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Optimising LTE Network Performance: An ANN Model Based on Normalised Throughput Data

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Abstract

An effective design that schedules a proper resource allocation and allows efficient use of the available radio resources is an important step in improving the Long-Term Evolution (LTE) system performance to fulfill all user requirements according to the Quality of Services (QoS) criteria. However, some persisting issues affect the resource allocation in the LTE networks, caused by poor network performance that degrades the network fairness index, increases the average delay, and decreases data throughput, particularly during the video flow. In this study, the researcher proposed a novel technique using the Artificial Neural Network (ANN) model that was based on the normalized data techniques to accurate and more reliable data output for the LTE downlink scheduling algorithms, intending to satisfy the LTE network specification, proposed by 3GPP. Thereafter, the researcher compared the performance of the various proposed methods based on their throughput. the throughput was regarded as an important factor that helped in assessing the algorithm's efficiency. The simulation results indicated that the proposed algorithm could significantly improve the scheduling throughput of the real-time streaming compared to the popular LTE-DL algorithms.

Keywords: LTE network; ANN; resource allocation; normalised

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تحسين أداء شبكات طويلة الأمد باستخدام نماذج شبكات الذكاء الاصطناعي لتحسين الإنتاجية على الشبكة

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الملخص

يعد التصميم الفعال الذي يقوم بجدولة التخصيص المناسب للموارد ويسمح بالاستخدام الفعال للموارد الراديوية المتاحة خطوة مهمة في تحسين أداء شبكة التطور طويل المدى (LTE)لتلبية جميع متطلبات المستخدم وفقًا لمعايير جودة الخدمات(QoS) ،ومع ذلك تؤثر بعض المشكلات المستمرة على تخصيص الموارد في شبكاتLTE ، بسبب ضعف أداء الشبكة الذي يؤدي إلى انخفاض مؤشر عدالة الشبكة، وزيادة متوسط التأخير، وتقليل إنتاجية البيانات، خاصة أثناء تدفق الفيديو. في هذه الدراسة اقترح الباحث تقنية جديدة باستخدام نموذج الشبكة العصبية الاصطناعية (ANN) التي تعتمد على تقنيات البيانات المعيارية، لاستخلاص مخرجات بيانات دقيقة وأكثر موثوقية لخوارزميات جدولة الوصلة الهابط LTE ، بهدف تلبية مواصفات شبكةLTE ، المقترح من 3 .GPPبعد ذلك قام الباحث بمقارنة أداء الطرق المختلفة المقترحة بناءً على إنتاجيتها، واعتبرت الانتاجية عاملًا مهمًا ساعد في تقييم كفاءة الخوارزمية. وأشارت نتائج المحاكاة إلى أن الخوارزمية المقترحة يمكن أن تحسن بشكل كبير إنتاجية جدولة البث في الوقت الفعلي مقارنة بخوارزميات LTE-DL الشائعة.

الكلمات المفتاحية: شبكة ANN،LTE ، شبكات طويلة الأمد، تخصيص الموارد الإنتاجية.

1. Introduction:

The 3rd Generation Partnership Project (3GPP) implemented the Long-Term Evolution (LTE) strategy to fulfill the increasing demand for wireless networks. Additionally, Radio resource management scheduling algorithms were also used in this LTE setup as they assigned radio services to the final users based on different criteria related to the Quality of Service (QoS). However, the development of the downlink scheduling algorithms was a major problem noted during resource allocation in the LTE system. Different scheduling techniques were proposed for addressing this issue and an investigation of the downlink algorithms garnered a lot of research interest during the LTE implementation as several researchers started shifting to packet scheduling over LTE since it was regarded as a rapidly growing technology that can significantly affect the future of the wireless networks. In the LTE downlink algorithm used for QoS Class identifiers, the radio resource allocation step makes use of the QoS specifications and channel condition reports for determining the transmission orders for the users. However, inefficient resource allocation in the LTE networks can be noted due to poor network performance that deteriorates the data throughput, and network Fairness index, and also increases the average delay.

A better communication system could be developed after the QoS requirements were fulfilled by integrating the different Artificial Intelligence (AI) concepts along with the Machine Learning (ML) techniques for scheduling the end-user devices and designing wireless infrastructures. It has been noted that the use of AI techniques in the wireless communication system was based on their ability to encourage massive advancement for wireless traffic and the emergence of novel uses of wireless services that were never tested in the past and varied between generic multimedia services and video-based services. All these services require a higher data rate. This has been a major issue in the evolution and development of wireless networks in the past decade. Hence, there is a greater need for wireless networks to provide better communication services with higher reliability and low latency [1].

This study focuses on the resource allocation scheduling process at the receiver end for optimizing the downlink across the LTE network and ensuring the fulfillment of the QoS with regards to their throughput For this purpose, they investigated four LTE downlink scheduling in terms of throughput for real-time services.

The remaining paper has been organized in the following manner: The next section presents an overview of related studies that study the ANN models for networks. Section 3 presents a review of the LTE downlink scheduling techniques; whereas the researchers described the architecture of their proposed ANN model that processed the LTE Downlink Scheduling Algorithms in Section 4, followed by the description of the simulation environment and results. The conclusions are presented in the final section.

2. Literature Review:

In the last few years, many researchers have used ANN models to enhance the performance of the downlink communication system in LTE networks. Many models were used, wherein some studies considered channel estimation, while others investigated the condition of the user devices or estimated the mobile location. Furthermore, some researchers also carried out predictive analyses

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of various ANN models for predicting and classifying the data over the LTE network.

In the study [5], the researchers investigated the performance of 2 ANN models, i.e., for prediction and training algorithms (i.e., Levenberg-Marquardt and Bayesian regularisation). They primarily focused on the integration of ANN in the LTE network during the mobile handover start-up phase. They compared the Received Signal Strength (RSS) and the hysteresis fringe parameters for the adaptive neural hysteresis fringe reduction algorithm. The study aimed to resolve the channel estimation problem noted in the LTE networks. In another study, the researchers proposed a real channel environment estimation technique using the ANN and Support Vector Machine Regression (SVR) models that considered the standardized signal structure of the LTE Downlink system [6]. This technique was used under the impulsive non-linear noise that interfered with reference codes after considering the high-mobility conditions. The researchers studied the performances of the SVR and the ANN using the simulation results. They noted that the SVR showed a better performance than the Decision Feedback (DF), Least Squares (LS), and ANN algorithms. In [7], the researchers presented a method relay for the reference symbol information. This information was used for estimating the total frequency response by the channel. This technique was summarised in 2 steps, i.e., channel differences were adapted after the application of the ANN-based learning methods that were trained using the Genetic Algorithm (ANN-GA). Secondly, the researchers estimated the channel matrix to improve the performance of LTE networks. They used different ANN-based estimator algorithms for validating the proposed algorithms like the Feed-forward neural network, Layered

Recurrent Neural Network, Least Square (LS) algorithm, and the Cascade-forward neural network for a Closed-Loop Spatial Multiplexing (CLSM)-Single User Multi-input. The results of this comparison indicated that the proposed ANN-GA algorithm showed better accuracy than the others. Furthermore, the significant increase in the network subscribers led to network resource allocation issues. To resolve this problem, the researcher proposed a downlink algorithm that ensured effective and faster resource allocation solutions for real-time video applications [8]. This solution used an ANN algorithm that allowed resource allocation after considering the UE conditions. They noted that though the AI techniques used for resource allocation on the LTE network generated faster results, the ANN-based training process could take a long time. Hence, a dynamic resource allocation can be carried out by realizing the daily ANN training processes whenever the eNodeB is intense. In this [14], the researchers used a technique for classifying bacteria. The results indicated that ANN was effective and feasible. In [15], the researchers classified the aerial photographs using the NN. They noted that NN was suitable for classifying the remotely-sensed data, exceeded the maximal probability classification for the classification accuracy, and showed a positive effect. In [16], the researchers used the NN for classifying the spoken letters. They noted a 100% (training) and 93% (testing) classification accuracy. All these studies indicated that the NN could be used for classification owing to its better performance. ANN models could be used for optimizing the resource allocation algorithms for the communication networks. Furthermore, the ANN technology could be used to overcome the resource allocation problems noted in the LTE network. A few of the common ANN activation functions that were applied included the sigmoidal, binary, and hyperbolic sigmoidal functions that were based on the RBFNN, MLPNN, recurrent neural network, and the perceptron model. All these functions were used for developing network communication. The researchers also considered the backpropagation and the gradient descent algorithms as training algorithms for ANN. ANN is used for conducting different tasks, like approximation and prediction of functions, pattern classification, prediction, and clustering. However, the performance of the algorithm was significantly affected by data preparation and the setup used for the NN structure. In a recent study [25] authors address problems in the cloud performing art scenario, such as restricted spectrum and computation resources in the frequency domain during video competition access and differences in transmission and computation requirements between the coexisting enhanced mobile broadband (eMBB) and the ultra-reliable low-latency communications (uRLLC) services. a priority scheduling algorithm based on the puncture decision is proposed for the slice resource allocation problem in multi-service coexistence scenarios, simulation results show that the algorithms proposed in this paper can efficiently satisfy the latency requirements of eMBB real-time services and, at the same time, achieve a better fairness guarantee. In [26], the authors developed two new policies for RT and NRT traffic, namely Adjusted Largest Weighted Delay First (ALWDF) and Fair Throughput Optimized Scheduler (FTOS), and then joined them to introduce the Advanced Fair Throughput Optimized Scheduler (AFTOS). It aims to maximize spectral efficiency and user throughput considering fairness, delay, and packet loss ratio. Although the study highlights a wide range of performance metrics and the results prove that AFTOS outperforms Maximum Throughput (MT), PF, and Modified Largest

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Weighted Delay First (MLWDF), the implementation relies on LTE systems with small cells. A comparative analytical study of the PF and MLWDF LTE scheduling algorithms was conducted in reference [28], two instances are analyzed one examines the impact of user numbers on QoS, while the other assesses the effect of user speed on QoS. The results demonstrate that, particularly for real-time applications involving VoIP and video, both the packet loss ratio and the delay increase with the number of users.

3. Downlink Scheduling in the LTE:

Dynamic resource allocation called the packet scheduler algorithm, is regarded as an important feature in network communication and helps in controlling the assignment of RBs to the User Equipment (UEs) to prevent sell interference. A scheduler algorithm helps in acquiring an adequate allocation for Physical Resource Blocks (PRBs) (e.g., frequency, power, time, etc.) to the UEs which fulfill the QoS requirements, according to a few scheduling standards for enabling a fair distribution of the available resources amongst the users [18]. These downlink scheduling algorithms are described using the metric $M_{i,k}$ wherein resources were allocated to every UE, based on the parallel between the metrics of i_{th} users, who had the highest $M_{i,k}$ values, and k_{th} RB was allocated. The popular downlink scheduling algorithms have been described below and categorized based on the service they provide for real-time and non-real-time applications.

3.1. Proportional Fair (PF) Algorithm:

The PF technique allocates the user's existing available radio resources and considers the prevalent channel characteristics and previous data concerning throughput that act as the weighting factor for the predicted data rate. The objective of the PF technique is to maximize the overall throughput, besides providing a fair data flow. [19].

$$M_{i,k}^{PF} = \frac{d_{i,k}(t)}{R_i(t)} \quad (1)$$

This measure ascertains the fraction of presently accessible data rate, $d_{i,k}(t)$ and the average of the previous rate of data, $R_i(t)$, while; i corresponding to the flow in the k^{th} sub-channel.

3.2. Maximum Largest Weighted Delay First (MLWDF) Metric:

This channel-aware technique served several data access streams with different QoS needs. MLWDF considers fair distribution and delay and ensures system throughput. This algorithm handles real-time and the non-real-time data flow addressed, wherein the PF is used for the non-real-time flow, while the following weighting expression is used for real-time data flow by applying the following weighting metrics:

$$M_{i,k}^{M-LDWF} = \propto_i \ D_{HOL,i} * M_{i,k}^{PF} \quad (2)$$

$$\propto_i = -\frac{\log \delta_i}{\tau_i}$$

Wherein; $D_{HOL,i}$ denoted the Head of Line delay of packet faced at time t, for the i^{th} user; τ_i denoted the delay threshold for a packet for each user i^{th} that was considered for real-time data; δ_i denoted the maximal possible of a HOL packet delay that may cause the user i^{th} to exceed their threshold delay [20].

3.3. Exponential / Proportional Fairness (EXP/PF):

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The EXP/PF technique has been formulated for supporting multimedia services for systems that use multiplexed time. This algorithm considers the properties of the PF algorithm and the exponential function for decreasing overall delay during transmission of the package. To improve the infinite-buffer flow, the PF algorithm is applied [19], while the EXP/PF can be applied for serving the real-time traffic in the following manner:

$$M_{I,K}^{EXP/PF} = \exp\left(\frac{\alpha_i D_{HOL,i} - x}{1+\sqrt{x}}\right) . \frac{d_k^i(t)}{R^i(t-1)} \quad (3)$$

Where;

$$x = \frac{1}{N_{rt}} \sum_{i=1}^{N_{rt}} \alpha_i \, D_{HOL,i}$$

3.4. Frame Level Scheduler (FLS):

This scheduler is implemented using the 2-level structure to ensure a specified delay value interval between the real-time data flows. The transmitting of the total data th in the actual time flow is determined on the highest level of the scheduler structure. The lower-level works on every TTI and assigned RBs per flow. In this algorithm, the bandwidth requirements were estimated at the upper level. Then, the PF methodology was employed for sharing the reserve spectrum amongst the users showing the best efforts [21]. The researchers calculated the amount of data that was transmitted using the equation below:

$$u_i(k) = h_i(k) * \; q_i(k) \quad (4)$$

Here, $u_i(k)$ refers to the quantum of data moved corresponding to the i^{th} flow and the k^{th} frame. This was acquired by transmitting a $q_i(k)$ queue

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level signal over a linear time-invariant filter with and response, $h_i(k)$; * denotes discrete-time convolution [19].

3.5. Artificial Neural Network Model Processing for LTE downlink Scheduling Algorithms

This study has focused on normalizing the data for the LTE downlink scheduling algorithms as it could improve its resource allocation performance concerning throughput. This was carried out with the help of the proposed ANN model. This model includes some initial phases that are summarized as follows:

a. Firstly, determine the LTE system data that needs to be processed using ANNs.
b. The second step comprises pre-processing to eliminate conflicting data.
c. Creating data partitions is the next step wherein training and testing sets are created.
d. Subsequently, the ANN structure is decided in terms of input, hidden, and output nodes, activation function, and the model interconnect linking nodes.
e. The validation experiments of the proposed LTE downlink algorithms and data classification are considered for network training.
f. Lastly, model selection requires measuring infrastructure performance. This research aims to identify the best network model using diagnostics.

The Mean Square Error (MSE) is regarded as the ANN model training performance index. It helps in decreasing the number of mathematical operations and the memory needed for any computer tasks. This further decreases the MSE value of the training data. MSE states that the neurons that are present in the hidden layer were similar to the number of rounds required during the training process while executing the ANN model. Eq. 5 describes the MSE used for computing.

$$MSE = \frac{1}{2}\sum_{i=1}^{R}(t(n) - a(n))^2 \quad (5)$$

Wherein; e (a (n)) refers to the actual output generated by a network, (t (n)) indicates the expected output, and R refers to the number of rounds. A scheduling algorithm dataset was presented in this study that included 50 data samples.

Here, the properties of the proposed ANN model have been described in detail. Fig. 1 presents the topology of the proposed ANN model.

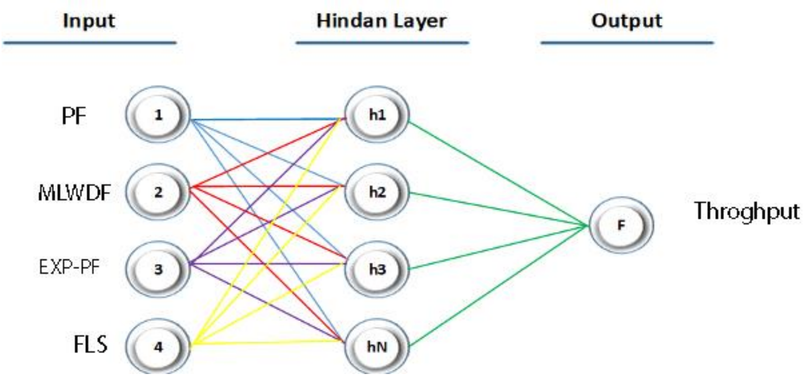

Figure 1:ANN Topology Concept

3.6. Proposed ANN models for LTE downlink scheduling:

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Here, the researchers have described 3 ANN models that were used for normalising the LTE system data. These included the Approximate RBFNN (ARBFNN), Exact RBFNN (ERBFNN), and the Generalised regression neural network (GRNN). They help in resolving the issues related to the allocations for improving the video flow over the LTE network. These models have been described in detail below.

3.6.1. Radial Basis Function Network Architecture:

There are three layers comprised within the networks under The Radial Basis Function (RBF), included: an input layer, a layer that is non-liner hidden with an activation function of RBF, as well as the linear output layer. Furthermore, modelling of the input can be achieved as a real number vector ($x \in \mathbb{R}^n$). Whereas the network output represents a scalar function from the input vector, ($\varphi: \mathbb{R}^n \to \mathbb{R}$), that s described as:

$$\boldsymbol{\varphi}(\boldsymbol{x}) = \sum_{i=1}^{N} \boldsymbol{a}_i \boldsymbol{\rho}(\| \boldsymbol{x} - \boldsymbol{c}_i \|) \qquad (6)$$

Where (N) refers to the hidden layer neuron number, (c_i) denotes the Neuron's center vector, (i), and (a_i); while (ai) indicates the neuron's weight (i), used in the neuron's output linearly.

Consequently, functions dependent on the center vector distance are symmetrically radial towards such vector, thence resulting to the nomenclature "radial basis functions"[22]. Regarding the basic form, individual hidden neurons are linked to the inputs directly. and the RBF is regarded in its Gaussian form as follows;

$$\boldsymbol{\rho}(\| \boldsymbol{x} - \boldsymbol{c}_i \|) = \boldsymbol{exp}[-\boldsymbol{\beta} \| \boldsymbol{x} - \boldsymbol{c}_i \|^2] \qquad (7)$$

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These Gaussian basis functions are seen to be local to their centre vectors as follows:

$$\lim_{||x||\to\infty} \rho(\| x - c\_i \|) = 0$$

One can normalise the RBF networks. Here, the mapping is done as follows:

$$\varphi(x) \stackrel{\text{def}}{=} \frac{\sum_{i=1}^{N} a_i \rho(\|x - c_i\|)}{\sum_{i=1}^{N} \rho(\|x - c_i\|)} = \sum_{i=1}^{N} a_i u(\| x - c_i \|) \qquad (8)$$

Where:

$$u(\| x - c_i \|) \stackrel{\text{def}}{=} \frac{\rho(\|x - c_i\|)}{\sum_{i=1}^{N} \rho(\|x - c_i\|)} \qquad (9)$$

This is called the "Normalised Radial Basis Function"; whereas "RBFNN" was utilized to classify moreover data. All the NNs are trained for estimating the posterior probabilities of a class membership by mixing the hyperplanes and the Gaussian basis functions[23].

3.6.2. General Regression Neural Network (GRNN) Algorithm:

The Generalised Regression NN (GRNN) model was seen to be a variation of the RBNN model. It was first proposed by Specht in 1991 [24]. The use of GRNN could include purposes of prediction, classification, and regression of target data. Thus, it could serve as a reliable solution offered for dynamic online systems. It depicts a better NN technique that was based on the nonparametric regression. The model is based on the idea that each training sample acts as a means to the radial basis neurons. Mathematically, the GRNN is represented as follows:

$$y(x) = \frac{\rho(\|x-c_i\|)}{\sum_{k=1}^{N} k(x,x_k)} \quad (10)$$

Here; $Y(x)$ denotes the value predicted for the x input; K refers to the weight activation of a pattern layer neuron at k; while $k(x, x_k)$ was an RBF (Gaussian kernel) as specified below:

$$k(x, x_k) = e^{-dk/2\sigma^2}, d_k = (x, x_k)^T(x, x_k) \quad (11)$$

Here; d_k was the squared Euclidean distance between the input x and training samples x_k.

3.7. Performance Metrics

3.7.1. Quality of Service

Quality of Service is a technique for managing data traffic to reduce Packet Loss flow in the network. The existence of Quality Service can help by ensuring users get better and guaranteed performance. [27] Throughput is the speed (rate) of effective data transfer. The throughput value is obtained from the total number of data packets that arrive in a specific time interval and then divided by the duration of the time interval.

Throughput= $\frac{\sum P_r}{T_t}$

Tt = Packet delivery time at the source

$\sum P_r$ = received packets.

Average Throughput: It represents the average data rate maintained over the physical layer. It is computed by counting the packets, knowing packet size, and transmission time; the size of packets per unit time per user determines throughput. It is used for assessing network performance when accessed by several users. Throughput is defined as the average successful message delivery speed. It is typically measured using bits per second (bps or bit/s).

3.8. The Analysis Sequence for the Proposed Artificial Neural Network Algorithm

The numerous steps for creating the normalized LTE DL scheduling algorithms used for ANN models are clarified ahead.

3.8.1. ANN Model Normalisation

As mentioned in the previous section, we start by defining the data that must be collected and processed for the proposed model; the proposed ANN model was composed of 2 input nodes (User; Throughput) and one output (one node). Additionally, to reduce the data error, data needs to be normalized using the two steps described below:

Step1:

data1=data; K=max (data);

DataN (: 1) =data (: 1)/K (1);

DataN (: 2)=data(:,2)/K(2);

The output is the normalised data.

Step. 2: Data will be split into two separate parts (training and testing data). Fifty samples were considered for this step; 80% of data were used for training (40 samples) and 20% (10 samples) for testing. Moreover, to perform the data separation (test data, training data), we need to specify the initial value of the number of nodes (a = 0) for dataN (r(i),:) = [], and r indicating the rounds in

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the network. All test samples will be chosen from the original data file. dataN comprises the training data needed to prepare for output and input data.

3.8.2. Validation Processing

Model testing requires replotting the training set. Subsequently, the network simulator response for inputs over the same range: (y-label (input), vs x-label(user)) is obtained. The proposed ANN model is applied for DL data scheduling (normalized data), where the outputs will be tested and validated to obtain the results.

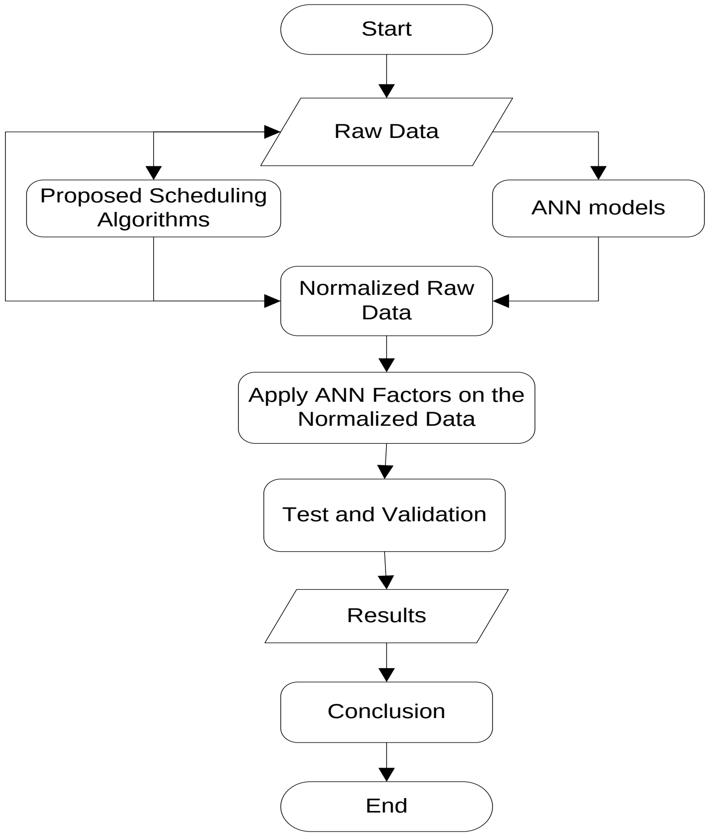

Figure 2: Normalized Data Validation Process

3.9. Simulation Environment and Results:

Here, the researchers presented the results for the 3 ANN models used for the LTE downlink scheduling process. Detailed simulations were carried out with a Network Simulator LTE_Sim [21] that helped assess the proposed algorithms' efficiency (PF, MLDWF, EXP-PF, and FLS). Table 1 presents the parameters used for simulations. The simulator is run on an interference scenario for a single cell, after regarding 7 cells with a fixed eNodeb. Each cell had a radius of 1.5 Km; the number of users was randomly distributed in every cell, starting with 3 users. The interval between users was 3, while the maximal number of users was 30.

Table 1: Simulation parameters used for the models:

Parameters	Parameters values
Number of clusters	1
Number of cells	7
Frame Structure	FDD
UEs number	30
Cell Radius	1.5 Km
Speed of UE	3 km/h
Bandwidth	10 MHz
simulation duration	46s
Video bit-rate	256 kbps
Flow duration	40s
Maximum delay	0.1

3.9.1. ANN Model Normalised Throughput

- **Throughput Model**

For the subsequent investigation, we contrasted the data throughput of the video services. In particular, the throughput is limited by the delay and loss of the previously analyzed packets. In the present use case, users traverse slowly, as depicted in Figure 3. Moreover, the active cell serves only a few users. For three users, the video stream average data rate is 2142 kbps. Nevertheless, as the connected user count increases, the throughput available for one user dips to 1600 for 30 users. This throughput reduction is evident in the MLWDF approach. The PF technique leads to degraded performance for all users; FLS and EXP_PF have symmetrical results.

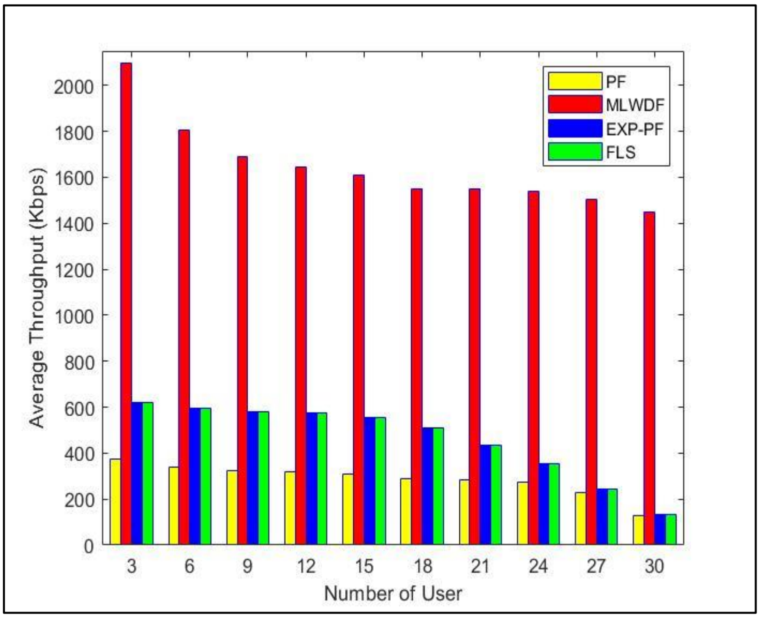

Figure 3: Average Throughput vs Number of Users

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- **Normalized Throughput Model**

Figure 4 shows in this section that the performance of the proposed algorithm is evaluated with simulations. Performance investigated in terms of throughput and average user rate of starvation (i.e., the proportion of users who do not transmit). The normalized throughput decreases as the number of users increases for both strategies.

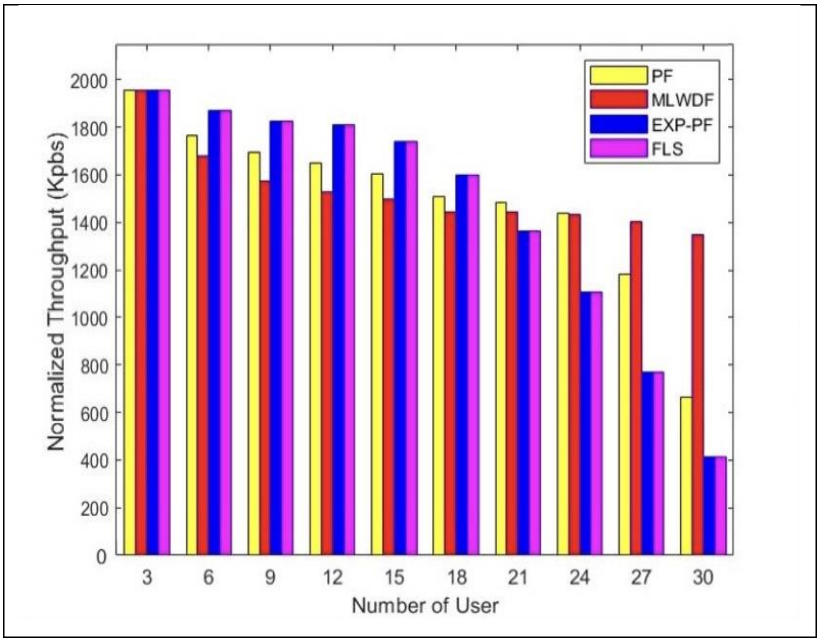

Figure 1: Normalized Throughput vs Number of Users

4. Conclusion:

The issues related to the allocation of resources over LTE networks are regarded as a major challenge that can provide a satisfactory QoS to the active users for every transmission time interval, TTI. The resources available on the network are distributed amongst all the users in such a way that they can fulfil their needs. The researchers investigated the different scheduling algorithms (such as PF, MLDWF, EXP-PF, and FLS), and based on the LTE Fairness Index. For this purpose, a new optimized scheduler supporting the downlinked direction of the LTE networks by applying the ANNA technique for different radio services was proposed in this paper study.In this study, they have investigated the performance of a popular resource allocation algorithm that was used in the LTE downlink stream for satisfying the QoS requirements. The results of the proposed method are illustrated by considering the video traffic over LTE network, the results indicated that the proposed method showed an improved performance than the other algorithms based on all calculated metrics. The algorithm showed an improved percent value, along with a higher fairness factor.

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