a small number of sub-carriers. In addition, noise variance estimation is proposed based on a combination of two consecutive observations of the pilot, assuming a slow channel change. The authors also demonstrate that the proposed estimator is efficient, and by simulation confirm that both the LMMSE channel estimator and the MMSE equalizer can use the estimated noise variance instead of the exact value without loss of performance. In [52], the analysis and comparison of the connection level and the estimation of the performance of channel models for wireless communication in the IoT has been studied. NLOS was used in this study. In [53]presented a possible blind source isolation with an application for channel estimation and multi-node identification in MIMO green and multimedia communication systems. This research presented the improvement of accuracy, robustness and computational load of Blind Source Separation (BSS) and its application in estimating blind MIMO IoT interference channel, multi-node IoT data detection, separation and identification in OFDM-based MIMO IoT network. The superiority of possible corrections in BSS to its model, AMUSE and SOBI as well-known second-order techniques, has been evaluated and clarified through experiments performed on MIMO IoT networks of various combinations. In [54]provided channel estimation for 5G cellular IoT and fast-fading channels. LTE Cat-M1 (eMTC) is a 5G standard optimized for low power consumption and excellent coverage. The authors are building a modem for the Cat-M1 standard. One of the main components of the IoT Cat-M1 modem is its channel estimation block.

In [55] deep learning is used for channels synchronization and estimation in the random-access channel of narrowband IoT. The authors performed very well in estimating Time of Arrival (ToA), Carrier-Frequency Offset (CFO), channel amplification, and frequency of collisions from the received transmission mixture. In [56]provided multiple non-OFDM access with channel estimation errors for linking IoT applications. One of the basic requirements for next generation wireless or mobile communication systems is the efficient support of a large number of connections for IoT applications, and Non-Orthogonal Multiple Access (NOMA) plans can be used for this purpose. In this paper, the authors hypothesize that they use QPSK modulation and link NOMA schemes to channel estimation errors. In this paper, the authors propose a high-link NOMA scheme that can reduce performance degradation due to channel estimation errors.

Due to using Spiking Neural Network (SNN) in this article, we must reference to [57] too. In some recent and newer methods such as [58], channel estimation method proposed for high rate IoT in MIMO mode which use combination of two algorithms named Recursive Least Squares (RLS) as first tracker and the Interacting Multiple-Mode (IMM) as second tracker for channel estimation. The optimum rate in channel estimation obtained in simulation. Also, in [59], Convolutional Neural Networks applied to Industrial Internet of Things (IIoT) to extend data management, computational complexity and workflows in scheduling, and geographical localization accuracy to reduce energy consumption. These proposes can minimize resource requirements in IIoT, but if this network deploy in wide range, it needs edge computing for minimize any resource allocation and requirements.

3. Proposed Method

The first step is that we should notice that our systematic model is based on. Providing a narrowband IoT structure and determine its channels is based on OFDM need to options deployment, physical channels and signals, link frame structure, and resource unit definition. The signal channel and derivative channel abnormalities are then investigated, and a NDMRS is generated to give a mapping to the time frequency network. The two LS and MMES estimation algorithms are then used in the EKF developed with Deep Learning to estimate the channel using NDMRS to determine the complex channel conditions of OFDM-based narrowband IoT systems. Two LS and MMSE algorithms are used for random sorting in the efficient conversion range, and to develop their structure, including occupying additional frequency band resources and increasing the computational complexity significantly, use the EKF with deep learning. Then, the LMMSE approximation is used to reduce computational complexity. Finally, the signal processing of the OFDM-based narrowband IoT connector receiver signal is checked. In this section, the channel estimation for the entire time frequency network is calculated using the dimensional linear interpolation of the channel estimation time in a sub-frame of a source unit. Then, the mismatch between the radio frequency baseband processing and the sampling rate between the transmitter of the OFDM-based narrowband IoT transmitter and the LTE base station receiver are considered to equalize the frequency domain channel. In this section, the PAPR rate is measured in order to connect the narrowband IoT network based on OFDM. By determining the BER and the SNR and MSE along with energy determination and PAPR, as well as quality of services measures including throughput and delay, will be the evaluation and measurement criteria in channel estimation. Table (1), represented used parameters in this study to create model. Any parameters noticed and described in Table (1) used in equations and we placed them in the form of a table to avoid redundancy of the description.

Table 1. Main parameters of proposed model

Description	Mathematic Symbols
Network graph	$\xi = (I \cup \{A\}. E)$
n data provider set	I
Data submitter (transmission)	A
Network communication set	E
Measurement number for e iteration	T_e
i raw data record in e iteration	$r_{i,e,t}$
i raw data provider in e iteration	$R_{i,e}$
Raw data domain	$\mathscr{R}$
Cumulative function	α
Summarizer function	$fs: \mathscr{R}^{T_e} \rightarrow S^{T_e}$
Data record summarizer	$s_{i,e,t}$
i summarizer date in e iteration	$S_{i,e}$
Summarizer domain data	S
e local error in iteration and t time	$\epsilon_{e,t}$
e global error in iteration and t time	$\varepsilon_{e,t}$
Data groups	$G \subset I$
Data groups numbers	m
Internal data integration groups	$a_{e,t}^{G}$

Data supplier (transmitter and receiver)	a, a_1, a_2
Local group error for G group	$\epsilon_{e,t}^{G}$
Total group error for G group	$\varepsilon_{e,t}^{G}$

At first, the data in channels and channel state must be modeled. Hence, the local error is in the form of Eq (1) at the narrowband IoT.

$$\epsilon_{e,t} = \frac{1}{n}\sum_{i=1}^{n} \epsilon_{i,e,t} = \frac{|r_{i,e,t} - s_{i,e,t}|}{|r_{i,e,t}| + |s_{i,e,t}|} \tag{1}$$

In Eq (1), any parts are different between raw data and summary in the provider i (transmitter or receiver of data). A higher-level local error in channel recognition obtains better security and confidentiality. It is noteworthy that local error cannot depend on cumulative function. The confidentiality precision of data in recognizing channels is calculated by general error which is in accordance with Eq (2).

$$\varepsilon_{e,t} = \frac{|\alpha(R_{e,t}) - \alpha(S_{e,t})|}{|\alpha(R_{e,t})| + |\alpha(S_{e,t})|} \tag{2}$$

Based on literatures, the data confidentiality is possible under the Eq (1) and (2) conditions which is the average difference between raw data $R_{e,t} = \left(r_{i,e,t}\right)_{i=1}^{n}$ and the summarized data$S_{e,t} = \left(s_{i,e,t}\right)_{i=1}^{n}$. The higher overall error and lower response will be maintaining the data confidentiality in communicating and channel state. To maintain the data confidentiality in devices connectivity, they must compute a cumulative distribution function between raw data and cumulative data, which is called a local group error as Eq (3).

$$\epsilon_{e,t}^{G} = \frac{|r_{i,e,t} - a_{e,t}^{G}|}{|r_{i,e,t}| + |a_{e,t}^{G}|}, i \in G \tag{3}$$

Similarly, the cumulative distribution function must be computed between aggregated data and cumulative data, which is called the sum of the group error as Eq (4).

$$\varepsilon_{e,t}^{G} = \sum_{i \in G} \frac{|s_{i,e,t} - a_{e,t}^{G}|}{|s_{i,e,t}| + |a_{e,t}^{G}|} \tag{4}$$

The calculation of the throughput in the channel estimatin is given by the Eq (5), the delay calculation is in the form of the Eq (6), and the bit error rate calculation is in the form Eq (7).

$$Throughput = Max_{Window_{Size}}^{f_w(t+1)} \times Delay^{f_w(t+1)} \times RTT^{N_{data}} \tag{5}$$

$$Latency_{D(n)} = \left(\frac{1}{\left(\frac{4}{tan^2\frac{\theta}{2}}\right)^{\frac{2}{f_w(t+1)}} \sqrt{a(N_{data})}} \right) \tag{6}$$

$$\begin{aligned} BER &= 1 - (1 - B_e)^{N_{data}} \\ &= 1 - e^{N_{data} log(1-B_e)} + f_w(t+1) \end{aligned} \tag{7}$$

In Eq (5), $Max_{Window_{Size}}$ is the maximum window size in the evaluation of transmitting and receiving data, which can be calculated after calculating the delay in Eq (6). RTT Is the time it takes to send data in sweep along the way in the IoT. It is worth noting that the calculation of latency has been done end-to-end. In the SNR as a quantitative and qualitative measure in the context of the IoT as a quality of services issue, there is an important problem. A value below 12 indicates a serious noise problem in the data. A value above 20 is a satisfactory state and a value greater than 30 is the appropriate amount. In fact, the higher the index, the better, is a better signal in the original data. The SNR is defined as the signal strength rate to the noise power ratio, which is according to Eq (8).

$$SNR = \frac{P_{signal}}{P_{noise}} \tag{8}$$

P is the mean value of the signal strength. Due to the fact that most signals have a dynamic range, they are logarithmically denoted by dB, which is given by Eq (9) for the power signal and Eq (10) for the noise signal.

$$P_{signal,dB} = 10log_{10}(P_{signal}) \tag{9}$$

$$P_{noise,dB} = 10log_{10}(P_{noise}) \tag{10}$$

Up to here, we discussed about EKF in channel measurement and calculation with recognizing. Now, we use Spiking Neural Network as deep learning model in it. Spiking neural networks or SNNs are inspired by information processing in biology, where scattered and asynchronous binary signals communicate and process in parallel. SNNs in neuromorphic hardware show desirable properties such as low power consumption, fast inference, and event-based information processing. This makes them interesting candidates for efficient implementation of deep neural networks, the method of choice for many machines learning tasks. A wide range of training methods are provided for SNNs, which includes the conversion of conventional deep networks to SNNs, limited pre-conversion training, and diverse biological motivations. The purpose of the study is to define the SNN training methods and to summarize their advantages and disadvantages. The relationship between SNNs and binary networks is also discussing at the rest of this article. Neuromorphic hardware operating systems have great capabilities for activating deep networks in real-world applications. Neuromorphic approaches and conventional machine learning should not be considered as just two solutions to the same problem classes, but instead can identify and exploit the specific benefits of their task. Spiking deep learning offers good opportunities to work with new types of event-based sensors, abuse of time codes and local learning on the chip [57].

In this study, only feed-forward networks are considered that calculate mapping from input to output. Spiking neural networks were initially studied as biological information processing models in which neurons exchange information through spikes. It is assumed that all spikes are stereotypical events, and as a result, information processing is reduced to two factors: first, the timing of spikes, for example, movement frequencies, and the relative timing of pre- and post-synapse spikes. Second, the identification of the synapses used means which nerve cells are connected, whether the synapse is stimulating or inhibitory, synaptic power and short-term plasticity, or modifying effects are possible. Both neurons are the point at which input spikes instantly alter their membrane (physical) potentials or model as multi-chamber models with complex spatial (dendritic) structures depending on the level of detail of the simulation neurons. So that dendritic currents can interact before that. Physical potential also has been modified. Different models of spike neurons, such as integrating and fire, spiking response or Hodgkin- Huxley model, describe the evolution of membrane potential and spike production at different levels of details. Typically, the membrane potential of the stream merges with the entry of the spikes, creating a new spike each time the threshold is crossed. After the spike is created, through the axon to all the nerve cells connected with the delay, the small axon is sent and the membrane potential is adjusted to a certain base. Fig.1. shows this.

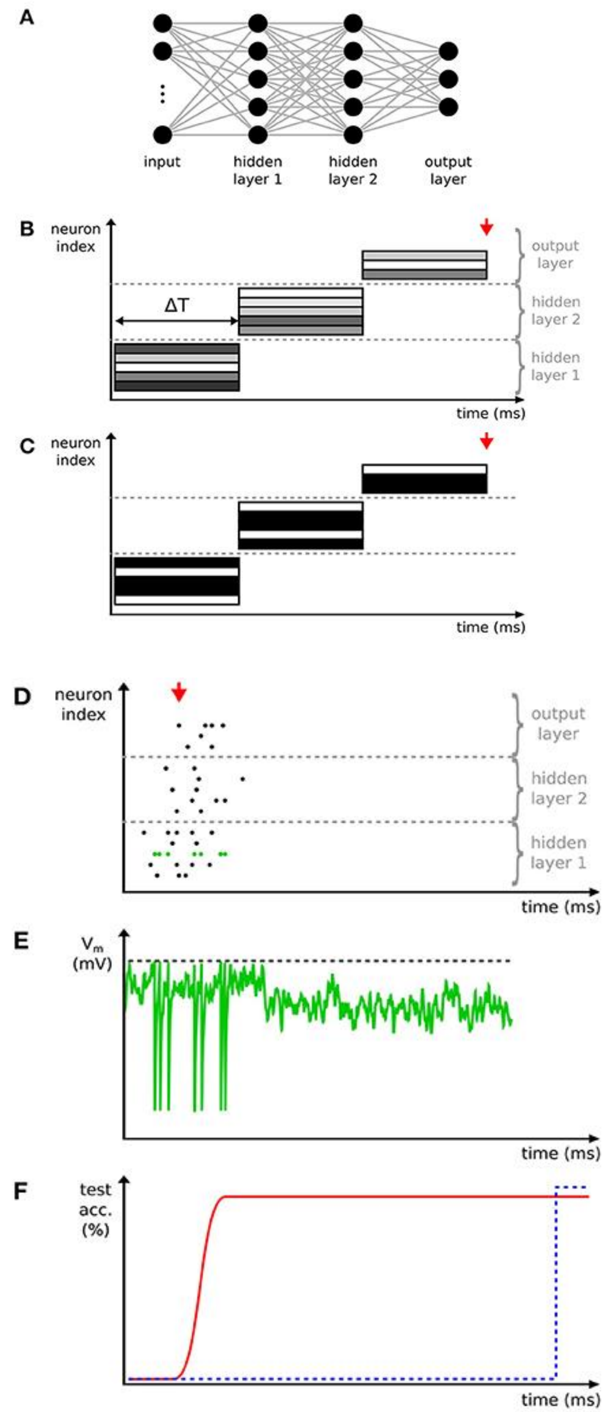

Fig. 1. SNN main structure and mechanism [57]

Direct communication between analog and spiking neural networks is established by considering the activation of an analog neuron as equivalent to the rate of firing of a spike neuron, assuming a stable state. Many neurometric models have used such rate codes to explain computational processes in the brain. However, spike neural models can also model more complex processes that depend on the relative timing between spikes or the timing of some reference signals, such as network fluctuations. Temporary codes are of great importance in biology, and even a spike or small changes in the time it takes to shoot a neuron can cause a variety of reactions, because most decisions must be calculated before a reliable spike estimation [57]. In addition to the biological definition of SNNs, they have a pragmatic functional representation that in the field of neural engineering, SNNs are commonly referred to as spikes and are event-based. Here, an event is a collection of digital information that is determined by the origin and destination address of a time marker. Unlike biologically motivated SNNs, it may have several bits of load information. The source of this protocol is the address index or AER protocol, which is used to connect to event-based sensors via digital connection to neural chips or digital hardware after processing. Event-based visual sensors use the loading bit to differentiate between silent and on visual events, but the loading bit can also be used to send other types of information related to post-synapse targets such as Integrated and Fire. The motivation for studying SNNs is that the brains indicate significant cognitive function in real-world tasks. With successive efforts to improve our understanding of brain-like calculations, it is expected that models that are closer to biology will also be closer to natural intelligence than more abstract models, or at least more efficient computationally [57].

SNNs are ideally suited for processing space-time information from neuro-sensors that are themselves energy efficient. Sensors capture accurate information about the environment, and SNNs can use efficient time codes in their calculations. This information processing is also event focus, meaning that whenever a small amount of information is not recorded in the SNN, it does not calculate much, but when a sudden explosion of activity is recorded, the SSN creates more spikes. Assuming that information is usually scattered from the outside world, this leads to a very effective way of calculating. In addition, the use of time domain input is another valuable piece of information compared to framework-based approaches, where an artificial timeline entered by the sensor is introduced. This can lead to efficient calculation of features such as optical flow or stereo inequality, and in combination with spike-sensitive learning rules, can lead to more efficient data training.

In deep SNNs, asynchronous axis-based computing mode results in the rapid dissemination of prominent information through multiple network layers. To take advantage of this effect in practice, SNNs must be run on neuromorphic hardware. In combination with an event-based sensor, this processes quasi-simultaneous data processing, meaning that the first approximate output of the final layer is available immediately after the first input spikes are recorded. This is true even for multi-layered networks, because as soon as the bottom layer provides sufficient activity, the spikes immediately spread to the higher layers. It does not to wait for the full input sequence to complete, which is unlike convolutional deep neural networks, where all the layers need to be fully charged before the final output can be calculated. The primary output spikes are necessarily based on incomplete information, so it has been shown that deep SNNs improve their performance and improve the processing time of the spike more than their input. SNNs can also be trained specifically to reduce approximate inference delays. SNNs are the preferred computational model for the operation of highly efficient energy-efficient neuromorphic hardware devices that support data-driven processing mode and keep computations local, thereby preventing access to expensive memory [57].

Despite recent advances one of the main challenges and disadvantages of deep SNNs is that their accuracy in standard metrics such as MNIST, CIFAR, or ImageNet is not as good as that of their machine learning counterparts. To some extent, this can be attributed to the nature of these benchmarks, which are present in conventional frame-based images. Therefore, a kind of image conversion to the Spark sequence is required, which is usually inefficient. Another limiting factor is the lack of training algorithms that take special advantage of the features of Spark neurons, such as efficient time codes. Instead, most approaches use approximations based on the rate of use of convolutional deep learning neural networks, meaning that no progress can be expected. Deep SNNs may be useful in such cases, as the results may be faster and more optimized and it can get more efficiency than convolutional neural networks, especially if SNN runs on parallel hardware. Training algorithms for SNNs are also more difficult to design and analyze, because of their non-computational and discontinuous computational methods, which makes direct use of successful techniques behind the scenes, as well as for deep neural networks can be difficult [57].

The performance of SNNs in conventional AI standards should only be seen as a proof of concept, but not as the ultimate goal of research. If SNNs imitate, they should be expected to be optimized for behavioral-related tasks such as decision-making based on continuous input flow when moving in the real world. Image classification is a random image that is suddenly overlooked on the retina without any background support. While brains are able to solve such things, they are certainly not optimal for it. Currently, the Internet environment lacks a set of good metrics and evaluation metrics that can measure effective performance in the real world [57].

4. Simulation and Results

MATLAB used as simulation platform to implement the proposed approach. Due to simplicity of coding in MATLAB, it used instead of powerful simulation tools such as NS-3, NS-2, OPNet, OMNet++, GloMoSIM, JSIM, IoTSIM and so on. Also some evaluation criteria used to guarantee the proposed approach and comparison to other methods. Initial structure for narrowband IoT is necessary in simulation. It is essential to provide a basic dimension to the narrowband IoT. Defining parameters in simulation worlds is too important to examine the proposed approach and results in a concrete manner in order to obtain assumptions and goals from it. In the simulation world, defining the dimensions of a grid means that it will not be covered outside of it, but in the real world, using the tools and the equipment, the uncovered points can be partly close to the coverage range. The Table (2), shows the initial values for the general settings of the narrowband IoT, including the number of sensor nodes (which includes equipment such as Bluetooth, etc. for communication with the narrowband IoT), sampling rate, primary energy, network dimensions, etc. and adjusts their initial parameters with empirical visibility.

Table 2. Initial settings of narrowband IoT network

X and Y dimension supported in narrowband area	$100 \times 100\ \mathrm{m}^2$
Sensor nodes number in narrowband	300 nodes
Package number in narrowband to transmit	100 packages
Maximum size of packages in narrowband to transmit	100 MB
Minimum size of packages in narrowband to transmit	1 KB
Sampling time in seconds	8 seconds
Initial SNR in transmitting and receiving data	5 dB
SNR range based on drop in transmitting and receiving data	20 – 20 dB
Nodes deployment in narrowband environment	Random
Modulation for transmitting and receiving data	BPSK
Z-WAVE initial threshold in fault tolerance time	0.1
Energy of each nodes	1 Joule
Total energy of narrowband	300 nodes × 1 Joule = 300 Joule
Symbol numbers	100000
Sub-carriers numbers	256
Channel estimation period length	32
Pilot frequency	4 MHz
Time steps for channel estimation	5
Channel frequency	100 MHz

Probability of detection and channel estimation considered in narrowband IoT-OFDM which presented in Fig. 2.

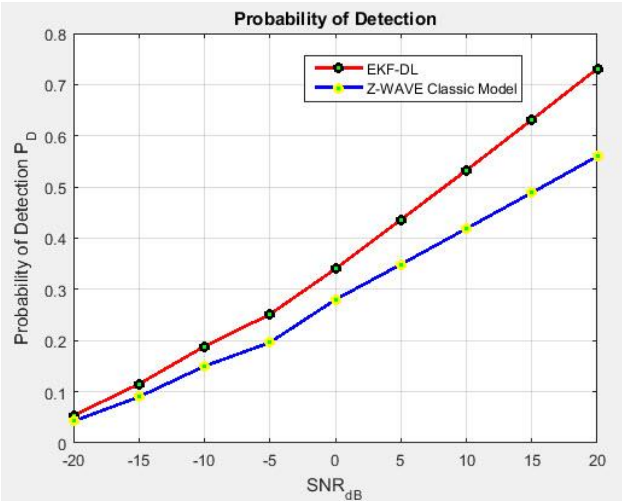

Fig. 2. Probability of detection output for channel estimation of narrowband IoT-OFDM

According to Fig. 2, it is clear that the proposed approach EKF-DL has a better probability of detection capability than Z-WAVE protocol in the channel estimation. The highest probability of detection is the superiority criterion. The proposed method has added more capabilities to the Z-WAVE protocol to maintain the channel estimation at the time of their probability of detection. Also Probability of Miss Detection (PMD) in channel estimation consider (which could be due to the existence of severe noise and interruption in the narrowband IoT-OFDM) which can be affect in data loss rate and preventing its data over fitting in channel. The lower probability of miss detection can be guaranteed to improve the loss data rate. Fig. 3. Represented the probability of miss detection.

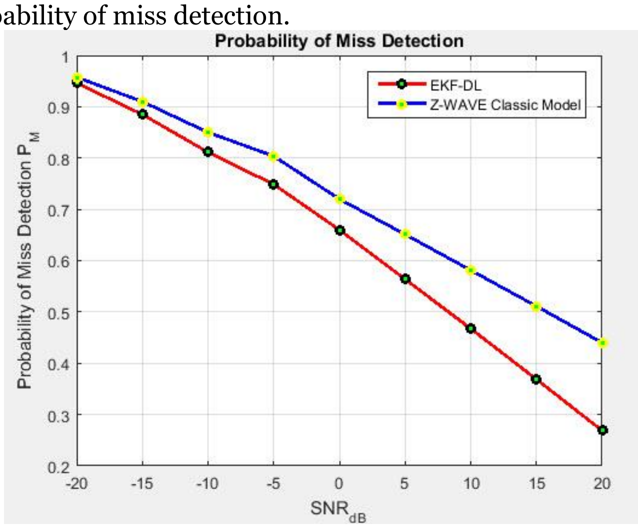

Fig. 3. Probability of miss detection

It is shown in Fig. 3. That the proposed approach EKF-DL has the better probability of miss detection than the Z-WAVE protocol in the channel estimation of narrowband IoT-OFDM. The result of this section represented that the proposed EKF-DL method has a functional superiority in minimizing the probability of miss detection. This can certainly prove to be as low as possible to reduce the data loss rate in transmitting them from origin to destination in the context of the narrowband IoT-OFDM. Fig. 4. Represented the data loss rate.

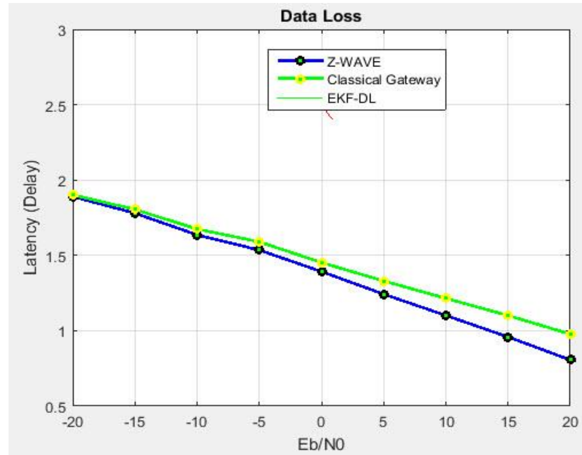

Fig. 4. Data lose rate

Based on Fig. 4 and the previous description, the proposed approach EKF-DL has equal data loss rate with the classical gateway model, but Z-WAVE is lower than that. It should be noted that the data loss rate in the Z-WAVE communication protocol is desirable, but may be different at the time of channel estimation in this study with 8 bits of information in the BPSK modulation-based communication channels. It should be assumed that the upcoming chart proves this. In the following, after creating a safe environment, quality of services criteria to evaluation consider. Initially, it is considered that the delay in Fig. 5., which shows the delay after applying the proposed approach for the secure gateway on the narrowband IoT-OFDM compared to the Z-WAVE protocol and the classic gateway.

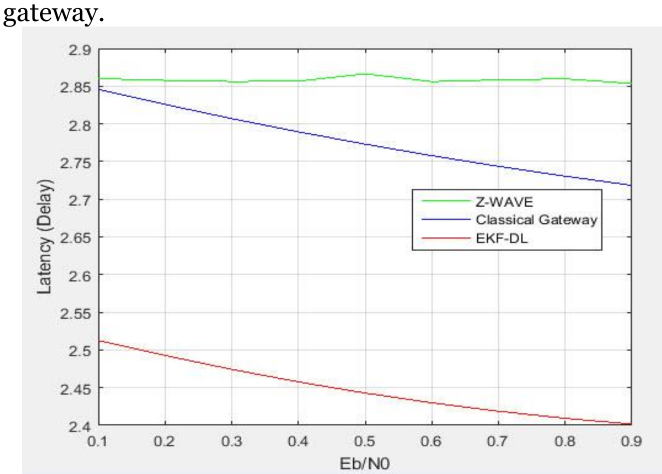

Fig. 5. Delay of proposed approach in comparison to others

In Fig. 5, the delay diagram of the proposed red-color scheme is characterized by a lower delay rate than the previous two methods including the Z-WAVE and the classical gateway in the same conditions. In the following, examination of the amount of data transmitted in bits considered. If the environment is in stable channel estimation mode, the data is decoded by the receiver and in the transmitter part, encrypted. The results of the throughput in the narrowband IoT-OFDM shown in Fig. 6.

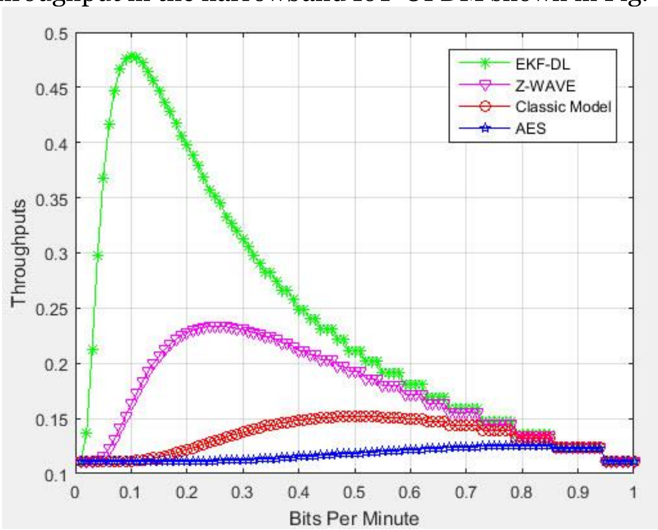

Fig. 6. Throughput rate for proposed approach in comparison to others

According to Fig. 6. Which is compared with the Z-WAVE, the classic model and the use of the AES algorithm, it is shown that the green graph has a higher permeability rate than the other methods. But over time, this rate is declining and is roughly the same in other ways. Fig. 7. Shows the proposed ROC approach in comparison to Z-WAVE, the classic model and the use of the AES algorithm.

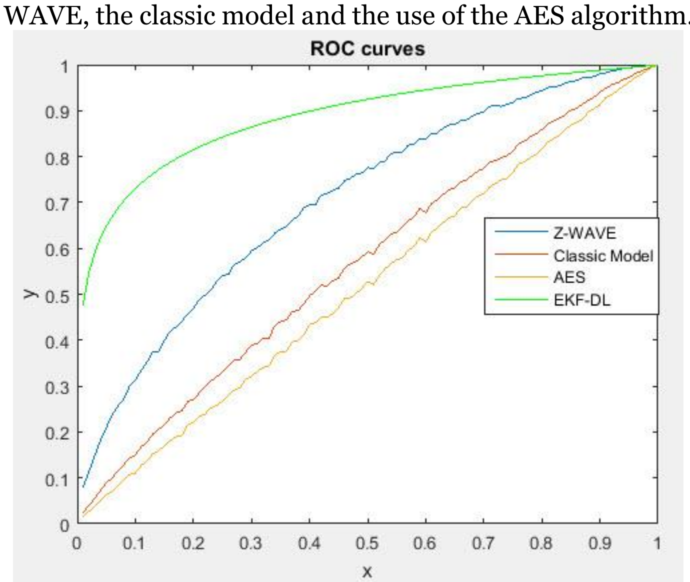

Fig. 7. Proposed method ROC curve in comparison to other methods

Based on Fig. 7, represented that proposed method has better ROC curve in comparison to others. Now the main operation of channel estimation will be done with the proposed method. The first important part is the BER (bit error rate), which is compared with EKF and LS-MMSE methods. Its output is as shown in Fig. 8.

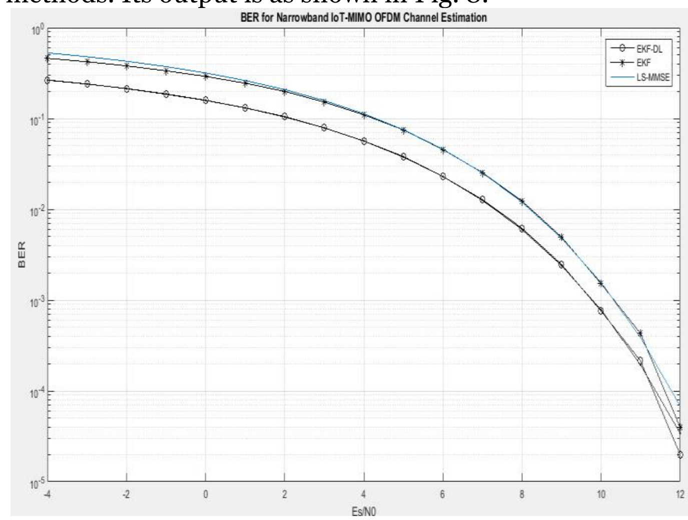

Fig. 8. Proposed method BER

Fig. 8, represented that the BER of the proposed method EKF-DL has a functional advantage over LS-MMSE and EKF. It should be noted, however, that the EKF method has a relatively close result to the EKF-DL. Then it is necessary to determine the MSE (mean square error) s between these methods, the output is as shown in Fig. 9.

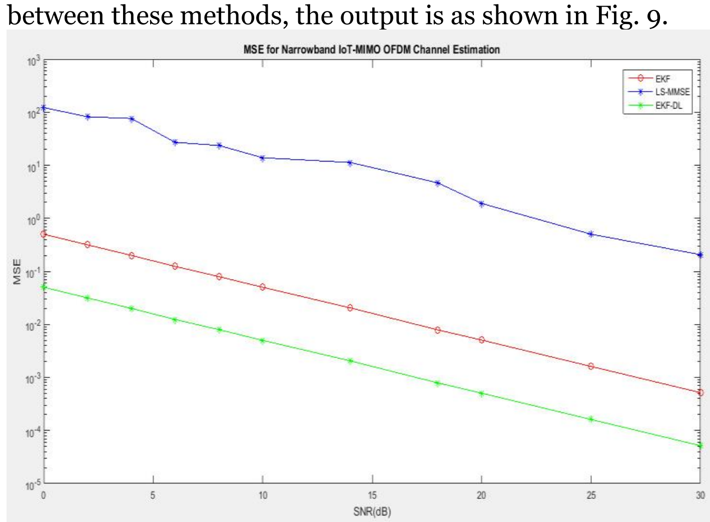

Fig. 9. Proposed method MSE

Based on Fig. 9, it is clear that the proposed EKF-DL method has a better performance in terms of SNR (signal-to-noise-ratio) in dB terms in terms of MSE than the LS-MMSE method and then EKF. The overall results represent that the proposed approach presented in this study has the ability to estimate the channel in the narrowband IoT-based MIMO/OFDM.

5. Conclusion

Internet of Things (IoT) in narrowband mode need to perform channel estimation due to modulation-based multi-channel systems conditions. So, this article surveyed about this topic to improve computational complexity and quality of service criteria such as Bit Error Rate (BER), Signal to Noise Ratio (SNR) and Maximum to Average Power Ratio (PAPR). We used OFDM as modulation and due to its weaknesses in latency, we developed it with intelligent methods based on Extended Kalman Filter (EKF) with combination of Deep Learning. Also we compared our results with classical methods of channel estimation such as Least Squares (LS) and Linear Minimum Mean Square Error which we obtained better results in computational complexity and quality of service criteria. Also we compared our results with some protocol such as Z-WAVE and AES that we gained better results, too. It should be noted that the advantages of the proposed channel estimation in IoT narrowband is to optimize probability of detection, probability of miss detection and data loss as security parts in channel estimation. Also we measure some quality of services criteria such as delay, throughput, SNR and BER. Also we tested the energy of this method in IoT narrowband channel estimation. It is noteworthy to notice that every parameter we described represented in simulation and obtained results indicated the optimal condition for any of them.

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