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A Review on Adaptive Neuro-Fuzzy-Based Quality of Experience Optimization Model for Communication Network

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ABSTRACT
Ensuring positive user experiences in communication networks is largely dependent on Quality of Experience (QoE) optimization. An extensive overview of methods for QoE optimization in communication networks is provided in this paper. One potential method for modeling and optimizing complex systems with uncertain and nonlinear properties is by ANFIS (adaptive Neuro-fuzzy inference system). ANFIS models provide the flexibility to reflect the inherent uncertainties and complexities of communication networks while offering adaptive learning capabilities by fusing fuzzy logic principles with neural network capabilities. The study highlights how important it is to optimize network characteristics dynamically based on user subjective experience in order to increase user satisfaction and service adoption. To extract and synthesize techniques, parameters, assessment criteria, and application area(s) that have been employed in QoE optimization, we conducted a systematic literature review (SLR) for this review study. 450 pertinent studies from six electronic repositories were found using the search criteria; From among these, 17 studies opted for further analysis based on inclusion and exclusion criteria. These were comprehensively verified for the methodology and criteria used in the chosen studies and, as a result, were recommended for further studies. Our data shows that throughput and delay are the most used network metrics, and that ANFIS is the most used approach. The goal of the review is to pinpoint an essential method for primary parameter modeling and optimization that yields superior outcomes and should be taken into account when optimizing parameters to limit network buffering and outages in communication networks. As a result, this will guarantee that network services in communication networks are effectively automated.

KEYWORDS;- QoE optimization, network parameters, Neuro-Fuzzy, ANFIS

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I. INTRODUCTION

Background of the study

Large part of services relies on the communication networks, examples being cloud service, real-time apps, and multimedia streaming. Alongside technical performance, the quality of user experience, or QoE, evaluates the overall success of these services [19]. QoS i.e. Quality of service refers to the degree of conformity of a service that a provider offers to a customer in line with a contract between them. QoS uses a range of technologies to ensure the quality of network traffic transmission in computer networks as well as discover network faults [4]. It also guarantees the end-user easy and good access to service (s). All of these put together greatly affect the QoE assessment. The relationship between QoS and QoE comes under the purview of critical factors that affect QoE.

QoE, as defined by the ITU, is often the subjective perception of quality of a service or application [19]. Within the context of communications networks, QoE is the level of satisfaction, or conversely, frustration by the user over a specific application or service [7].

The user network QoE is significantly shaped by network factors. Throughput, delay, jitter, packet loss, and resource allocation are crucial factors having an immediate impact on users' perceptions of the network quality and contentment. The quantity of capacity for a given service is determined by bandwidth allocation and throughput, while delay and packet loss have an impact on the responsiveness and dependability of real-time applications. The distribution of resources like CPU and memory, affects how well applications and services operate [10].

There have been plenty of models created for network parameter optimization in communication networks QoE using both conventional quantitative methods and qualitative methodologies. The most popular traditional quantitative method for determining user satisfaction is the mean opinion score (MOS). The MOS is expressed as a single rational number, typically between 1 and 5, where 1 represents the lowest perceived value and 5 indicates most recognized excellence. Depending on the evaluation scale that is applied for the crucial assessment, the other MOS range of values is likewise constructive. Since user opinion is ambiguous and subjective, it cannot be appreciably elevated by quantitative procedures; as of yet, this model is quantitative in nature [19].

There are a lot of intelligent technologies currently being used for network parameter optimization in communication networks QoE with a view toward network automation. The development of quality estimation models makes use of various Artificial Intelligence approaches such as Fuzzy Inference Systems (FIS), Decision Trees, Adaptive Neural Networks (ANN), Support Vector Machines, etc. [8].

Fuzzy logic is frequently in use to assess customer satisfaction on a qualitative level. It draws conclusions from unclear and imprecise facts by taking advantage of ambiguity and a lack of knowledge [17]. When inferences need to be drawn subjectively, the fuzzy inference system (FIS) makes use of linguistic terms and variables. Additionally, fuzzy logic is easy for developers to construct given that there isn't a need to retrain the model if new input data or rules are added to the system, thus rendering it useful for tasks in progress when the scope changes [12].

However, there are a number of disadvantages, including scalability, to using fuzzy logic alone for network parameter optimization in communication networks QoE intended for network automation. Complex and large-scale problems might present difficulties for fuzzy logic systems. At increased levels of inputs, outputs and rules, this system's computational complexity and memory requirements increase exponentially. This scalability problem can limit the application of fuzzy logic systems to certain levels [38].

The ANFIS model is the one expected to perform better than the fuzzy model because less processing time is required for the former as compared to fuzzy logic. ANFIS also supports those Takagi-Sugeno based systems that allow optimization and adaptiveness. Hence, it is amenable to mathematical analysis [25].

Fuzzy systems are unable to detect machine learning or neural networks in order to accommodate knowledge representation and automated learning at the same time. As a result, ANFIS outperforms fuzzy logic when utilized alone in QoS and QoE performance for communication network applications such as VOIP, HTTP, video streaming, email, and so on.

Apparently, the fuzzy logic method has specified technical constraints, and so the hybrid model, like ANFIS (Adaptive Neuro-Fuzzy Inference Systems), incorporates some subjective components such as responsiveness, perceived quality, and user engagement [19]. ANFIS combines a kind of neural network with fuzzy logic. Neural networks in ANFIS have the advantage of being able to back-propagate and train fuzzy logic membership function parameter values to create fuzzy decisions or use some hybrid algorithms. It can be inferred that varying values of the QoS indicators heavily affect video QoE, thereby warranting a study on the relationship between video QoE and QoS parameters pertinent to content type.

The main objectives of this review study are to assess first the impact of the QoS parameters on communication network QoE. Second, the paper proposes a Neuro-fuzzy hybrid approach to optimize communication networks QoE network parameters toward automated management based on user preference or usage through the ANFIS approach, thereby controlling buffering and network outage.

This study has most of the current literature on the subject. Here, I would provide my empirical findings to answer the research questions, which were intended to assist direct and shape this review. The document is structured as follows: background/introduction to the review; related works; methodology used in this review; discussions of the review.

II. RELATED WORKS

Table 2.1: Table of comparative review of previous studies

TITLE	SOURCE	REFERENCE AND YEAR	BRIEF DESCRIPTION	ALGORITHM USED	PARAMETERS USED	SERVICE AREA/ APPLICATION AREA	EVALUATION CRITERIA
Neuro-Network Model of Quality of Experience for Video Streaming Estimation over 5G Network.	(IEEE) Institute of Electrical and Electronics Engineers	[6]	Proposes using a FAM (fuzzy ARTMAP; Fuzzy Adaptive Resonance Theory (Fuzzy ART) neural network i.e. allowing the	Fuzzy ARTMAP (FAM) neural network	variables related to human profiles, jitter, packet loss, and delay	a technique for streaming videos using a 5G network	- (PSNR) Peak Signal to Noise Ratio - MOS i.e. Mean opinion score

			learning of new information without losing previously learned information, utilized for the autonomous learning component.				
An Adaptive Neuro-Fuzzy Model for Quality Estimation in Wireless two or three dimensions Video Streaming Systems.	IJITEE (International Journal of Innovative Technology and Exploring Engineering)	[18]	Such that the perceived visual quality of experience could be determined, an experimental development endeavors to achieve a highly efficient link between QoE and QoS for 2D and 3D videos streamed wirelessly.	An Adaptive Neuro-Fuzzy	Collection of media and packet loss parameters.	Streaming video from 2 to 3Ds via a wireless network.	-Correlation coefficient -RMSE.
Energy Aware Cluster and Neuro-Fuzzy Based Routing Algorithm for Wireless Sensor Networks in IoT.	Association for Computing Machinery (ACM)	[37]	For the sake of efficient routing in wireless sensor networks on the Internet of Things, an innovative Neuro-Fuzzy Rule-Based Cluster Formation and Routing Protocol was devised.	Neuro-Fuzzy	Metrics of energy usage, packet delivery ratio, latency, and network lifespan.	IoT-based sensor networks	Mean performance of LEACH, FLCFP, HEED, FBCFP algorithms
Neuro Fuzzy Model Based Routing Protocol in Mobile Ad-Hoc Networks.	IJCNIS (International Journal of Computer Network and Information Security)	[36]	Three methods: Neuro-fuzzy models, neural networks, and empirical equations of genetic algorithms—were combined to develop MANET performance models. The results shows HYPER-NF-NET (hyper Neuro fuzzy network) simulator, which employs soft computing approaches, cuts the routing discovery	Empirical equations of genetic algorithms, Neuro-fuzzy models, and Neural networks.	- Load retransmission attempt, Delay, data drop and throughput -Network size/number of network nodes, average mobility, route congestion level/blocking, network topology, number of connections, and route maps	Mobile Ad-Hoc Networks (MANETs)	- Hyper-NF-Net to NS2 route finding time ratio expressed as percentage. -Comparative Performance Factor (CPF)

			time using the NS-2 simulator by 20%.				
A black widow optimization-Based Neuro-Fuzzy Model for Designing an Efficient Cluster routing Protocol in a VANET environment	IJFSA (International Journal of Fuzzy System Applications)	[20]	Presented the EBW-NFO algorithm; evolutionary black widow optimization (BWO)-utilizing Neuro- fuzzy optimization technique. Connection and stability improved throughout communications, and the EBW-NFO method delivered a reliable clustering routing protocol that deliberates mistrust value parameters, mobility constraints, and QoS requirements in mobile environment of Vehicular Ad hoc Network (VANETs)	Neuro-fuzzy optimization algorithm (NFO)	Energy, latency, bandwidth, packet delivery ratio, delay, and throughput.	Mobile environment of Vehicular Ad hoc Networks (VANETs)	- DoS attacks and Sybil Detection rate - Delay value (ms) - Time Vs Throughput in ms
Developing a Neuro-fuzzy Model for Determining Shortest Routing Path in a Computer Network	Journal of computer science and its application (JCSA)	[2]	A neuro-fuzzy approach was used to deliver efficient network routing. The quickest path and best cost were estimated. The study further assessed the effectiveness of these neuro-fuzzy algorithms integrated with open shortest path first (OSPF) and genetic algorithms for message routing on the basis of end-to-end delay. Delay time was computed. Results showed that, in terms of delay time,	Neuro-fuzzy, Dijkstra's algorithm, Genetic algorithms	Delay time	Computer networks	Comparison of Neuro-fuzzy with Dijkstra's algorithm and genetic algorithm delay performance evaluation in seconds

			the neuro-fuzzy model's performance is similar to that of the genetic algorithm.				
Quality of Experience and quality of protection provisions in emerging mobile networks	Institute of Electrical and Electronics Engineers (IEEE Wireless Communications)	[22]	It was suggested to apply the neural network (NN) methodology as an effective method for self-optimization and adaptive assessment of the user-perceived quality in the context of 5G network.	Neural networks (NN)	Packet loss, delay, jitter, packet loss rate, and throughput	5G mobile network.	-Comparison between the neural network (NN) and adaptive assessment of the user-perceived quality in the context of 5G network.
Neural Network for Quality of Experience Estimation in Mobile Communication networks.	Institute of Electrical and Electronics Engineers (IEEE)	[31]	Neural networks were used to automatically sort various key performance indicators (KPIs) (related to QoS and QoE). QoE calculation is assured to be repeatable regardless of user interaction and requires a fresh training data step for subsequent systems.	Neural networks (NN)	Throughput, latency, and/or jitter	Mobile Communication networks i.e. High speed packet access (HSPA) network	-Mean Relative Error (MSE error)
A QoS-Provisioning Neural Fuzzy Connection Admission Controller for Multimedia High-Speed Networks.	Association for Computing Machinery (ACM); Transactions on networking	[32]	Recommended the neural fuzzy connection admission control (NFCAC) concept as an integrated technique that combines a neural network's capacity for learning and a fuzzy logic controller's language control capabilities. The outcomes of the simulation showed that the suggested NFCAC can preserve the	Neural fuzzy	Bandwidth	Multimedia high-speed networks	- system utilization in percentage (%)

			QoS contract while achieving excellent system utilization, rapid learning, and an easy-to-use design process.				
A Neuro-Fuzzy Model for Intelligent Last Mile Routing.	International Journal of Civil Engineering and Technology (IJCET)	[34]	The suggested method chooses the best path for packet transmission while considering QoS, QoE, and packet transfer rate. The QoS message size, buffer size, and latency were used. Neuro-fuzzy algorithm had 0.545 seconds delay time. These techniques ensure that link latency and packet loss rate are reduced and that the best route is chosen for packet delivery	Neural fuzzy	Message size, buffer size, and latency/delay	Computer networks	-RMS error (Root Mean Square error) -Dijkstra's shortest path algorithm
Estimating and Synthesizing QoE Based on QoS Measurement for Improving Multimedia Services on Cellular Networks Using ANN Method.	Institute of Electrical and Electronics Engineers (IEEE); IEEE Transactions on Network and Service Management	[30]	This method is based on the QoS parameters. Instead of employing actual people, the QoE model and calculation of the QoE score were created by effectively learning the characteristics of ANN from the acquired information. The synthesis of the qualitative parameters is the guiding paradigm for networks that enhance performance through user-centric strategies. The state parameters	Artificial Neural Network (ANN)	-End parameters for Facebook conversational services (throughput download photo, duration time, post photo throughput post photo, etc.); -End parameters for YouTube streaming services (throughput, buffering duration, buffering count, duration to first play, etc.); -End-of-line service parameters (LINE Send Duration (s), LINE Send	- conversational services - Streaming services in LTE networks	-correlation coefficient -Linear regression

			considered for synthesis mainly drive the outcome as applied under a user-centric strategy to boost performance by subjectivity with the QoS parameters.		Time (Ms.), LINE Load Photo Duration (Ms. Web browser service endpoint parameters, including web duration time(s), web throughput, download apps, etc. -Data parameters (Channel Quality Index, Block Error Ratio in LTE networks, Transmission Power of Physical Uplink Shared Channel, Uplink Shared Channel, etc.) -Radio parameters (Received Power, Reference Signal, Signal to Interference and Noise Ratio, Reference Signal Received Quality, etc.)		
Adaptive Neuro-Fuzzy Inference Models for Speech and Video Quality Prediction in Real-World Mobile Communication Networks.	Institute of Electrical and Electronics Engineers (IEEE); IEEE Wireless Communications	[9]	Whether it is contemporary broadband mobile communication networks or service centers, an advocate for a unified approach of predicting Quality of Service (QoS) is based mainly on Neuro-Fuzzy inference systems.	Neural fuzzy	Bandwidth, availability, and coverage	Conversational and Streaming services in Wireless multimedia communications	-Non-linear regression -Root mean squared error (RMSE) - BER (bit error rate)
Energy-Efficient Secure Adaptive Neuro Fuzzy Based Clustering Technique for Mobile Adhoc Networks.	Intelligent Automation & Soft Computing (IASC)	[23]	A non-probabilistic, energy-efficient, secure adaptive Neuro fuzzy clustering method (NPEE-SANFC) has been proposed for mobile ad hoc networks. The time for which a	Adaptive neuro fuzzy based clustering algorithm	Throughput, Energy consumption, latency, and network longevity.	Mobile ad hoc networks (MANETs).	NPEE-SANFC, FUCHAR, COBMA, EMPSO algorithms evaluation results

			network lingers and energy will increase with the optimized selection of the Cluster head (CH) going through preliminary and final CH elections.				
Adaptive Neuro-Fuzzy Inference System-Particle swarm optimization-based clustering approach and hybrid Mothflame cuttlefish optimization algorithm for efficient routing in wireless sensor network.	International journal of communication systems (IJCS)	[35]	A hybrid Moth Flame optimization with Cut-off optimization algorithm (MFO-CFO) method and clustering using Adaptive Neuro-Fuzzy Inference System-Particle Swarm Optimization have been proposed for effective routing in wireless sensor networks (WSN). The ideal cluster head is selected based on the history of the nodes, degree of the nodes, and the residual energy (RE) as input parameters.	This clustering method is based on an Adaptive Neuro-Fuzzy Inference System-Particle swarm optimization. It is also accompanied by the hybrid Moth-flame cuttlefish optimization (MFO-CFO) algorithm.	Network Life Time (NLT), Energy consumption, End to end (E2E) delay, latency, throughput, channel load, bit error rate (BER), packet delivery ratio (PDR), packet loss and jitter.	wireless sensor network (WSN)	Fuzzy, Genetic Approach (GA), Multiple Access Data Gathering using Mobile Sink for Path Constrained Environment (MADGAMSPCE). PSO (Particle Swarm Optimization),
An Intelligent Adaptive Neuro-Fuzzy for Solving the Multipath Congestion in Internet of Things	Journal of Information Systems Engineering and Management (JISEM)	[1]	The research conducted by Aalsalem, 2023, utilized the Modified Squirrel Search Algorithm (MSSA) to modify the Membership Function (MF) and bring about congestion control through the Adaptive Neuro-Fuzzy Inference System (ANFIS). The results from the simulation demonstrate that the SI-	Adaptive Neuro-Fuzzy	Round Trip Time (RTT), Data Flow Rate, Bandwidth Overhead (BO), and Control Traffic Overhead (CTO).	Internet of Things (IoT applications)	Using the NN-IHH, ICOAP, FICCS, and SI-ANFIS algorithms, to calculate accuracy

			ANFIS method (Swarm Intelligence Adaptive Neuro-Fuzzy Inference System) showed great promise in traffic greediness minimization and achieved a remarkable accuracy of 93.58%.				
Improve Quality of Experience of Users by Optimizing Handover Parameters in Mobile Networks	Association for Computing Machinery (ACM)	[33]	(Rongcheng, Gang, & Weidong, 2020) suggested a handover method to enhance QoE while taking the QoE balance into account grounded on dynamic particle swarm optimization (DPSO) in a vital regulator. This outperforms the standard particle swarm optimization technique (SPSO) with regards to the convergence time condition and the solution quality guarantee.	Neuro-Fuzzy grounded on DPSO (dynamic particle swarm optimization)	Bandwidth, Throughput.	LTE Mobile Networks	Variance measure, QoE of users.
Energy Optimization of Wireless Sensor Network Using Neuro-Fuzzy Algorithms.	Neuro Information Processing Systems (NIPS)	[3]	Examining the hitches allied by energy-efficient algorithms and network longevity in wireless sensor networks (WSNs) was important for this study's ability to support several applications. Neuro-Fuzzy model was compared and demonstrated that it outperforms	Adaptive neural network	Packet delivery ratio, Throughput, Packet loss, energy consumption.	Wireless Sensor Network	Random Model and Fuzzy Model

			random model.				

III. METHODOLOGY

The systematic literature review meets the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines as mentioned in [29]. This gives a backing to the transparency and reproducibility of study selection, which is covered in four phases: Identification, Screening, Eligibility, and Inclusion.

Identification

This phase systematically searches for all potentially relevant records to capture the widest possible quantity of evidence and minimizes selection bias.

The PRISMA identification stage yielded 11,110 records identified through database searching. After duplicate removal, 3,325 unique articles proceeded to title and abstract screening.

Studies were excluded/removed if they: Focused solely on classical fuzzy or Machine learning models without ANFIS integration; lacked quantitative performance results; were reviews, book chapters, theses, or grey literature; provided insufficient methodological transparency.

Screening

This stage involved reviewing titles and abstracts to remove clearly irrelevant studies [28]. It intends to narrow down all the records to articles that reasonably meet the eligibility criteria, while ensuring systematic and reproducible assortment.

Set by the criteria for precluding definite inclusion or exclusion, such as resided in or aligned with the PICOS (Population, Intervention, Comparator, Outcomes, Study design) framework.

Eligibility

In this phase, full manuscripts of potentially relevant articles are retrieved and assessed for eligibility to confirm which studies candidly encounters inclusion criteria and be included in the synthesis.

Inclusion

This phase marked the final set of studies into the review process. Studies were eligible if they: Applied ANFIS, neuro-fuzzy, or hybrid intelligent models to QoE or QoS–QoE optimization; Reported empirical, experimental, or simulation-based results; were published in peer-reviewed venues within the past 12 years; included full-text availability in English.

Identification:

Records identified; (n = 11,110)
Records after duplicates removed; (n = 3,325)

↓

Screening:

Records screened; (n = 3,325)
Records excluded; (n = 3,233)

↓

Eligibility:

Full-text assessed; (n = 92)
Excluded; (n = 75)

↓

Inclusion:

Studies included; (n = 17)

Figure 3.1: PRISMA 2020 Flow Diagram [29]

3.1 Review Protocol

The review protocol step, the research questions were initially formulated. Research repositories were utilized to choose pertinent papers after the research topics had been determined. Research repositories that were utilized in this literature review were IEEE (Institute of Electrical and Electronics Engineers), ACM (Association for Computing Machinery), IJITEE (International Journal of Innovative Technology and Exploring Engineering), IJCNIS (International Journal of Computer Network and Information Security), IJFSA (International Journal of Fuzzy System Applications), JCSA (The Journal of computer science and its application), IJCET (International Journal of Civil Engineering and Technology), IASC (Intelligent Automation & Soft Computing), IJCS (International journal of communication systems), NIPS (Neural Information Processing Systems), JISEM (Journal of Information Systems Engineering and Management). Following the selection of pertinent studies, they were subjected to a series of elimination and worth criteria for filtering and evaluation. In order to address the research questions, the retrieved data obtained from research repositories was combined. The three components of the adopted method were the plan review, the conduct review, and the report review.
Research topics, publishing sites, first search terms, and publication choice criteria were recognized during **plan review phase.**

Data extraction was done during **conduct review phase**, which means that more details about the study questions as well as information about the authors, year and type of publication, were retained. Following accurate extraction of relevant data which was combined to yield a pertinent summary of the papers that had been published

Documenting research findings and research questions being answered got the review to a close during the **report review phase**.

3.2. Research questions

Based on the review protocol, four research questions or (RQs) were developed as identified below:

- RQ1- Which algorithms are employed for optimized models in the literature for communication networks?
- RQ2- which network QoS parameters combination has the models used in this SLR that significantly impact QoE in communication networks?
- RQ3- Which application areas have been used for evaluating respective algorithms in the reviewed literature for optimized models in communication networks?
- RQ4- Which evaluation criteria(s) have been utilized for evaluation of optimized models in communication networks?

3.3. Search strategy

The search was conducted by focusing on the fundamental ideas that are pertinent to the review's jurisdiction.

There are several application sectors for network QOE optimization; hence there are considerable amounts of published research undoubtedly outside the purview of this particular review. Quite a lot of smart technologies are in usage for network QOE optimization including Fuzzy ARTMAP (FAM), Adaptive Neuro-Fuzzy, Neuro-Fuzzy, Neural networks, empirical equations of genetic algorithms, Neuro-fuzzy optimization algorithm (NFO), Dijkstra's algorithm, Artificial Neural Network (ANN), Adaptive neural network etc. as outlined in the table of comparative review of previous studies in this SLR. The search query was first entered using the terms "algorithm" AND "network QoE."

Several methods were used to retrieve online content in connection to network quality of experience. We looked through abstracts to identify relevant keywords. We conducted many searches across multiple online repositories.

To ensure that no pertinent information was overlooked, the criteria for exclusion were used, and all of the results were scrutinized using the abstract, search terms, and other criteria.

Following the use of these search terms, 11,110 research articles were retrieved from 6 online repositories. For each of the retrieved documents; the title, journal name/ source, reference of the article, brief description, algorithm(s) used, network QoS parameters used, service/ application area and evaluation criteria were captured so as to further extract the table of comparative study on related work for this SLR.

3.4. Exclusion criteria

The studies were assessed and ranked in accordance with the exclusion criteria for the purpose of providing margins for the comprehensive review procedure in order to execute the elimination of irrelevant research papers. The following are the exclusion criteria (EC):

Exclusion criteria 1 – Articles that are not in computer science area of study

Exclusion criteria 2 – Articles that appear in other languages rather than in English

Exclusion criteria 3 –Duplicate retrieved articles from other repositories

Exclusion criteria 4 – Articles that have only abstracts without full text provision

Exclusion criteria 5 –Old publications past 12 years ago

Based on the data garnered from the publications, research questions were responded to appropriately, with an emphasis on both addressing the research questions and determining if the research articles satisfy the exclusion criteria.

Table 3.1: Papers distribution based on accessed databases

NAME OF DATABASE	PAPERS RETRIEVED	PAPERS AFTER EXCLUSION	PERCENTAGE INCLUSION (%)
ACM	621	3	17.647
IJITEE	310	1	5.882
IEEE	828	5	29.412
IJCNIS	300	1	5.882
IJFSA	312	1	5.882
JCSA	221	1	5.882
IJCET	145	1	5.882
IASC	129	1	5.882
IJCS	144	1	5.882
NIPS	151	1	5.882
JISEM	164	1	5.882
Total	3,325	17	99.997

Merely 92 studies were retained for additional examination following the application of the initial three exclusion criteria. As can be seen in the above Table 3.1, 17 studies were chosen for additional analysis after all five exclusion criteria were applied.

However from the Table 3.1 above, it is evident that most of these papers were picked from IEEE and ACM after exclusion criteria. Other databases returned high number of papers like IJITEE but after observing selection criteria, a few were retained.

The distribution of retrieved papers from various journals after exclusion criteria is illustrated in figure 3.2 below

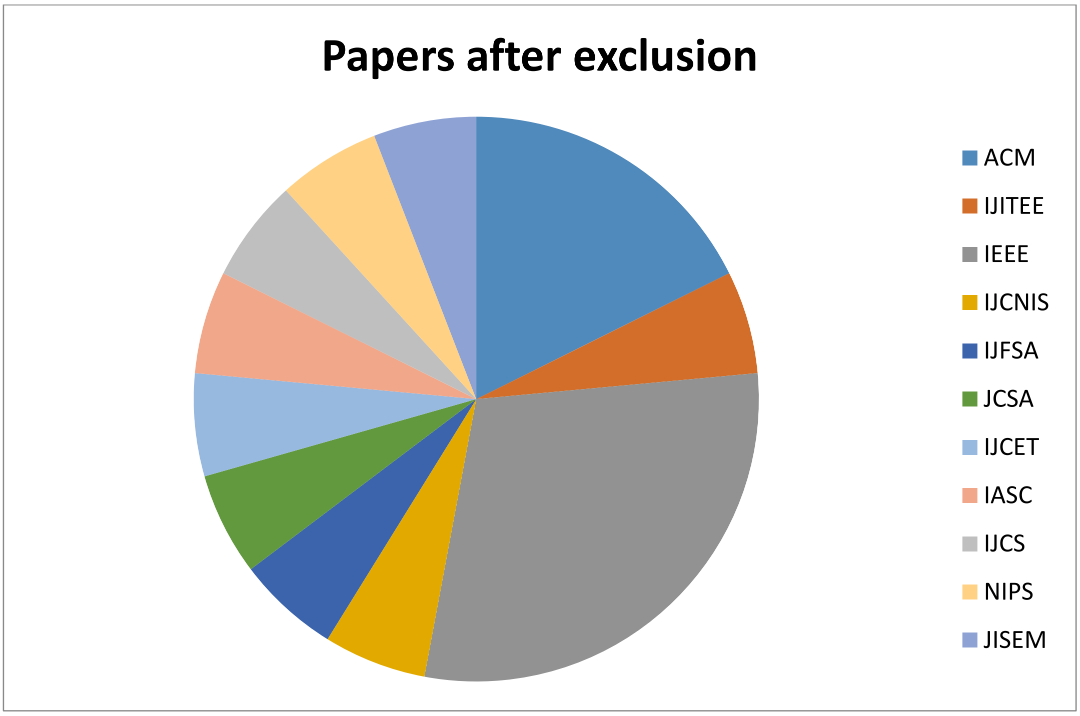

Figure 3.2: Distribution of papers after exclusion

Data have been gathered and compiled from the chosen papers to discourse the four research questions. Information acquired was mostly utilized to discourse research questions and determine the studies if satisfied exclusion criteria. Comparative evaluation of prior studies, Table 4.1, presents the chosen studies satisfying exclusion criteria. Entirely the retrieved data was merged and carefully chosen during the data synthesis process, as well the research questions were responded to appropriately. Section IV below presents the discussions associated with this SLR in relation to the research questions

IV. DISCUSSION

The discussion in Table 2.1shows the publication title, publication source, publication reference, brief description, algorithm used, network QoS parameters used, service or application area and evaluation criteria from selected studies that passed the exclusion criteria. Further discussion is covered as per the four research questions.

1. **RQ1-Which algorithms have been used in the literature for optimized models in communication networks?**

Table 4.1: Table of utilized Algorithms as per reviewed papers after exclusion criteria

ALGORITHMS USED	SCENARIOS APPLIED AS PER REVIEW OF PREVIOUS STUDIES	% INCLUSION
Fuzzy ARTMAP (FAM) neural network	1	4.76
An Adaptive Neuro-Fuzzy	4	19.05
Neuro-Fuzzy	8	38.10
Dijkstra's algorithm,	1	4.76
Genetic algorithms	2	9.52
Artificial Neural Network (ANN) or Neural networks (NN)	4	19.05
Adaptive neural network	1	4.76
Total	**21**	**100.00**

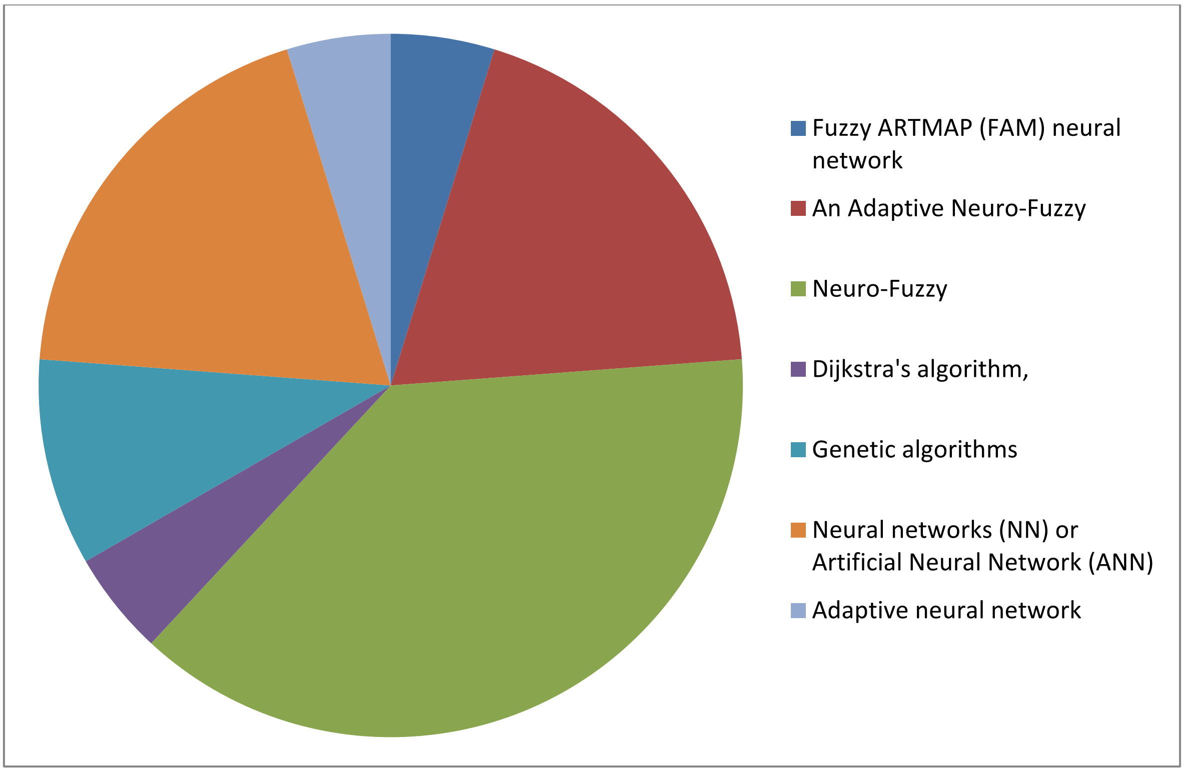

Figure 4.1: Distribution of algorithms as per review papers after exclusion criteria

Summary of algorithms used after exclusion criteria are represented in Table 4.1and Figure 4.1. However, there are some algorithms which are closely related but are not necessarily synonymous. For instance “Neuro-fuzzy” and “neural networks/ artificial neural networks”. Both “neuro-fuzzy systems” and “neural networks” are based on principles of computation inspired by biological neural networks; they serve different purposes and employ different computational mechanisms. Neuro-fuzzy systems focus on integrating fuzzy logic with neural networks to handle uncertainty and imprecision, while neural networks are general-purpose computational models capable of learning complex relationships from data.

Moreover, "adaptive neural network" is often used interchangeably with "neural network”. Technically speaking, this is incorrect because "adaptive neural networks" are neural networks that have the capacity to adapt and learn from input over time, whereas "neural networks" are computer models motivated by composition and operation of natural neural networks in human brains. Several learning techniques, such back propagation, hybrid etc. can cause this adaptation by changing the network's parameters in response to patterns seen in the data.

Nonetheless, "neural network" as well as "artificial neural network" (ANN) refers to same computational concept motivated by the functioning of natural neural networks.

In summary, while both “neuro-fuzzy” and "adaptive neuro-fuzzy" or ANFIS models shares incorporation of fuzzy logic techniques and neural network, ANFIS is a definite type of neuro-fuzzy structure with its own distinct architecture and learning algorithm. ANFIS is often considered a subset of neuro-fuzzy systems, but not all neuro-fuzzy systems are ANFIS models.

Based on this SLR, it’s a clear indication that the most utilized algorithm as per review of previous studies is neuro-fuzzy. This algorithm typically consists of a neural network component for learning and adaptation, combined with fuzzy inference systems for linguistic modeling and rule-based reasoning.

The necessity for Adaptive Neuro-Fuzzy Inference Systems (ANFIS) has increased recently due to the advancements made in this technique. On the basis of T-S fuzzy model i.e. Takagi-Sugeno fuzzy inference system, ANFIS models adaptively modify the fuzzy inference system's parameters through the use of a hybrid learning approach known as backpropagation through a fuzzy system (BPFS).

Likewise, they have a fixed architecture consisting of a set of fuzzy if-then rules, each with adjustable parameters that are optimized during training using gradient descent techniques. This makes such models worthwhile for function approximation, system identification, and control applications due to their ability to capture complex relationships between input and output variables. As a resultant of these important features exhibited by ANFIS over neuro-fuzzy, there is need to adopt ANFIS models as captured in this review topic.

2. **RQ2- which network QoS parameters combination has the models used in this SLR that significantly impact QoE in communication networks?**

The purpose of QoS parameters in networking is to ensure the integrity of communication network via a variety of technologies and to detect glitches in that traffic, as stated by [4].

Table 4.2: QoS and QoE correlated parameters mapping [21]

QOE FACTORS	CORRESPONDING QOS PARAMETERS
Accessibility	• Unavailability • Security • Activation • Access • Coverage • Blocking • Setup time
Retain ability	• Connection loss
Integrity of Service	• Throughput • Delay • Delay variation/Jitter • Packet loss

It is important to identify QoS metrics that map to respective QoE variables whenever valuing QoS of any network as shown in Table 4.2. The underlying QoS elements correlated with integrity of service QoE metrics are the most in use in this SLR. These are deliberated as crucial elements for QoS valuation of any communication network [21].

In this SLR, a number of QoS parameters have been in use. The criteria to select these parameters were not defined. Services (streaming, video conferencing, conversational services) and related QoS parameters should be judiciously recognized while undertaking network parameter optimization to curb network buffering and outages in communication networks.

In conclusion, integrity of service metrics are understood to be the fundamental in impacting communication networks, it is essential to incorporate all of them when undertaking QoE parameter optimization [13].This will significantly impact network automation. The four integrity of service parameters (independent variables) are deliberated below:

Delay/ latency: Occurs when information prolong some time to reach the destination point [16]. This is fundamental to communications and vital feature utilized in assessing services accessible in real-time like videoconferencing and (VoIP) voice over internet protocol.

Packet loss: Datum which fails to reach its destination when sent via computer networks [27]. Packet-based considerations are judiciously satisfactory for assessing service quality in networking [39]. Packet loss critically impacts valuation of peak signal to noise ratio (PSNR) as a vital aspect for valuation of QoE in video services [5].

Jitter is termed as variations in delay incidence [16]. It transpires due to irregular communication of deferring packets in a network resulting from routers' internal routing variations, flow overcrowding etc. It's a vibrant aspect for valuation of multimedia networks [39].

Throughput is the capacity of data in a specific period sent over a network connection [27] .Throughput is fundamentally identical to bandwidth usage.

The four parameters are extremely correlated as continuous existence of jitter in a network leads to delay, once delay perseveres it hints to packet loss while packet loss keep on in a network, it openly upsets the overall network throughput [14].

3. **RQ3- Which application areas have been used for evaluating respective algorithms in the reviewed literature for optimized models in communication networks?**

The digital era has enabled multiple modes of online communication and content delivery, each serving distinct purposes. Three common categories are streaming services, video conferencing services, and conversational services. While these platforms often overlap in their use of internet technologies, they differ significantly in terms of design, communication flow, and user interaction.

Streaming services primarily focus on the continuous delivery of multimedia content over the internet without requiring users to download entire files. This model enables access to both live and on-demand entertainment such as movies, music, and sports events. The communication structure is largely one-to-many, where content providers distribute media to a wide audience with minimal direct interaction [11]. Technologies such as buffering and content delivery networks (CDNs) are essential to maintaining quality and reducing latency. For example, platforms like YouTube, Netflix, and Spotify rely on streaming to ensure seamless access to media content. The emphasis here is on content consumption rather than interactive dialogue.

In contrast, video conferencing services are designed to facilitate real-time, two-way communication between multiple participants. These platforms support audio, video, and often collaborative tools such as screen sharing, whiteboards, and chat features. Video conferencing is widely applied in education, healthcare, and corporate environments, enabling geographically dispersed participants to interact as though they were in the same physical space. The communication model is many-to-many, requiring low latency to ensure synchronous communication [24]. Tools such as Zoom, Microsoft Teams, and Google Meet exemplify this category. Unlike streaming, which emphasizes passive viewing; video conferencing promotes active engagement and collaboration.

Meanwhile, conversational services are centered on interaction between humans and intelligent systems, often mediated by artificial intelligence (AI). These platforms leverage machine learning and NLP (natural language processing) to comprehend and react to user inputs in form of text or voice. Conversational services can be synchronous, as in live Chatbot, or asynchronous, as in messaging systems. Unlike streaming or video conferencing, conversational services are not primarily concerned with multimedia delivery but rather with enabling dialogue and task automation [26]. Examples include voice assistants like Siri and Alexa, as well as customer service Chatbot integrated into messaging platforms such as WhatsApp.

In summary, the distinctions between streaming, video conferencing, and conversational services lie in their communication models, levels of interactivity and technological underpinnings. Streaming focuses on delivering content to a large audience, video conferencing emphasizes real-time human-to-human interaction, and conversational services enable intelligent human-computer dialogue. Understanding these differences is crucial in selecting the right technology for specific organizational, educational, or entertainment needs.

Based on QoE, user satisfaction might differ based on network scenarios e.g. streaming, video conferencing and conversational services. In this SLR, previous models didn't incorporate all communication network validation scenarios inclusively thus there is an essential gap to handle all types of validation scenarios for communication networks QoE concerns.

This SLR intends to highlight this gap thus indicate need to validate optimized models in communication networks based on streaming, video conferencing and conversational services instantaneously for best outcomes as the scope of communication lies in these broad aspects.

4. **RQ4- Which evaluation criteria(s) have been utilized for evaluation of optimized models in communication networks?**

In this SLR, various evaluation techniques have been utilized to validate the models as captured in Table 2.1 i.e. table of comparative review of previous studies. This includes R^2 (coefficient of determination), RMSE (root mean square error), PSNR (Peak Signal to Noise Ratio), MSE (mean squared error)) etc. The criteria to select these evaluation techniques were not highlighted.

Based on this gap, there is need to select the best evaluation technique of optimized models in communication networks considering several criteria to ensure comprehensive and meaningful assessment. The choice of the best evaluation technique depends on a number of facts, such as the study's specific goals, the type of optimized model, the resources that are available, etc. There is no one-size-fits-all answer, but several common evaluation techniques are widely used and can be effective depending on the context.

This SLR proposes a number of best practices to ensure better results for evaluation of optimized models in communication networks. For instance, Cross-validation as a method utilized to evaluate performance and generality ability of machine learning trial product. The process is separating datasets in different folds, train models on various folds groupings, then assessing the performance of the model using the remaining dataset. Stratified cross-validation, "leave-one-out" and "k-fold cross-validation" are samples of main cross-validation techniques.

Likewise, "Holdout validation" comprises splitting datasets into two fold parts i.e. training set and validation set. Models are trained utilizing training dataset as well as assessed utilizing validation dataset to assess its performance. Holdout validation is straightforward and efficient but requires careful selection of the training data and validation data proportions.

To assess the effectiveness of a model, use performance metrics such as F1-score, accuracy, precision, coefficient of determination (R-squared), recall, mean squared error (MSE), root mean square error (RMSE), area under the ROC curve (AUC-ROC), etc. It's recommended to choose performance metrics that are relevant to the objectives of the study and provide insights into different aspects of model performance.

Moreover, conduct comparative analysis against baseline models, alternative approaches, or industry standards to benchmark workability of optimized models. Compare vital performance factors, computational efficiency, scalability, and robustness to identify model's strengths and faults. Where necessary, deploy the optimized model in a real-world communication network environment and monitor its performance under actual operational conditions.

In conclusion, it's recommended to use network simulation or emulation tools to recreate various network scenarios and evaluate the model's performance under controlled conditions. Simulate different levels of latency, packet loss, bandwidth etc.to assess the model's robustness and adaptability.

V. CONCLUSION

The review objective is to identify a vital technique for modeling and optimizing primary network parameters with outstanding effects to be preserved for parameter optimization to restrain network buffering and outages in communication networks. This will consequently ensure effective automation of network services in communication networks.

Based on this systematic literature review (SLR), **For RQ1,** it's a clear indication that the most utilized algorithm as per review of previous studies is neuro-fuzzy. This algorithm typically consists of a neural network component for learning and adaptation, combined with fuzzy inference systems for linguistic modeling and rule-based reasoning. In summary, while both "neuro-fuzzy" and "adaptive neuro-fuzzy" or ANFIS models shares incorporation of fuzzy logic and neural network, ANFIS is a precise type of neuro-fuzzy with its own distinct architecture and learning algorithm. ANFIS is often considered a subset of neuro-fuzzy systems, but not all neuro-fuzzy systems are ANFIS models.

Grounded on this SLR, For **RQ2**, statistics shows that throughput and delay are the most used network QoS metrics in communication networks. One of the objectives of the review is to pinpoint essential primary parameters for modeling and optimization that yields superior outcomes and should be taken into account when optimizing parameters to limit network buffering and outages in communication networks. This work recommends metrics allied to integrity of service i.e. throughput, packet loss, delay, and jitter for primary parameter modeling and optimization that yields superior outcomes and should be taken into account when optimizing parameters in communication networks.

For **RQ3**, this study reveals that while streaming, video conferencing, and conversational services represent the dominant application areas in communication networks, most existing models have not been validated across all these scenarios inclusively. This limitation creates a critical gap in ensuring robust Quality of Experience (QoE) across diverse network environments. Therefore, future research should prioritize designing and testing optimized models that simultaneously address these three broad categories to achieve comprehensive validation and improved user satisfaction.

For **RQ4**, the review highlights that although a variety of evaluation criteria—such as PSNR, RMSE, MSE, and R^2 have been applied in assessing optimized models, the rationale behind their selection is often not explicitly stated. To enhance the reliability of results, researchers should adopt best practices by carefully aligning evaluation techniques with study objectives, employing methods such as cross-validation and comparative benchmarking, and leveraging context-appropriate performance metrics. Furthermore, testing models under simulated or real-world network conditions is essential to ensure scalability, adaptability, and meaningful performance assessment in practical communication networks.

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