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AN INTELLIGENT RESNETS RESOURCE ALLOCATION FRAMEWORK FOR 5G NETWORKS

S. Ramasamy[1], P.N. Periyasamy[2] and M. Sathiya[3]
[1,2]Department of Computer Science and Engineering, Hindusthan Institute of Technology, India
[3]Department of Information Technology, Karpagam Institute of Technology, India

Abstract

This paper presents a resource allocation technique for industrial applications for 6G networks, which are characterised by the presence of many heterogeneous parameters that have an effect on the quality of data transmission. The purpose of the project is to achieve the greatest possible efficiency in the application of the resources that are presently while achieving a higher level of control over a diverse collection of sensing nodes operating within a hybrid network. The system model that has been proposed is a workable option for efficient resource allocation. The performance of the proposed method, in addition to similarities to the performance of other methods has been analysed. The proposed methods offer performance that is comparable to or better than the baseline, while simultaneously significantly reducing the SI exchange overhead and improving the system resilience to sensing intervals, some of which may be unavoidable in practise.

Keywords:

ResNets, Resource Allocation, 6G, IoT

1. INTRODUCTION

Two typical examples of domains that are particularly well adapted to the traditional Internet of Things (IoT) are intelligent medical care and smart homes. Smart homes are homes that are equipped with the latest in technological advancements. This was a reaction to the rising cost of both assets and machinery. This infrastructure will place a primary focus on business sectors such as energy and industrial management, both of which are important to the idea of Industry 4.0. The primary focus of this infrastructure will be on business sectors. The 6G network connects a wide variety of industrial machines and equipment [3, 4] so that the information gathered by sensor nodes can be used to influence intelligent decisions that can be made in real time based on that data. These decisions can be made based on the collected information.

Data aggregation is an important component in the implementation of shared spectrum access with cellular users. This is because data aggregation is necessary to achieve greater spectral efficiency and support massive applications for the IoTs. Computing on the edge of the network and machine learning both play an essential role in ensuring the authenticity, connectivity, and management of resources of massive IoT deployments. In addition to that, the network layer that these programmes use for their infrastructure is built with random access strategies.

To successfully manage dense networks and devices utilised in industrial 6G applications, the massive IoT strategy will require a solution that is more effective towards omnipresent networking. This is a prerequisite for the strategy. Because of the interactive process in which more and more devices are added to make the scale of communication continue to increase, the amount of data that sensor nodes need to sense, process, and communicate has also significantly increased. This is because of the process in which more and more devices are added to make the scale of communication continue to increase. This is because there are now a greater number of gadgets that are connected to the internet. The industrial 6G applications data centre is expected to produce enormous amounts of data soon.

The compilation and coordination of all this information is a challenging task [4]. The automated operation of industrial machinery and the system to enhance production and communication effectiveness [5]-[6] through data mining are both dependent on the information that can be gleaned from the massive amounts of data that are stored. However, the successful automated operation of industrial machinery is dependent on the information that can be gleaned. It acts as a benchmark for determining the degree to which 6G devices are intelligent and as a starting point for the development of intelligent software for those devices [7].

Massive IoT applications that run on 6G wireless networks might run into a significant problem with their energy consumption as a result of the widespread implementation of smart metres and smart grids, which was made possible by the development of innovative data mining technologies. This could be a result of the fact that smart metres and smart grids were made possible by the development of data mining technologies. When considered from the point of view of the system underlying technical infrastructure [8], the perception layer, the network layer, the platform layer, and the application layer are the four components of any commercially accessible 6G system that are of the utmost significance.

During the mining process, a significant number of sensor devices are utilised to acquire information from the perception layer [9]. Because there is only a finite amount of bandwidth available for low-latency work collaboration, sensor nodes in the network are required to take part in cooperative communication [10]. This is done to achieve greater productivity, a shorter delay, and a lower cost of network transmission. The emergence of the approach known as edge computing has brought with it the possibility of a solution to the problems of inefficiency created by cloud computing. In the context of this conversation, the term edge refers to a location within or close to the device [11] that is capable of performing data processing, thereby decreasing the necessity for data to be transmitted to a far-off data centre.

It is of the utmost importance to find a solution to the problem of conducting reasonable resource allocation to lower the energy consumption of nodes and to accomplish effective collaboration between nodes [12]. Finding a solution to this problem is of the utmost importance. This is being done to ensure that the system quality-of-service (QoS) specifications are satisfied.

To address the problem of resource allocation for 6G industrial applications, which are characterised by the presence of a large number of heterogeneous parameters that have an effect on the quality of data transmission, the objective of this paper is to address that problem. These applications are characterised by the presence of numerous different parameters, each of which has an impact on the quality of data transmission.

The work presents a resource allocation technique, with the goal of dividing the entire industrial 6G system into several different clusters for the purposes of making calculation and networking easier. The purpose of the project is to achieve the greatest possible efficiency in the application of the resources that are presently at one disposal while simultaneously achieving a higher level of control over a diverse assortment of sensing nodes operating within a hybrid network.

2. RELATED WORKS

A number of sensor nodes are dispersed at random throughout the framework of the MAS-based industrial 6G system paradigm described in this article. To streamline administrative tasks and cut down on the number of times that data has to be processed twice, the model incorporates data mining and presents the concept of data mining as a means to achieve these goals. By utilising cluster analysis as our primary tool, we can break down a WSN into a number of smaller and more self-sufficient networks that are easier to handle.

Each networks is made up of a collection of components that are able to recognise one another. Each sensor node cluster conducts a unique set of duties. They can, in a broad sense, be separated into two distinct classes. One such instance is the CH role as administrator of the event, which they play as part of their CH responsibilities. There is the possibility of numerous CHs existing within a cluster, which serves not only the purpose of distributing IoTs but also the purpose of having multiple CHs.

According to the model of the system, the nodes for the IoT are grouped together at the beginning in accordance with the Poisson formula. In compliance with the example provided in Fig. During the first stage of the process, collaborative communication will be utilised to determine who will serve as the manager agent (MA) for the multiagent strategy. When it comes to industrial applications for 6G networks, which require high dynamic clustering performance parameters, the system model that has been proposed is a workable option for efficient resource allocation. This is because the system model was designed to accommodate these kinds of applications [12].

When referring to the component in question within the framework of the task network, another name for it is the task agent. (TA). Our goal is to achieve the highest possible level of system effectiveness while simultaneously lowering the total quantity of energy that is consumed by the procedures of clustering and election of CH. This will allow us to accomplish both of our goals simultaneously. As a direct result of this, the study that was proposed provides estimates regarding the precise location of the MA. The image presents a flowchart of the proposed operational procedure for the system [13]. The depicts how our work starts with the dynamic formation of clusters based on the real-time signals collected by sensor nodes whenever the massive IoT or conventional 6G systems receive a task. These clusters are formed based on the data collected by the sensor nodes. After that, we move on to the next step, which is defining the MA for the purpose of controlling resources within the cluster and predicting where the MA will be located. After that, there is an equitable distribution of resources across all the groups, using the overall energy and memory utilisation of the 6G system as the foundation for the distribution.

When all the observations from each cluster have been compiled, the CH that is designated to that cluster will submit a confirmation request to the CM. This will take place once all the observations have been compiled. CNN is employed to maximise the accuracy of the findings while simultaneously minimising the influence of duplicate data. This is accomplished by analysing the data in a way that is both parallel and concurrent. The Gaussian copula theory (GCT), which was used to carry out an analysis of the most effective data collection for association.

3. PROPOSED METHOD

When analysing the DL of a wireless network with N nodes, each of which services one or more devices through an autonomous and mobile collection of XSs, we consider the fact that the network is composed of N nodes. The collection of all M_n devices in the n^{th} in XS is referred to as $M_n = \{1,\cdots,M_n\}$, and the collection of all M_n devices in the network is referred to as N=$\{1,\cdots,N\}$.

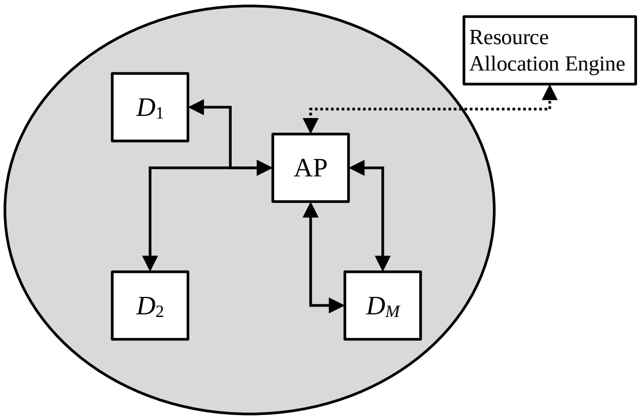

Fig.1. Transmission/sensing after the allocation of resource

As in Fig.1, every inXS has an access point (AP) built into it, which gives it the ability to synchronise its communications with those of other associated devices. It is clear from looking at Fig.1 that the AP is outfitted with a local resource selection mechanism. To make decisions, this engine gathers information from other devices in the immediate vicinity and sends it to itself via a connection that is only one bit wide.

When they are used in applications, such as when they are installed in XSs that are mobile robots to assist in manufacturing, they adhere to a predetermined movement pattern. One example of this is when they are used. Transmissions within each inXS are carried out at any given moment over one of the K=$\{1,\cdots,K\}$ shared orthogonal frequency channels denoted by K (K<<N), with a transmit power level that falls somewhere within the range [κ_{min},κ_{max}], where κ_{min} and κ_{max} represent the minimum and maximum allowable transmit power levels, respectively.

Transmissions are carried out with a transmit power level that falls somewhere within the range [*min*, *max*], where *min* and *max* represent the minimum and maximum allowable transmit power levels. The study allows Z discrete degrees of transmit intensity, which are $Z=\{1,\cdots,Z\}$. We are going to proceed under the presumption that there is no interference within the intra-subnetwork because communications taking place within each inXS are orthogonal. It is acceptable to assume that APs will provide each connected device with its own individual dedicated block of time and frequency spectrum. This will allow each device to function as efficiently as possible.

3.1 CHANNEL MODEL

The radio channel that extends from the APs to the network devices is characterised by large-scale fading, such as path loss and shadowing, as well as small-scale impacts on individual network devices. It has been determined that the formula for calculating the path loss of a relationship between two locations A and B at a distance d_{AB} is as follows:

$$L_{AB}=\frac{c^2 d_{AB}^{-\alpha}}{16\pi^2 f^2} \tag{1}$$

where

$c \approx 3\times10^8\ \mathrm{ms}^{-1}$ - speed of light, f - carrier frequency and α - path-loss exponent.

The model is based on a Gaussian random field because it is the most general type of random field. The formula is used to calculate the shading that should be applied to the relationship between A and B.

$$X_{AB}=\ln\left\{\frac{1-e^{\left(-\frac{d_{AB}}{d_c}\right)}}{\sqrt{2}\sqrt{1+e^{\left(-\frac{d_{AB}}{d_c}\right)}}}\right\}\left(S(A)+S(B)\right) \tag{2}$$

where S - Gaussian random process, d_c - correlation distance and h - Rayleigh distributed small scale fading.

To provide an explanation of the temporal relationship of h, we make use of Jake Doppler model.

The following equations can be utilised to calculate, for any set of nodes, let say A and B, the received power (or interruption power) on the connection at the given moment t:

$$P_{\mathrm{AB}}(\kappa_A(t)) = \kappa_A(t)L_{\mathrm{AB}}(t)X_{\mathrm{AB}}(t)|h_{\mathrm{AB}}(t)|^2 \tag{3}$$

where,

$\kappa_A(t)$ - transmit power.

In the event that it functions over the frequency channel $c_k{:}k\in K$, the signal-to-interference-and-noise ratio (SINR) for the m^{th} device that was received by the n^{th} inXS at time t can be expressed as follows.

$$\gamma_{mn}\left(c_k,\kappa^k(t)\right)=\frac{P_{nm}\left(c_k,\kappa_n^k(t)\right)}{\sum\limits_{i\in I_k(t)} P_{ni}\left(c_k,\kappa_n^k(t)\right)+\sigma_{nm}^n(t)} \tag{4}$$

where

$I_k(t)$ - set of APs

$\kappa_k(t)$ - transmit powers.

$\sigma_{nm}^2(t)$ - receiver noise power

$$\sigma_{nm}^2(t) = 10^{(-174+NF+10\log_{10}(W_k))}, \tag{5}$$

W_k - bandwidth of ck and

NF - noise figure of the receiver.

Using the Shannon approximation, the capacity that was attained as:

$$\zeta_{nm}(c_k,t) \approx W_k\log_2(1+\gamma_{nm}(c_k,\kappa_k(t))). \tag{6}$$

3.2 PROBLEM FORMULATION

The challenge of resource allocation for fully distributed joint channel and power selection is where most of our attention is going to be focused throughout this paper. This issue can be understood as a multi-objective optimisation problem, which means that N objective functions (one for each in XS) need to have their values maximised at the same time for the problem to be solved successfully.

Formally stating the problem can be done by determining the objective function to be the minimum capacity that can be attained at each inXS:

$$\zeta_n = \min\left(\left\{\zeta_{nm}\right\}_{m=1}^{M_n}\right);\forall n\in N). \tag{7}$$

This will allow the problem to be stated in a more accurate manner. The situation is stated as:

$$\max_{c,\kappa}\zeta_1\left(c_1(t),\kappa_1(t)\right),\ldots,\max_{c,\kappa}\zeta_N\left(c_N(t),\kappa_N(t)\right) \tag{8}$$

where

$c{:=}\{c_n|n=1,\cdots,N\}$ - channel indices set,

$\kappa{:=}\{\kappa_n|n=1,\cdots,N\}$ - transmit powers.

$BW(c_k)$ - channel bandwidth.

It requires the simultaneous optimisation of multiple conflicting non-convex objective functions, the problem that is described is difficult to solve. This entails a substantial obstacle to overcome. The fact that the inXSs are independent and do not communicate with one another, in addition to the requirement that signalling overhead within subnetworks be reduced, makes the situation even more difficult to solve.

3.3 RESNETS

As a result of the rapid development of computer technology and the improvement in the performance of computer hardware, deep learning has gone a long way in recent years. The advancement of deep learning can be largely attributed to these two contributing elements. The CNN is an advanced, multi-tiered feedforward neural network that is not only immune to the consequences of errors but also can educate itself. It can come up with answers to difficult questions even when presented with uncertain circumstances and difficult circumstances.

Its ability to generalise is significantly better than that of other methods that are presently being utilised in the industry. An input layer, several layers of convolution, pooling layers, an entirely connected layer, an output layer, and a final layer that is completely connected are the layers that make up a standard CNN architecture.

ResNet-34 residual structure component not only serves as the network backbone but also serves as the network beating heart, making it an integral part of the network. We were able to construct CNN structures with greater flexibility and increase the recognition rate of wood knot defects without running into the traditional problems associated with increasing the depth of neural networks, such as gradient disappearance or gradient explosion.

This allowed us to increase the recognition rate of wood knot defects. This was made possible by the residual building block, which employs a shortcut connection to bypass the convolutional layers. This was made possible by the residual building block.

Multi-Convolutional Layers (Conv), Batch Normalizations (BN), Rectified Linear Unit (ReLU) Activation Function, and a Shortcut are the components that make up the Residual Building Block. The outcome of the unit that was not used can be represented by the expression that follows:

$$y = F(x)+x$$

where F is the residual function, x - residual input, and y – residual output.

The rest of the network is constructed completely of the first convolutional layer, in addition to a few of the most fundamental building blocks.

4. TRANSFER LEARNING

The training of a CNN needs to make use of a significant number of distinct datasets that have been labelled to achieve the best possible projection performance. However, getting your hands on that much data can be challenging, and the cost of image annotation can rapidly add up to a significant amount of money. Transfer learning, which has been demonstrated to have a high level of success, is one method that can be utilised to train a neural network with a constrained number of datasets. It has been demonstrated that this is indeed feasible.

Because there is not a significant amount of data to work with in this experiment, it produces overfitting problems. In addition, the model calls for a greater number of training epochs, which, in the end, results in an inferior level of model identification. Because of this, the model can be pre-trained on ImageNet to increase its capacity to recognise wood knot defects by utilising the idea of transfer learning. This can be done to make the model more accurate. The amount of time that was required for ResNet-34 to finish its training was substantially reduced as a result of its adaptation to the data that was described in this paper.

4.1.1 ReLU Nonlinearity:

The activation function rectified linear unit, also known as ReLU, is frequently utilised in artificial neural networks. The function that we have identified as the regularised version of ReLU is as follows:

$$f(x)=\max(0,x)$$

where f - ReLU and x - input.

Using the ReLU function to set the outputs of some neurons to zero makes the network sparse. This, in turn, decreases the interdependence of parameters and eliminates the possibility of overfitting. The linear unit update, also known as ReLU, is a time-saving alternative to more complicated techniques such as sigmoid functions and other functions.

The sigmoid and tanh functions, when applied to back propagation, bring gradients for deep neural networks very close to zero when the networks have achieved the saturation region. It is very simple for gradients to vanish, which can lead to a reduction in convergence and the loss of information. This can also occur very quickly. ReLU is a useful tool for finding a solution to the problem of convergence in deep neural networks. This is because its gradient does not generally change over the course of the training process.

ReLU is unidirectional in nature, its behaviour is more comparable to that of biological neurons than it is to that of other types of artificial neurons. CNNs that are equipped with ReLU are capable of learning at a significantly faster rate in comparison to their contemporaries that are equipped with sigmoid units.

4.1.2 Adaptive Moment Estimation (AME):

With just one iteration, the Adam algorithm can perfect the optimisation of an arbitrary objective function. This is all that is required to make this happen. It is possible to make dynamic adjustments to the weights of a neural network to account for newly acquired training data by employing a method known as adaptive low-order moment estimation. This adjustment can be made to take into consideration the data. This technique only needs a modest quantity of memory, yet it performs admirably when it comes to calculating, and it is not difficult to put into action.

The Adam algorithm can moderate the learning rate more effectively than it was able to do so in the past when back propagation and revised parameters are used together. Previously, the Adam algorithm was only able to do so to a limited extent. Adam achieves good results even when working with insufficient gradients and objective functions that are prone to instability. Adam is in a better position to successfully learn new things and arrive at conclusions at a more rapid pace.

4.1.3 Cross Entropy:

During training, the cross-entropy was used as a loss function, which led to b and being revised. The following is a description of the cross-entropy function, which can be found in the definition:

$$H\left(p,q\right)=\sum_{i=1}^{n} p_i\left(x\right)\log_2 q_i\left(x\right) \tag{3}$$

where H - cross entropy, x - input, p - probability, and q - predicted probability.

The method was effective in resolving the issue of the weight and bias updates requiring an excessive amount of time, which was a problem that pursued the variance loss function. The resolution of this issue was made possible by the success of the methodology. There is a probability that errors will be made while updating the weights and variations.

When the error is extremely minimal, the process of adjusting the weights and the deviations requires a noticeably longer amount of time.

5. RESULTS AND DISCUSSIONS

The ResNets has now been trained, and its performance, in addition to similarities to the performance of other methods has been analysed. The deployment area is assumed to have a side length of 50 metres and to contain N = 20 inXSs. Each inXS is assumed to have a single controller that serves as the AP for a sensor-actuator pair unless something else is specified.

When moving at a consistent speed of v = 1-3 metres per second throughout the territory, each inXS action conforms to the limited random waypoint mobility standard. We will continue with the assumption that the total bandwidth of the system is B = 25 MHz, and that this bandwidth is split evenly across K = 5 channels. This assumption will guide our next steps.

We configured the broadcast power for all inXSs, except for ResNets, to be 10 dBm. Because we consider a total of six distinct transmit power levels for ResNets, spanning from 20 dBm to 10 dBm with intervals of 2 dB, the resulting action space is 301. The transmit power levels are kept at a degree of precision that is deemed to be appropriate by making use of a power differential that is equal to 2 dB. The Table.1 includes the simulation conditions that can be adjusted. When it comes to defining deployment and other system variables, configuration choices are typically used as the threshold point.

Table.1. Simulation Parameters

Parameter	Value
Number of controllers, N	20
Cell radius (m)	3.0
Deployment area	50 × 50
Velocity, v (m/s)	3.0
Number of devices, M	1
Number of channels, K	5
Mobility model	Waypoint mobility
Pathloss exponent, γ	2.2
Shadowing standard deviation, σ_s (dB)	5.0
De-correlation distance, d_c (m)	2
Lowest frequency (GHz)	3
Transmit power levels (dBm)	[-20:2:-10]
Noise figure (dB)	10
Per channel bandwidth (MHz)	5

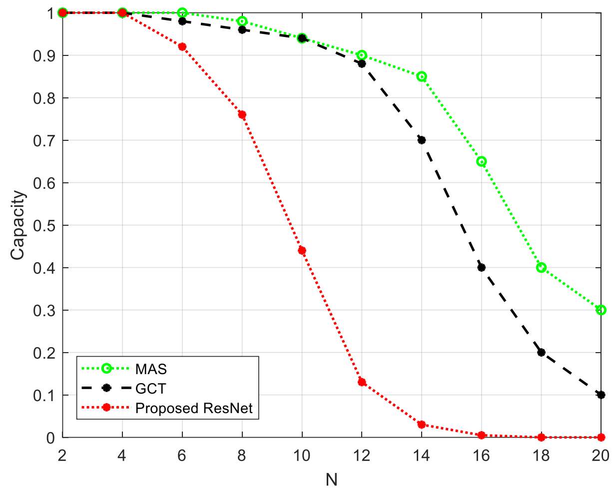

Fig.2. Capacity Levels

It possible that the perceived improvement in performance occurred at the expense of an increase in capacity below the same percentile. DL is not any more effective than the greedy baseline, even though it utilises the same data that ResNets does. It is highly likely that the increased efficacy of the ResNets is the outcome of a synergistic effect brought about by the combination of a low SINR quantization threshold and the utilisation of a wide variety of power settings.

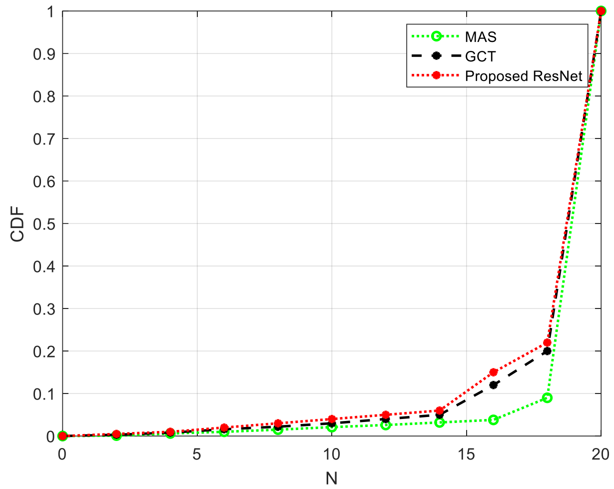

Fig.3. Selection Power Distribution at v = 1m/s

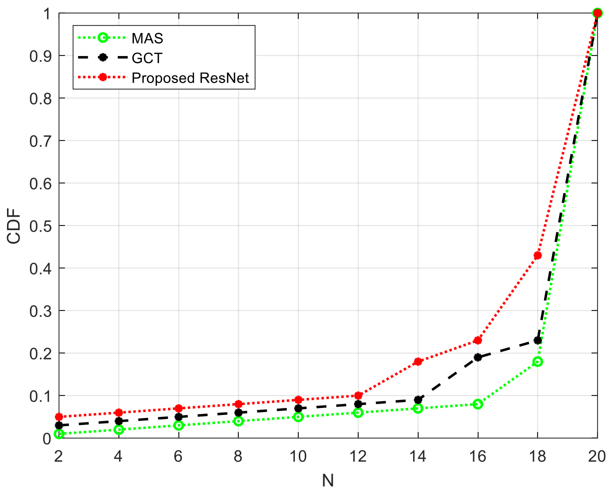

Fig.4. Selection Power Distribution at v = 2m/s

It is necessary to engage in deliberation while keeping the communication-theoretic goals of the system in mind to place the barrier in an appropriate position. We will investigate how the existence of something affects a person decision to communicate.

The Fig.2 – Fig.5 demonstrates that as the quantization cutoff is increased, there is a movement away from higher-power actions and towards lower-power actions. This occurs because higher-power actions require more energy to perform. The cutoff level can be anywhere from 2 to 16 decibels, and the median transmit strength will drop by approximately 3 decibels as a result. In this section, we demonstrate the percentage decrease in capacity that can be achieved with various sensing intervals in comparison to the capacity that can be achieved with perfect sensing as the benchmark. This is done by comparing the capacity that can be achieved with perfect sensing to the capacity that can be achieved with various sensing intervals.

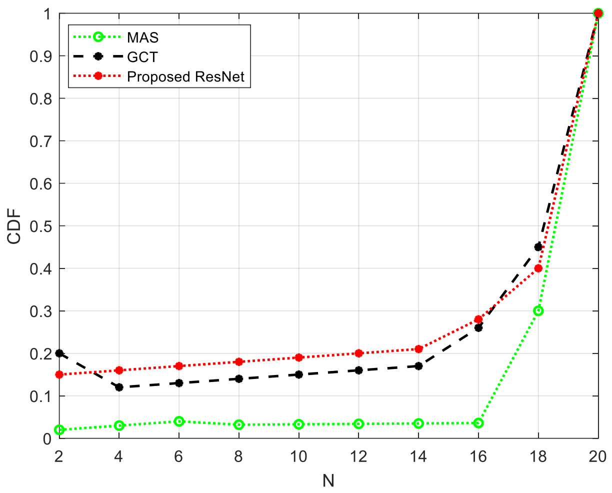

Fig.5. Selection Power Distribution at v = 3m/s

According to the findings, in contrast to the existing method, the recommended 1-bit information methods are less impacted by shifts in the length of the detecting intervals. This is the case because these methods only use one bit of information.

6. CONCLUSION

An increase in the detecting interval has only a minimal effect on the performance of the AME strategy, this makes it the most reliable choice among the available options. ResNets only reduce capacity by 50% at a latency of twenty-five transmission instants, whereas greedy can reduce capacity by anywhere from 70 to 80%. This suggests that the proposed methods offer performance that is comparable to or better than the baseline, while simultaneously significantly reducing the exchange overhead and improving the system resilience to sensing intervals, some of which may be unavoidable in practise. The proposed methods offer a compelling combination of benefits. Furthermore, this seems to imply that these enhancements can be accomplished while simultaneously lowering the exchange overhead.

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