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*Original Article*

# Cognitive Radio-based Context-Aware Link Adaptation for Coverage Extension of Narrow Band Internet of Things

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***Abstract*** - *Coverage extension with limited transmission power devices is one of the requirements and research challenges for battery-operated IoT nodes, which use a narrowband IoT wireless communication protocol. The link adaptation mechanism can solve this problem by selecting optimal parameters using cognitive radio. This research work proposes a context-aware link adaptation mechanism using a cognitive radio that uses a machine-learning algorithm. The proposed mechanism achieves greater coverage in the long run with lower SINR (signal-to-interference and noise ratio) and BER (bit error rate) through optimal selection of repetition rate, modulation, coding scheme, transmission power, number of subcarriers, and frequency based on the wireless channel condition and QoS requirement of the application. Here, every Narrowband Internet of Things (NBIoT) node is considered a cognitive radio node, which uses a frequency that is available for free. The proposed system-generated NBIoT uplink waveform and evaluated the performance using the optimal parameter derived from the proposed context-aware machine learning-based link adaptation scheme.*

***Keywords*** - *Cognitive Radio, Link adaptation, Narrowband internet of things, SVM Regression, Decision tree Regression, Internet of things.*

## 1. Introduction

The Internet of things (IoT) is one of the emerging technologies where millions of battery-operated devices are connected to the Internet. The wireless technology for connecting such a massive number of battery-operated devices without human intervention requires special consideration. The wireless technology for those applications needs to be energy-efficient and lightweight. There are many wireless standard protocols proposed for IoT applications in licensed bands like Narrowband Internet of Things (NBIoT), Extended coverage Global System for Mobile communications (EC-GSM), Long Term Evolution for Machines (LTE-M), Unlicensed band MY THINGS, Short for long-range (LoRa), and Sigfox. NBIoT gives good connectivity handling of 50k devices per cell with an increased level of 20dB with low power consumption, which may give ten years of battery life [1] [2] [3]. Each of them has its own pros and cons within that NBIoT gives good connectivity handling 50k devices per cell with an increased level of 20dB with low power consumption, which may give ten years of battery life [4] [5]. This research work focuses on NBIoT waveform generation and link adaptation for the extension of coverage. There is much literature on the coverage of extension and link adaptation proposed in the literature.

### *1.1. Background*

Repeating transmission data is considered a promising method for enhancing coverage. It links adaptation for NB-IoT systems with the modulation and coding scheme (MCS), and the repeated number is proposed by Yu, Changsheng et al. [6]. A theoretical framework analysis for the upper bound of achievable data rate with repetition factor is considered by Malik H et al. [7]. Maximum achievable data rates of 89.2 Kbps and 92 Kbps are evidenced for downlink and uplink. A novel strategy for optimizing NB-IoT shared channels via the selection of link parameters like modulation and coding scheme and number of repetitions is proposed by Luján et al. [8]. These parameters are optimized through the base station (BS) at a target block error rate (BLERt). NB-IoT, a machine learning-based adaptive repetition scheme, is proposed to improve network transmission efficiency [9]. Many repetitions reduce throughput and increase energy consumption, thereby reducing their battery lifetime. A method for enhancing coverage using machine learning algorithms with dynamic spectrum access is proposed [10]. The mechanism reduces the required number of repetitions by increasing the coverage with less energy consumption.

The NB-IoT spectrum allocation has a limitation of 180 KHz to 200 KHz, which is insufficient for massive connected IoT devices. The repeated transmission mechanism for coverage enhancement used in NB-IoT results in spectrum wastage. An NB-Cognitive Radio-IoT (NB-CR-IoT) technique is proposed to mitigate this issue [31]. The mechanism provides efficient dynamic spectrum access for the distributed heterogeneous networks of NB-IoT. A deep Q-learning algorithm solves the resource allocation problem by reducing the required number of repeated transmissions. Link adaptation is widely used for wireless resource optimization [12] [13]. For the uplink of Cognitive Radio (CR), a combined transmitter adaptation and power control with an assured aim at the signal-to-interference + noise ratios (SINR) are described [14]. A channel assignment approach with Guard-Band (GB) awareness is suggested to increase spectrum efficiency. Most GB-aware algorithms assume fixed-rate channels and allocate channels in sequential order. A GB-aware channel assignment is shown with several feasible rates at various time windows [30]. This method aims to increase network capacity and reduce the required number of channels for target rate achievement with interference constraints [16]. Utilizing cognitive radio (CR) increases energy efficiency and the efficient use of radio resources. However, because of the aggregated interference from primary base stations and cognitive base stations, resource allocation is complex [17] [18] [19]. To allocate resources, a multi-agent model-free reinforcement learning system called Q-Learning (Q-L) and State-Action-Reward-Next-State-Action (SARSA) is proposed [20]. In practice, the system assumes that cooperation among nodes is conceivable, but a multi-agent system requires more memory and has a higher computational complexity. Soft computing and cognitive radio are used for link adaptation and interference management; this work focuses on a cognitive radio-based solution for coverage extension. The main disadvantage is that the overhead of collaboration and the required space is not considered [21] [22] [23].

A set of appropriate cooperative sensing parameters for an NB-CR-IoT (narrowband cognitive radio Internet of Things) network that optimises throughput. In order to increase network throughput, this study proposes the network relay concept proposed by Srinivasa Rao et al. [27].

The EECDC clustering method uses geometry approaches to enhance application performance and quality of service (QoS). It is an energy-efficient and coverage-aware distributed clustering protocol for wireless sensor networks. The major characteristics of EECDC to extend the life of WSN are better coverage, energy efficiency, low traffic from nodes to base station, and balanced energy consumption. Simulation results show that EECDC is beneficial in extending network lifespan and enhancing network coverage proposed by A. Maizate et al. [28]. The open difficulties to show the future direction of 6G wireless coverage expansion from the standpoint of critical elements influencing service coverage effectiveness, i.e., the network access capacity, space segment capacity, and their corresponding connection. In addition, Min Sheng et al. propose further detail about the crucial elements that determine how well the components, as mentioned above, match, enhancing service coverage potential [29].

### *1.2. Approaches for Improving Coverage*

Signal repetitions, additional control channels, and bandwidth reduction, notably for the uplink, are used in NB-IoT to target a considerable coverage increase. A User Equipment (UE) transmission may be configured in various ways to improve its coverage. The repeats have two potential Redundancy Versions for the NPUSCH format 1 in charge of uplink data transmission (RV). The number of tones, subcarrier spacing, and repetitions determine repetition order. In addition to repeats, NB-IoT makes a variety of potential bandwidth allocations conceivable. Single-tone setups are required when signal strength is low and provide capacity. Higher data speeds are available for UEs with strong coverage via optional multi-tone setups. Keep in mind that the time required to complete the transfer will rise with both strategies.

The improvement in coverage is limited by the intended low range of SNR, where an accurate channel estimate emerges as a major problem.

### *1.3. Research Gap*

Existing methods mostly use the repetitions mechanism. Increased repetitions reduce the throughput and spectral efficiency and also increased the energy consumption; all the proposed mechanisms performed well only for the given context and performed the optimization. Even though some existing work uses a machine-learning tool, it is optimizing one or two parameters with some tradeoffs. There are millions of IoT devices that demand more spectrum. But the NB-IoT system allows only allocation spectrum from 180 kHz to 200 kHz, which is insufficient to handle the exponentially increasing NB-IoT devices.

### *1.4. Problem Statement*

This article intended to solve and develop a mechanism of multiple parameter optimization with the least tradeoff with an ability to analyze the context and perform the optimization.

### *1.5. Proposed Solution*

Soft computing and cognitive radio are used for link adaptation and interference management [24] [25] [26]. With reference to that, this work focus on the cognitive radio-based solution with machine learning for coverage extension.

This research work has the following novelty and contribution.

- Every NBIoT node is treated as cognitive radio, and NBIoT uplink-link adaptation cognitive engine software is implemented to realize link adaptation effectively and to allocate the frequency subcarrier dynamically based on availability.

- A multiple parameter optimization mechanisms is developed for NBIoT uplink-link adaption by machine learning with analysing the contexts of a given channel state and the QOS requirements of the application.
- An optimal selection of parameters like repetition rate, modulation, coding scheme, number of subcarriers, frequency of transmission, and transmit power is extracted to achieve greater coverage with improved performance of BLER for the context of channel state and QoS requirement of the applications.

The remaining part of the article is organized as follows: Section 2 deals with the link adaptation mechanism's methods, and Section 3 deals with the NBIoT standard waveform generation, link adaptation results, and analysis. Section 4 concludes the article with a summary of the research and future work.

## 2. Method

Spectrum scarcity may be resolved by merging cognitive radio with NB-IoT using a machine learning-based link adaption model that simulates the relationship between channel state information and BER via empirical observation of channel realization.

### *2.1. System Model for Link Adaptation Mechanism*

The coverage is classified into three groups according to the NBIoT standard and 3GPP LTE advance pro release 13. 1. Coverage Extension level 0: standard coverage with a 15 kHz sub-carrier spacing and an MCL value of roughly 144 dB. 2. Coverage Extension level 1: a strong coverage class with an MCL VALUE of around 154 dB and a sub-carrier spacing of 15 kHz. 3. Coverage Extension level 2: extreme coverage class, with an MCL of about 164 dB and a 3.75 kHz sub-carrier spacing.

The choice of the coverage class to be selected for the given user depends on the particular user's channel conditions. The extreme coverage class can be used for the user with a low power received power, i.e., worst channel experiencing user, and a normal coverage class is used for the user with high received power, i.e., best channel condition having user. Each selected coverage class will use some set of the transmission parameters like the number of repetitions. This form of class-based radio parameter link adaption system allows varying coverage to be delivered to UEs depending on their path loss. By analyzing the channel condition of individual user equipment, the cellular base station assigns a class of coverage and the number of repetitions from the set {1, 2, 4, 8, 16, 32, 64, 128} by the same transmission power or different transmits power on the repetition.

Fig.1 shows the system model of the proposed CR machine learning algorithm-based link adaptation for the coverage extension. There is n number of CR NBIoT nodes communicating via uplink to the CR base station.CR base station applies a machine learning mechanism to predict the channel response of individual CR UE nodes and uses that channel to make link adaptations. The results of the link adaption, including the number of repeats, the number of subcarriers, the modulation and coding scheme, the transmit power, and the ideal channel frequency, are conveyed to the CR UE for usage. It is assumed here in such a way that spectrum sensing is already done and free frequency to use available readily available. All CR UE uses the optimal parameter that the base station communicates.

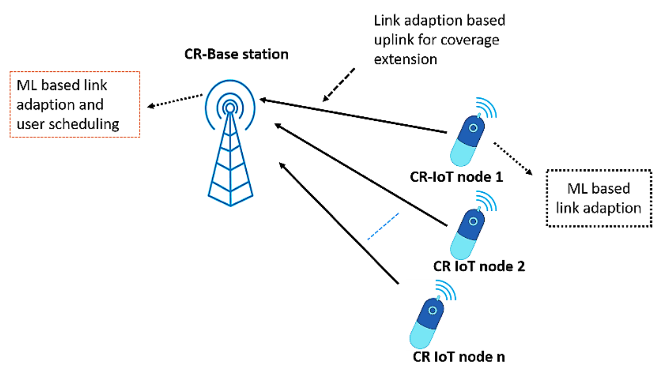


**Fig. 1 System Model of CR NB-IoT with Machine Learning-Based Link Adaptation**

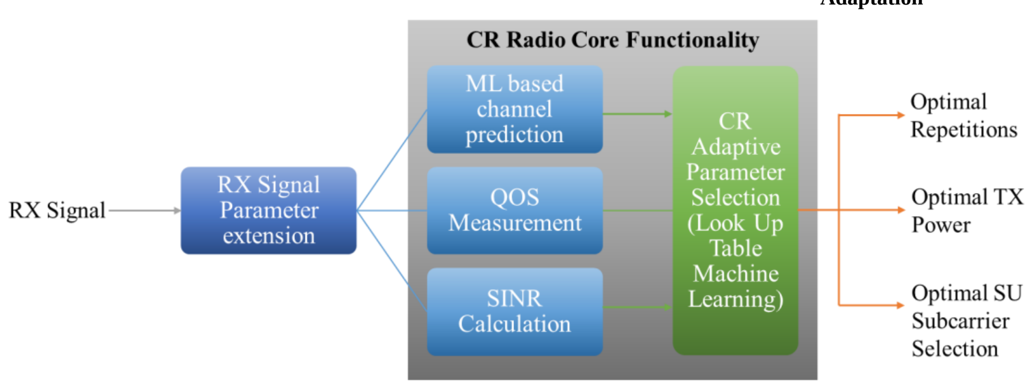


**Fig. 2 Proposed CR Machine Learning-Based link Adaptation Mechanism**

### *2.2. Proposed Model for Link Adaptation Mechanism and Algorithm*

Fig.2 shows the CR machine learning-based link adaptation. The CR base station receives the signal from CR UE and then extracts the parameter required for the link adaptation. Here instead of doing a channel estimate, channel prediction is used. When a massive number of CR NBIoT nodes are present, channel estimation on all the nodes is difficult; instead, channel prediction is carried out. Initially, offline for 3 different channel realization training data sets are created and used to transmit the signal using NBIoT signal format. The received signal and the realized signal are used to train the SVM regression, which learns to predict the N user channel. The predicted channel and the input parameter for the link adaptation block are the SINR parameter and target QoS (SNR, BER, coverage range). The link adaptation block uses a Decision tree regression algorithm and gives which optimal parameters are to be used by the user.

To test the proposed link adaption mechanism for the NBIoT standard, the simulation signal waveform must be generated per the standard of NBIoT. There is a standard algorithm or step define to generate a standard of NBIoT waveform for testing any research methodology for NBIoT standard.

### *2.3. The standard Waveform Generation Steps*

1. Find a resource grid and apply it to NPUSCH symbols
2. Simulate and generate the baseband waveform using single carrier frequency division multiple access modulations
3. Transmit the NPUSCH symbols waveform on an AWGN noisy and frequency-selective fading channel
4. Perform channel estimation
5. Do channel equalization
6. Do SC-FDMA demodulation
7. Get the block CRC after decoding the symbol
8. Use the block CRC for calculating block error

From step 1, give the standard waveform generation steps, procedures, and operations as per the NBIoT system standard, where the first step would be finding a resource grid and applying it for NPUSCH symbols, where appropriate resource grids are identified and applied. The second step would be to simulate and create the baseband waveform using the NBIoT-adopted single carrier frequency division multiple access modulation standards. The third step involves adding AWGN noise and transmitting it on a frequency selective fading channel based on the waveform needs of SDMA, which is the standard adopted for NBIoT, an increased concern of this study to analyze the performance.

This study is intended to analyze the performance of the proposed system in frequency selective fading channels. Step four consists of receiver-side operation, which includes channel estimation. To help with the link adaptation procedure. Step five involves channel equalization. Channel estimation values from step 4 are utilized to equalize and remove the channel effect so that decoding of the waveform can be done successfully. Step six involves demodulation after the equalization of the symbols. Step 7 involves the CRC procedure to check whether some errors are there in the receiving symbols. For applying CRC check on block error on using the CRC check, the calculation of block error rate is calculated, and it is used for performance measure under step 8.

## 3. Results and Discussion

The NBIoT uplink standard waveform is utilized to study the connection between the block error rate and the number of repetitions using the Monte Carlo simulation. The simulation setup parameters given in Table 1. were used to generate the uplink standard waveform.

**Table 1. Simulation Setup**

| S.no | Parameter | Value |
|---|---|---|
| 1 | Waveform Channel realization | Narrowband Physical Uplink Shared Channel (NPUSCH) |
| 2 | Physical channel | frequency-selective fading and Additive White Gaussian Noise |
| 3 | Number of UL-SCH transport blocks | 5 |
| 4 | Repetitions | 1,2,4,8,16,32,64 and 128 |
| 5 | SNR | -20 to 10 Db |
| 6 | Subcarrier Spacing | 15khz and 3.75kHz |
| 7 | Subcarrier Set | 11for 15khz and 47 for 3.75kHz |
| 8 | Modulation | QPSK |
| 9 | Number of resource units | 1 |
| 10 | Transport block length | 136 |
| 11 | MIMO configuration | 2X2 |
| 12 | channel Delay profile | Extended Typical Urban model (ETU) |
| 13 | Doppler frequency | 1Hz |
| 14 | Fading model type | Generalized Method of Exact Doppler Spread with Rayleigh Fading (GMEDS) |

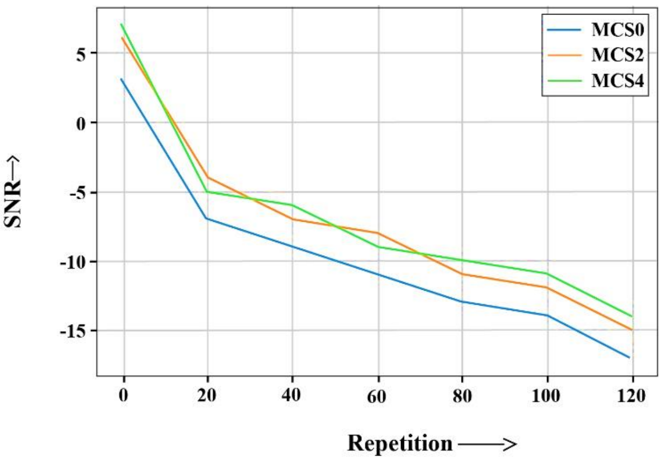


**Fig. 3 SNR analysis for various repetition and Modulation schemes**

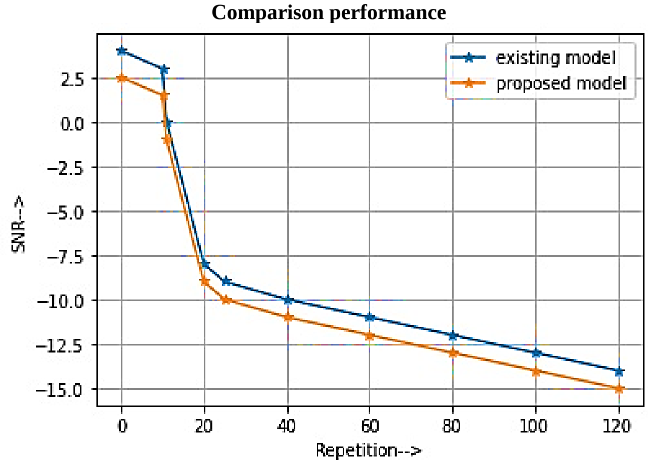


**Fig. 4 SNR performance comparison with repetition**

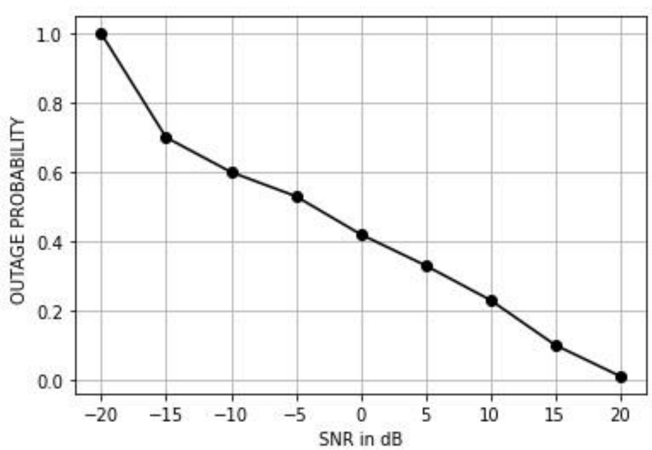


**Fig. 5 Outage Probability analysis with SNR performance**

Fig.3 shows the dependency of SNR and repetition rate, which is evaluated for NBIoT waveform for various modulation and coding schemes (MCS). The findings demonstrate that using a higher number of repetitions allows us to successfully decode the message even when the channel conditions are poor. Furthermore, when employing a wider number of modulation and coding schemes, one may effectively send a message even when the channel conditions are poor.

Fig 4 compares the proposed work's performance and the existing work. [6] and plotted in figure 5. It is evident that the proposed method is performance compared to the existing method. For every repetition value, the proposed method requires less SNR for the targeted BLER compared to that of the existing one. For example, for repetition 60, the proposed method requires -12 dB, but the existing method requires -11 dB, so the proposed method achieves a 1 dB gain. The proposed method achieves this performance gain by employing multi-parameter optimization with machine learning. The proposed method predicts the channel before communication and adjusts the multiple parameters accordingly, whereas the existing method does not.

Fig.5 shows the outage probability vs SNR evaluated. The graph suggests that the likelihood of an outage decreases as the signal-to-noise ratio increases. At a lower SNR of -15 dB, the outage probability is 0.7, and at a mid-SNR of 0 dB, it is 0.4. The outage probability is zero at a high SNR of 20 dB. So, from that graph, conclude that after 20 dB of SNR, that system has zero outage probability, which means its outage is 100 percent successful. When SNR is increased by 5 dB, performance improves by 0.1 probability for every 5 dB increase in SNR.

Fig.6 shows the outage probability in relation to the number of users evaluated. It is clear from the graph that if the amount of users increases, the outage probability is also increased. So, from this, there is an idea for 10 users; the outage probability is 0.98, which means the system outage is 98 percent. If the amount of a user is increased by 6 to 8 users, the 40% probability of an outage increases.

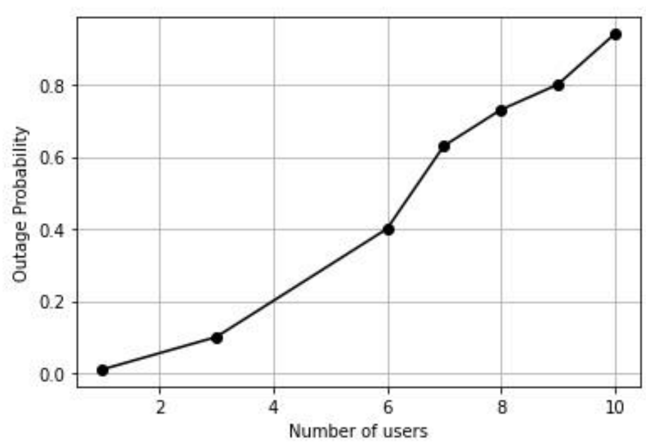


**Fig. 6 Number of users vs Outage probability**

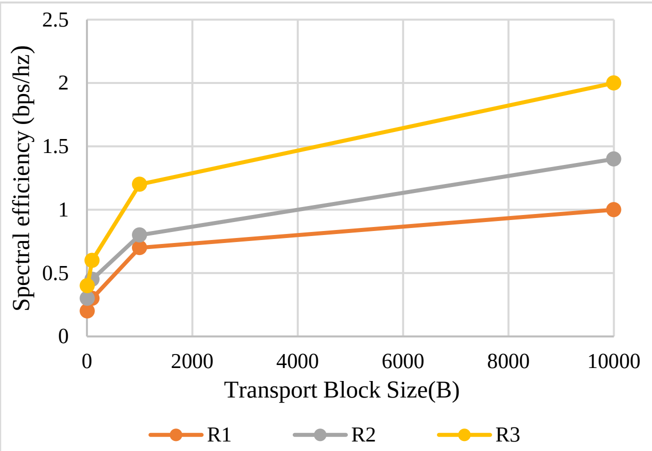


**Fig. 7 TBS vs Spectral efficiency analysis**

Fig.7 shows the TBS vs Spectral efficiency evaluated for different repetition rates from the graph; it can be observed that when R1, R2, and R3 represent repetition rate, Where R1>R2>R3, Here R1 is the highest repetition rate, R2 is the next highest Repetition rate, R3 is the lowest Repetition rate. Spectral efficiency is increased. From the graph, get an idea of the target transport block size and what could be the repetition rate. The concept of many repeats is used to obtain extended coverage. Without a doubt, this would improve Tx Reliability, but at the expense of spectral efficiency.

Fig.8 shows the SNR vs block Error rate evaluated for different repetition rates. It is clear from the graph that the BLER is reduced with an increased repetition rate. From the graph, get an idea of the target BLER, which could be the repetition rate. NBIoT, 700MHz, and 800MHz support three frequency bands and 900MHz.cognitive radio can work on those bands based on available free spectrum or interference level. Inferring from the graph, if the repetition rate is equal to 1, i.e., (NRep=1), only get 0 BLER after 2dbm SNR. For example, it cannot decode the signal if SNR is 0 since it can only receive one repetition. Signal decoding is done if SNR is higher than 2. That is a disadvantage. If raised NRep=8, will be able to decode the signal within correctly -10dbm, since -10dbm is bitter, became zero. The highest Nrep=128 will be increased even further. It would be capable of decoding at an SNR of -17.5dBm. Since the repetition rate is greater, it could accurately decode the signal even at low SNR.

Fig.9 shows that the SVM machine learning model is used for the wireless channel prediction, which is used as input for the adaptive parameter selection model. SVM is used in the regression model to predict the channel. The wireless channel is assumed to be exponentially distributed, and the channel training data are generated from the exponential distribution. Fig.9 shows the prediction or regression outcome of the SVM model for the three kernel types RBF kernel, linear kernel, and polynomial kernel. Only anticipated accuracy is used in the prediction channel and appropriately implements the connection, necessitating good channel prediction. As a result, this graph depicts how successfully the suggested model inaccurately predicts the channel. So, except for some higher levels of repetition at 5 and 6, this RBF kernel exactly predicts the channel. However, there is a slight variance in the linear model prediction. A non-linear model is a polynomial model. It can accurately detect and forecast channel changes. The figure shows that the polynomial and RBF kernel-based SVM model can track and model exactly the exponential distributed channel model compared to the linear kernel.

The performance of the SVM regression is evaluated in terms of error values and tabulated in table 2. The parameter selection is carried out using regression-based prediction. Decision tree regression is used to predict optimal parameters for the given context. Random training data sets are generated and applied to train the decision tree regression. After training, a random combination of the feature set is used, and the optimal sample values are obtained as Decision Tree Regressor [ 27.08806043 -17.48976917 10.25530971]. Here the first value indicates repetition rate; the second value shows optimal transmit power; the third value shows the subcarrier selection .those values stated in floating-point numbers will be rounded off to the nearest integer value of the possibility of the given parameter after taking the absolute value.

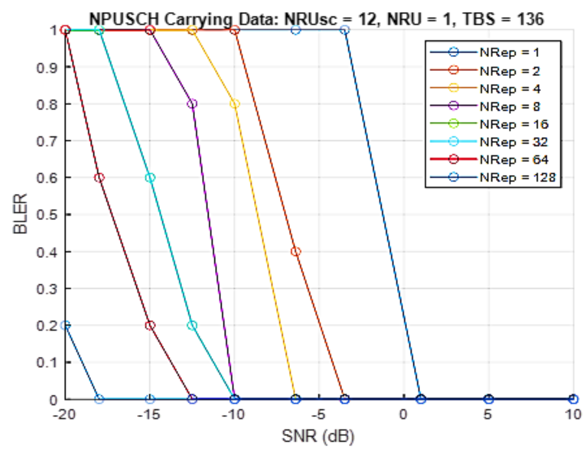


**Fig. 8 Signal-to-noise ratio comparison with a block error rate**

**Table 2. Performance of SVM regression with different kernel**

| Model | Mean absolute error | Mean squared error | Median absolute error |
|---|---|---|---|
| SVM regression with linear kernel | 27.69 | 1896.53 | 12.31 |
| SVM regression with RBF kernel | 23.19 | 1623.1 | 5.08 |
| SVM regression with polynomial kernel | 17.52 | 485.28 | 12.55 |

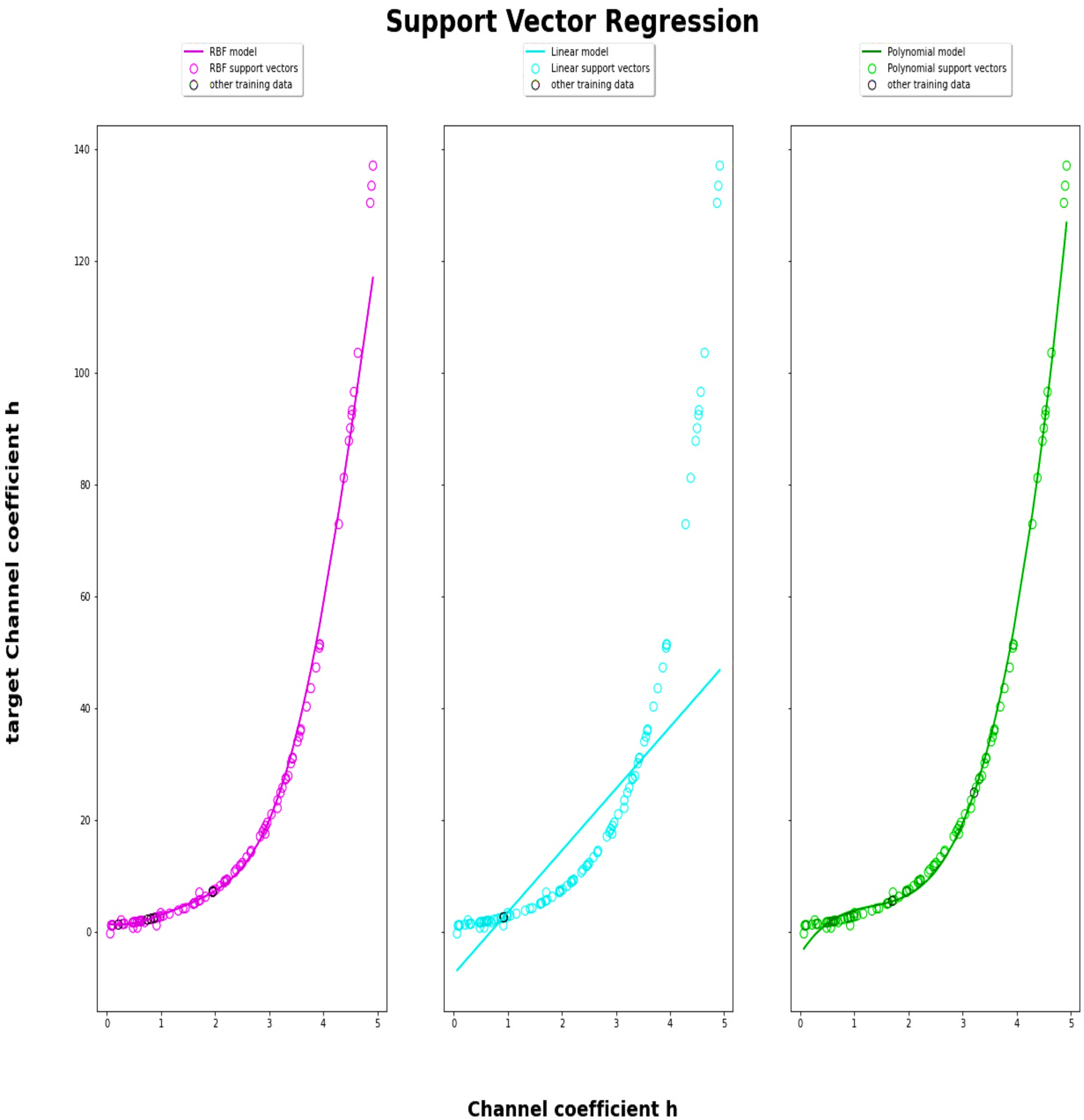


**Fig. 9 Channel Prediction Using SVM Regression**

## 4. Conclusion

Coverage extension is one of the main issues in narrowband IoT. This article solves the coverage extension problem with the cognitive radio approach. The machine learning approach of decision tree regression efficiently handles the tradeoff between the repetition rate and the coverage extension. Channel estimation is the critical factor that influences the optimal parameter selection, which is dealt with by the SVM regression mechanism that could predict the channel. The proposed methodology provides optimal parameter selection (link adaptation ) for the given context on an ad-hoc basis through the cognitive process of the cognitive radio with the help of a machine learning algorithm of SVM regression and decision tree regression. Future work will address both this constraint and the security concerns.

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