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Improving QoS in Information Central Networks (ICN)

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ABSTRACT

This research proposes a smart classification environment to improve the quality of service (QoS) in Information Central Networks **(**ICN).

This research uses keyword classification techniques to obtain the most valuable information through appropriate content prefixes in ICN.

In this research we have achieved an intelligent function that uses the artificial intelligence(AI) application to find the most appropriate approach to maintain QoS matrices.

We evaluated many artificial intelligence algorithms, including evolutionary algorithms(EA), intelligent swarm algorithms (ISA) and machine learning algorithms(MLA) using cost function to evaluate the classification performance of these algorithms.

For optimal solution in content prefix classification, we suggest a hybrid algorithm from previous algorithms to improve the classification performance.

Through experiments, evaluation results show that our proposal outperforms evolutionary algorithms and machine learning in terms of using network resources and response delay to optimize QoS.

***Keywords:* —** Information Central Networks - Smart Classifications - Quality Of Service - Artificial Intelligence.

I. INTRODUCTION

ICN (Information Central Network) is a futuristic internet environment that implements a naming scheme for routing content rather than adopting routing on content sites as is the case in (end-to-end) networks.

ICN networks increase the importance of data content to become the main inputs to access content entities and eliminate the interconnection between the content provider and its applicant depending on the site, this shift in the communication model represents an appropriate solution to meet the expected huge growth in content exchanges on the Internet with the growth of smart devices for future generations from networks, where access to information becomes possible, especially since mobile data traffic over the Internet is expected to increase sevenfold to 49.0EX.B by the year 2021, making the need to search for content more difficult [1].

The main difference between IP and ICN networks is that ICN applies the concept of prefix content format as an identifier of the forwarding process.

The content name prefix: is a chain hierarchy of characters separated by (/) within the full name of the Uniform Resource Identifier (URI). This prefix can be classified as follows:

"Content type / content name / router id / publisher ID"

The content name consists of keywords that can be named and linked as a defined name for the content, but the Internet currently relies on networks of the type IP, so users resort to try several keywords in the search engine and then choose the most relevant content.

The AI approach in ICN is still at an early stage, although previous studies in this field indicate opportunities for smart processing of the content prefix in ICN.

In this research, we evaluate and monitor the performance of a number of artificial intelligence algorithms and then discuss the performance of these classifications with the selected quality of service matrices, and of the algorithms that have been discussed evolutionary algorithms, smart swarms and machine learning methods, have been evaluated according to four criteria, namely: evaluation consequences, continued cost, and standard deviation Calculation time.

Through a comprehensive investigation using the MATLAB we choose the most appropriate smart classification methods for the proposed framework, then we explain how the framework can improve the efficiency of ICN by solving the problem caused by the similarity of contents in the classifications of artificial intelligence, where we propose a new classification in the ICN networks by collecting content requests from a large number of users to improve the QoS. Simulation results show that our proposal improves network efficiency in terms of reducing the use of network resources and response delay by handling content packets. This approach is an ideal solution for future Internet engineering using ICN networks.

II. THE IMPORTANCE OF RESEARCH AND ITS OBJECTIVES

Given that the current network devices require fast and efficient services, it is important that you learn dynamically from user inputs that are in the form of a series of keywords as attributes of the predicted content and return it prefixing the name of the content most closely related to increasing the quality of service, therefore we need a smart classification mechanism to obtain the most suitable components for a content prefix to improve content discovery and improve QoS.

We focus in this research, we focus on a general framework that classifies the content prefix by using the method of artificial intelligence to evaluate the relationship between the keywords entered and the required content.

Unlike previous work in this field, our study focuses on finding the most suitable smart approach that supports effective classification at the application and network levels.

III. RESEARCH METHODOLOGY

To evaluate the benefits of classification methods we simulate our suggestion to use NDNSIM, a commonly used simulator of the NDN (Name Data Networking) for the ICN platform within the NS3 framework.

a) The first scenario:

We execute the content request with an unclassified prefix.

b) The second scenario:

We apply the prefix categorized using our smart framework.

In both cases, each node has the same cache size as the content store (CS).

We also assume that all content objects have the same size for each scenario. Simulations were performed using two different interest arrival rates. In the first part, the user nodes generate a fixed and uniform distribution rate of 10 interest packet / sec. The simulation time used in both scenarios is (100 sec).

IV. ARTIFICIAL INTELLIGENCE

The primary parts of artificial intelligence are learning and adaptation processes. Through these processes applications of EA (Evolutionary Algorithm) have been developed and made to become one of the fastest growing areas of research in artificial intelligence and include EA: GA (Genetic Algorithm) and geographic-based optimization BBO (Biogeography-Based Optimization) and DE (Differential Evolution). [2].

SI (Swarm Intelligence algorithms) have recently been proposed as an ant colony, bees and migratory birds, as machine learning that includes supervised learning, unattended independent learning, and deep learning of networked devices has emerged so that the possibility of modifying and predicting correct behaviours becomes more accurate [3].

For evolutionary algorithms, the genetic algorithm depends on the homogeneity of the genetic structures and the behaviour of the genes that represent solutions within a specific grouping, and it is characterized by flexibility in modelling time and pairing constraints. Given that the genetic algorithm is a random improvement algorithm whose absolute optimization cannot be guaranteed, as a method of improvement, GA can obtain good initial affinity properties However, it may slow down significantly when the optimum solution area is defined [4].

Bio-improvement based on biogeography of mathematical models describes how a species migrates, arises and becomes extinct, and the individual is called a species, and it has variables considered as appropriate indicators to assess its quality as a solution, with improved indicators of appropriate places, the number of species increases and the rate of migration to and from these places and the improvement based on biogeography shared advantages With the genetic algorithm, transit and mutation depend, and the vital algorithm depends on migration and mutation [5].

DE differential development is a simple solution algorithm based on the internationally accepted research algorithm for optimization with minimal control coefficients.

For smart swarm algorithms, improving an ant colony (Ant-Colony Optimization) adopts the principles of exploration of the search process when the ants from their nest to the food source using an efficient traceability feature, the ant performs random marches to search for food and when it reaches the destination it takes what can then returns to its nest. During the return, it leaves traces on the way to benefit from other ants flocks [6].

The bee colony algorithm mimics the smart behaviour of bees in the search for food to make honey. The food source represents a possible improvement solution that matches the quality of the solution [7].

The reason behind improving the flocks of birds was the collective behaviour of birds when trying to reach an unknown destination, birds spread in the research area and their sites are constantly updated.

In supervised learning, the system is fed and learned from a set of examples provided with the correct answers. Otherwise, the supervised learning algorithm intends to discover the similarities between the inputs, where similar entries are grouped into groups.

Deep learning is placed between supervised learning and non-supervised learning. It is used when the answer is wrong but we do not get instructions on how to correct it [8].

V. ARTIFICIAL INTELLIGENCE IN ICN NETWORKS

Shahnbag used the ant colony optimization algorithm as an improved routing strategy in CCN (content central network) to choose the router service that promotes load balancing in the SCN (service central network) however this approach did not take CCN traffic and redundant interest packets in the network [9].

- The researchers expanded on studying the behaviour of multi-path ant colony and a possible mechanism for guiding ants to activate multi-path transport for the CCN nodes, the latest work shows the improvement in the ant colony using two-way ant to spread and exploit the multi-content transcription. The study helps to reach the perfect cache and efficient use of cache resources available in a specific area.

The bird swarm algorithm has been implemented on the CCN networks, by applying the algorithm to the information forwarding base to enhance quality of service [10].

- PSO-FIB uses the bird algorithm to maintain the possibility of forwarding.

The researchers proposed a hybrid algorithm between PSO and the R-Means aggregation algorithm to obtain a system for detecting peculiar anomalies in future types of security challenges in CCN networks [11].

- CCN machine learning is applied to discover temporary copies of content elements not covered in routing tables, then forward requests to the best destination by calculating the value of Q for exploration and exploitation in each hop.

Q-routing is proposed to solve the problem of packet forwarding in dynamic networks.

Researchers suggest a deep learning algorithm that can be used to solve the problem of renewing and forwarding content through the use of Q-routing with costing to reach the optimal solution for buffering routing decisions.

The reorientation strategy has been proposed in CCN based on the armed bandit strategy MABS, a technique in which MABS uses the network for each interest pack request, and makes better use of the acquired knowledge.

- The results show that the MABS algorithm reduces the number of hops to find content [12].

In this research, we suggest a content detection system that is a deep exponential network based content advertisement and buffering memory replacement algorithms for buffering. The model shows improvement in terms of reducing average latency, cache usage, and network capacity.

VI. SMART CONTENT PREFIX CLASSIFICATION TECHNIQUES

In ICN, the content prefix format is readable by us, and can be classified into different groups according to predefined rules.

This research proposes a general framework that can categorize the words entered by the user to ensure the content is discovered and recovered. Our framework begins implementation when users submit their content requests with the assumption that each request consists of a set of keywords entered, the keywords are generated in the pre-processing stage to remove unnecessary components such as repeated words, blank spaces, and unknown characters, then the entries that have been classified are transferred to the intelligent classification engine that processes and extracts the important features to obtain the most valuable keywords, creating practical outputs category smart features prefix known content that serves as the content of a unique identity, which in turn provides a link to link the prefix and the content that the user asks for. Post-processing output before it is sent to the network is processed as the attention packet ICN content name prefix, Figure 1 shows an overview of this procedure.

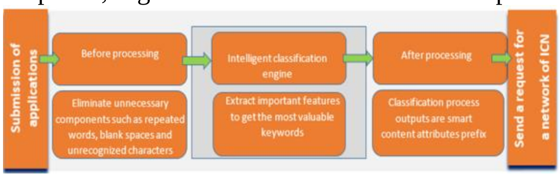

Figure 1: Suggested Smart Rating Engine framework.

VII. EVALUATING THE PERFORMANCE OF THE VARIOUS AI ALGORITHMS

We evaluate the AI algorithms associated with ICN according to four criteria:

Algorithm performance factor - average cost of the algorithm in each experiment - standard deviation of the function values - time required to perform calculations.

The performance evaluation entries are obtained through a series of keywords that are provided as separate user inputs with a data size within the [8 - 498] character.

We enter the input data set first in the pre-processing stage, after which the inputs to the specified algorithm are entered to evaluate its performance, then we develop the performance of each algorithm by collecting the results by performing thirty different operations, and the calculations are done using the MATLAB and the migration, mutation and crossing strategy for the algorithms has been standardized in the same way to reduce the effect of different factors so that we can compare algorithms in similar conditions, Table 1 shows the main parameters in the experiments and the most important parameters that we examined that were chosen through the reference study [13].

Table 1: Experiment metrics.

Parameter	Value
Max iteration	200
Npop	100
Alpha	0.99
Initial Temp	10
Crossover Percentage	1
Mutation Percentage	1
Crossover Inflation Rate	0.2
Mutation Rate	0.1

a) The factor of measuring the performance of the algorithm NEE: Is used NEE To measure the performance of algorithms and determine the optimal model , represents NEE The number of tests required to follow the algorithm to reach a value of optimal , and is to determine the efficiency of through the algorithm that has less value for NEE Be her highest efficiency , and to calculate the value of NEE The use of the application of optimization - based on education TLBO which supports algorithm optimization heuristic that require control several transactions essential , such as the size of solutions and the number of generations of these solutions and not depend on the rate of mutation or transit used in the algorithm genetic , where the account value of the NEE [14] :

$$NEE=2*G\_n*P\_n+P\_n \quad (1)$$

Where that G_n represents the number of generations in which the best solution is obtained , and P_n represents the number of solutions is shown in Figure (2) show average NEE is required to reach the optimum value for each algorithm and the results taken from 30 different experiments , each with 200 repeats each.

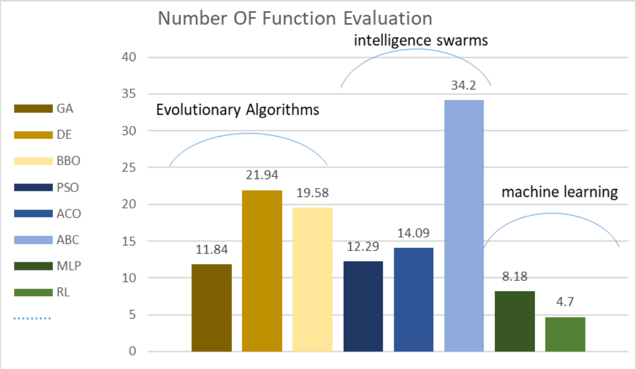

Figure 2: The average coefficient of measuring algorithm performance.

We notice that the genetic algorithm GA has the lowest value of NEE Between the algorithms of the evolutionary algorithm PSO is the lowest value among the group of smart swarm algorithms and in general we note that the deep learning algorithm provides the lowest value for NEE Between all algorithms so, it performs the highest efficiency.

b) Cost Function of the algorithm CF: Is a measure of the cost of resources required to achieve the algorithm function, the account values CF for algorithms to monitor the efficiency and cost of each algorithm. You can calculate the CF Using the process of analysis serial hierarchical (AHP), The measuring of AHP depending on QoS factors.

Suppose a set of candidate algorithms $A_N = \{ A_1, A_2, \ldots\ldots, A_n \}$ Group QoS factors $q_m = \{q_1, q_2, \ldots\ldots, q_m\}$ Where n represents the number of candidate algorithms and m QoS factors , it is supposed to be for each factor for the QoS q_j Value for weight w_j , And this weight indicates the effect of the quality of service factor on the dependent cost of the algorithms CF On as follows [15]:

$$A_N = \sum_{j=1}^{m} (q_j * w_j) \qquad (2)$$

You can calculate the scores relative between the set of points quality service using the equation :

$$\left\{ \begin{array}{l} R_{qiqj} = \left(1 - \frac{s_{qi}}{s_{qj}}\right) * 10 \quad ;j > i \\ R_{qiqj} = \left(\frac{1}{R_{qjqi}}\right) \quad ;j < i \\ R_{qiqj} = 1 \quad ;j = i \end{array} \right\} \qquad (3)$$

Where that R_{qiqj} is the relative result between the coefficients q_j , q_i Also that S_{qi} And S_{qj} Are the grades for each of them .

$X = \{ X_{ij} \}$: is a matrix M * M , Where the X_{ij} It represents a priority for each factor , and is configured to as follows :

$$X = \begin{bmatrix} 1 & R_{q1q2} & R_{q1q3} & R_{q1q4} & R_{q1q5} \\ R_{q2q1} & 1 & R_{q2q3} & R_{q2q4} & R_{q2q5} \\ R_{q3q1} & R_{q3q2} & 1 & R_{q3q4} & R_{q3q5} \\ R_{q4q1} & R_{q4q2} & R_{q4q3} & 1 & R_{q4q5} \\ R_{q5q1} & R_{q5q2} & R_{q5q3} & R_{q5q4} & 1 \end{bmatrix} \qquad (4)$$

We get the size of relative weight by X_{ij} in the following equation , when each element of the array is divided X On the sets column 's done in the equation Previous :

$$R_{qiqj} = \frac{X_{ij}}{\sum_{i=1}^{M} X_{ij}} \qquad (5)$$

The matrix X appears Regular weights in the equation :

$$W_{norm} = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} & w_{15} \\ w_{21} & w_{22} & w_{23} & w_{24} & w_{25} \\ w_{31} & w_{32} & w_{33} & w_{34} & w_{35} \\ w_{41} & w_{42} & w_{43} & w_{44} & w_{45} \\ w_{51} & w_{52} & w_{53} & w_{54} & w_{55} \end{bmatrix} \qquad (6)$$

After that we calculate the average values of each row to give priorities for each factor:

$$\overline{w}_i = \frac{w_{i1} + w_{i2} + w_{i3} + w_{i4} + w_{i5}}{5} \qquad (7)$$

This results in the natural wave w_j Which is a vector is a priority, because it shows the weights relative between the elements, we note that the sum of all elements in the transmission priority is (1).

$$W_j = \begin{bmatrix} \overline{w}_1 \\ \overline{w}_2 \\ \overline{w}_3 \\ \overline{w}_4 \\ \overline{w}_5 \end{bmatrix} \qquad (8)$$

Because it is calculated from W_j The range of QoS factors that is the sum of all elements in the vector priority is (1) symbolizes his vector the following : q_j = [SDERV]

Where the use of five transactions namely: SINR (S), Delay (D), Energy (E), RSSI (R), Speed (V) To measure the cost function of quality of service .

Cost Function : It is a measure of the cost of using the resources needed to allocate it to meet a user's demand, according to specific QoS requirements .

In the network of modern future it is expected to generate user traffic over large content and hence the quality of service for users is very important, is considered laboratories SINR Factor to ensure the quality of the signal is good in the case was the network connected by the user 's wireless , in addition to this , the global delay and energy represent the modelling of the differential between the average cost of the delay and the average cost of energy as the most important factor for scheduling the optimum is to balance the network between the delay and the cost of energy , can factor the RSSI The order of the network wireless available building on the allocation of priority from the list of networks available within the coverage of the user in a period of time specified , in a while the speed shows the speed and direction of the user .

To evaluate CF, we use MATLAB Which provides a set of disciples to measure the cost of the absolute to calculate the cost function of the total, which was obtained by in each experiment for by each factor QoS for the corresponding element of the vector w_n Arranged sequentially, table (2) shows the worst cost and average for the algorithms specified that have been obtained by after 30 repeat. Indicate the results that the cost of the overall algorithms that have been assessed the least cost to the allocation of the quality of service is the most efficient based on the status of the network that achieved by the algorithm genetic [16].

Table 2: Average Cost of Subscription.

	Evolutionary Algorithm (EA)			**Swarm Intelligent (SI)**		
	GA	DE	BBO	PSO	ACO	ABC
Best	117.65	117.26	117.78	118.37	362.26	117.76
Worst	158.40	182.32	273.50	180.47	550.19	167.87
Average	118.81	121.38	121.09	120.41	370.67	121.41

c) Standard deviation S D: Indicates the performance of the SD The consistency of the components of the algorithms and the result is shown in Figure (3) that the algorithm BBO has the lowest average of SD among evolutionary algorithms , and that PSO has the lowest rate SD Among groups of smart swarms , while deep learning gives the smallest value to SD In general , which refers to the quality of service more stable because the more increased the value of the SD as was the QoS is less stable [17] .

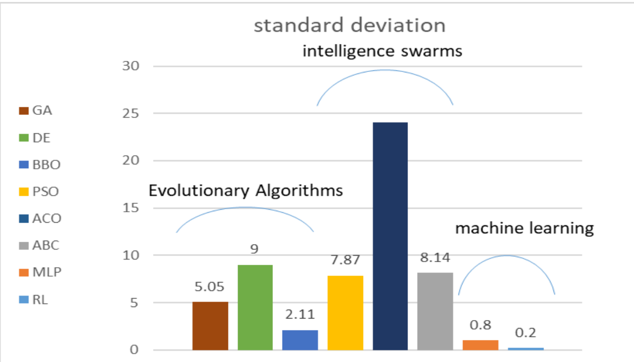

Figure 3 : The average coefficient measuring the deviation standard .

d) The time needed to perform the calculations CT is the time required to complete the algorithm experiment and reflects the CPU time calculation and the smallest number indicates the least amount of time required to finish one run for each experiment and this value is especially important in processing content request during real time where it should be Response time quickly to reduce the arrival time, Figure (4) shows the results obtained in each algorithm where these results showed that the BBO and ABC algorithms work better than the other evolutionary algorithms and smart swarms respectively, but the deep learning algorithm gives the smallest values compared to the rest [18].

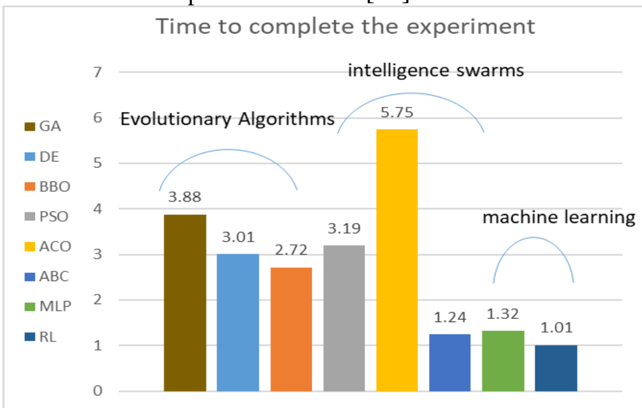

Figure 4: The average of the standard deviation.

We summarize the performance of the algorithms of intelligence artificial selected in the table (3), which results indicate to the efficiency high for the performance of education deep on the algorithms of learning other than where (CT, SD, NFE), The while excel algorithm genetic on the rest of the algorithms of the evolutionary achievement of a minimum value for the cost.

Table 3: Evaluation results.

c	**EA**			**SI**			**ML**	
	GA	**DE**	**BBO**	**PSO**	**ACO**	**ABC**	**MLP**	**RL**
NFE	11.84	21.94	19.58	12.29	14.09	34.20	8.18	4.70
SD	5.05	9.70	2.11	7.87	24.06	8.14	0.08	0.02
CT	3.88	3.01	2.72	3.19	5.75	1.24	1.32	1.01

VIII. SUGGESTED SMART HYBRIDIZATION TECHNOLOGY

We evaluated the performance of the algorithms of intelligence artificial used in the networks of ICN We have noticed that the deep learning algorithm is the best among automated learning algorithms (ML) and the genetic algorithm which is part of the evolutionary algorithm group (EA) is the best to solve the problem of classification , especially in the case prefix content ICN , there were attempts to integrate the application of algorithms evolutionary with machine learning in the intelligence artificial and proven tests that were conducted in this area , which is trying to integrate techniques of EA And ML is useful in both the speed of convergence and the quality of the solution . One known modification of this approach was the classification learning system LCS, which has become a powerful tool among a host of applications.

Deep learning algorithm RL Include the search for the structure of the structure of the final after traffic in several stages of which science subject to supervision and unattended to reduce the minimum value of resources [19]. Genetic algorithm different from deep learning algorithm that it may reach the convergence of the final before prematurely because of the reliance great on the operations of the exchange and the boom, and that there is a problem with access to limit the optimal after access to the closest optimal solution, so we propose a hybrid genetic algorithm with an RL algorithm to classify a smart content prefix in ICN, we present the Pseudo Code in Figure (5):

1: Function GA-RL Discovery Component ()	16: **End For**
2: Initialize GA Population of Chromosome	17: // Perform Mutation
3: Initialize RL Temperature	18: **For** SubIteration = 1: MaxSubIteration
4: **For** each iteration	19: Perform Mutation
5: Set mutation and crossover	20: Evaluate Mutants
6: Evaluate the cost function	21: **End For**
7: Calculate priority vector by AHP	22: **End For**
8: **End For**	23: **End If**
9: **If** termination criteria are not achieved, **then**	24: Merge Offspring's in the Population
10: Select a pair of Chromosome for Mating	25: Sort New Population
11: **For** it = 1: MaxIteration	26: Compare New Population using RL Rule
12: // Perform Crossover	27: Update New Population
13: **For** SubIteration = 1: MaxSubIteration	28: Temperature Reduction
14: Perform Crossover	29: Update Best
15: Evaluate Offspring	30: Solution Found Store Best Cost

Figure 5: GA- RL Pseudo-cod.

The reasons underlying behind the choice of GA and RL are that they have proved efficiency and strength in search operations [20], which makes them suitable to solve the problems of optimization of large, on the reverse algorithms other. GA has strong global search capability while RL has strong local search capacity and no pre-existing problems, GA and RL hybrids can overcome the limits of both methods by considering their advantages and improving solution efficiency.

Hybridization is carried out by utilizing the rules of the RL algorithm to validate the results of the GA and to detect unacceptable mathematical results.

Figure 6 summarizes our proposal for intelligent adaptive classification technology that integrates previously assessed AI algorithms and adaptation to the classification learning system.

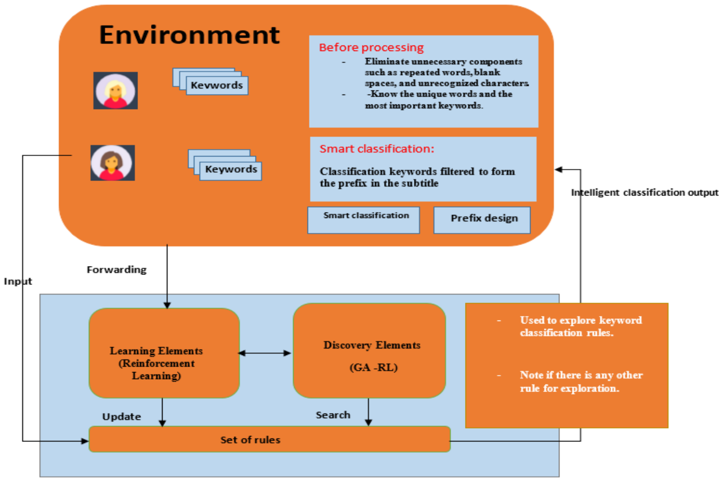

Figure 6: A suggest for intelligent classification using Hybrid RL and GA.

There are two main components to classification techniques which are the learning component and the discovery component. The learning component is characterized by the advantages of deep learning and monitors the environment and then chooses and performs procedures, if the appropriate procedure is adopted, and if it is not appropriate it is excluded. The discovery component is characterized by the advantages of the hybrid algorithm (GA- RL) ,process the development of solutions from through the introduction of continued efficiency that commensurate with the prediction of the exact solutions appropriate, then we evaluate the performance of a component discovery by using the algorithm genetic and comparing it with the approach proposed (GA- RL), Shows the figure (7) as a result of the performance of technical proposed.

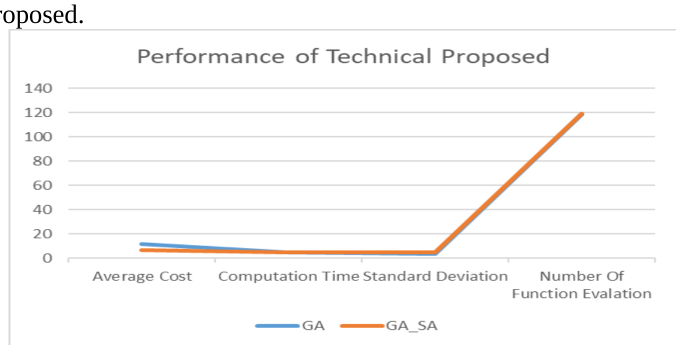

Figure 7: A smart classification proposal using RL with GA- RL Hybrid.

Based on them we conclude that the RL rules formed the merger in the new solutions phase of GA to increase the effectiveness of a component discovery for by integrating groups of solutions and thus choose to implement hybridization as the discovery of the technology classification smartphone proposed to classify keywords [21].

IX. PERFORMANCE EVALUATION AND DISCUSSION

Content and Forming it in attributes (the value of the content as the name of the content) the name prefix is ready to be sent to the ICN When you receive the package request, the router mediator examines the content you're doing and then scheduling tasks outstanding as is described in the ICN model guide.

To evaluate the benefits of classification methods,we simulate our suggestion of using NDNSIM [22]. A simulator common use of networks of data called NDN Platform for the ICN Within a frame NS3 Where the topology of the network used in this simulation is the topology tree of (5) layers as is shown in Figure (8).

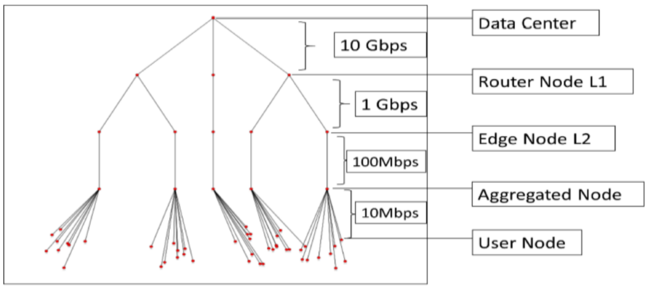

Figure 8: Network topology.

Suppose that the root node in the first layer acts as a data encoder connected to three routing nodes for the main content in the second layer , and in the third layer these basic nodes connect to five terminal nodes , which also relate to five aggregated nodes in the fourth layer , users in the same region connect to the aggregate node for each Of them , they send requests (interest packs) for the content they want on ICN , Given to that all contract - oriented is execute as a contract ICN (NDN Protocol) , We are two scenarios for communication data attention , for the simulation of the first : we implement request content by using the not classified prefix , but for the simulation of the second we apply the classified prefix by using our smart frame , in both cases each node contain on the three structures of data for (PIT, FIB, CS) With the same size as the content store CS Storage in memory storage temporary

We also assume that all content objects are the same size in each scenario. The implementation of simulations operations is done by using two of the rates and the arrival of attention to the different, in part I generate a contract user rate distribution of a fixed and uniform of 10 packets interest per second, the time of the simulation used in both cases is 100 seconds.

Simulation show that classified content prefix achive a decrease in the use of resources of the network, as is shown in Figure (9).

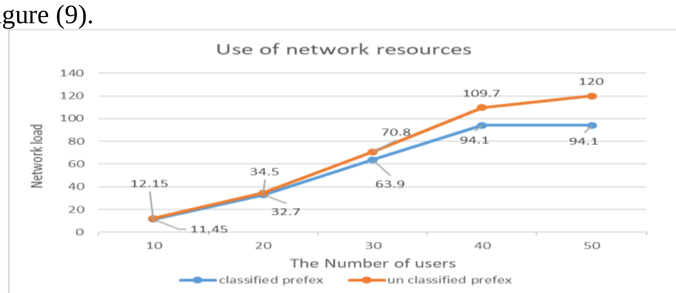

Figure 9: Using network resources.

As show simulation that prefix content classified checks a decrease in the loss of packets as it is shown in Figure (10).

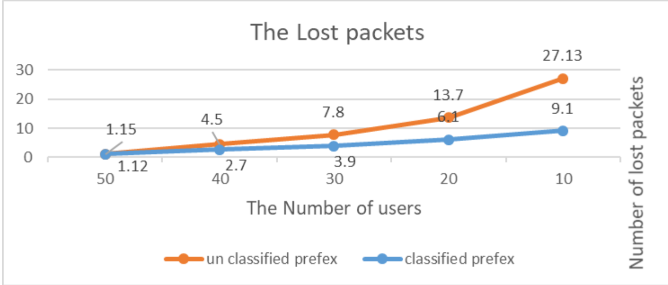

Figure 1 0: Packet Loss.

A similar trend is observed in Figs. 11 and 12 when a value is changed Zipf (Packet distribution rate).

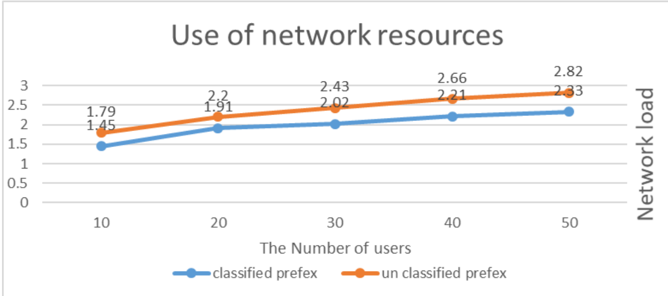

Figure 11: Use of network resources after a rate change Zipf.

Results show that the proposal achieves lower loss of packets as well as to decrease the use of resources of the network when you use the prefix content seed, especially after increasing the number of users, i.e. that our proposal Negotiable expansion as can be to achieve the benefit of the highest for the performance of the network when the network becomes larger with large amount of the users content.

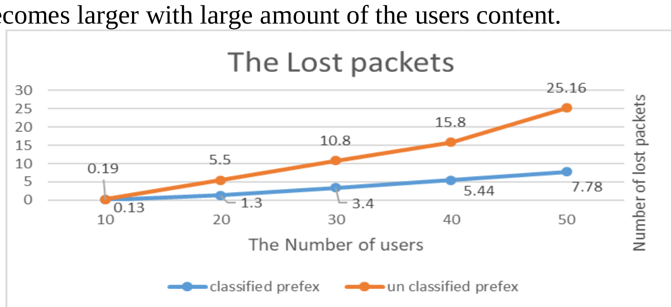

Figure 1 2: Packet Loss after rate change Zipf.

In general, the results show of the assessment that the method of classification can improve performance of quality of service of the terms of reducing the load network and the loss of packets efficiently and that because classified keywords share in helping to discover content with loads of low relatively to deal with the prefix name of the content. This improvement indicates that the proposal smart frame can identify and filter modules input core between the number of large of the users of given content .

X. CONCLUSION

There is no doubt that ICN will play a vital role in the communications transformation model in the near future where expected to increase the number of content elements are large.

In this research a new hybrid classification model based on artificial intelligence was proposed to achieve a smart classification technique , for this purpose we integrate a deep learning algorithm (RL)To enhance the genetic algorithm (GA) To become GA- RL It works as a component of the hybrid discovery model in the content prefix classification ICN To reduce the frequency likely convergence early , in addition to that we implement the GA- RL With a scheme based on deep learning by component learning to improve the performance of classification , the motivation behind this study is to conduct studies on the evaluation test of the performance of algorithms with relevant , which is based on the intelligence artificial in the context of ICN.

Evaluation results show that the proposed method using GA- RL The proposed achieve a lower score in the rate NFE The performance is higher than GA , i.e. that access them to the case of optimization faster with the efficiency of the highest , this shows on the proposed model to achieve a smart solution, as able to form keywords that introduced by the user PRECURSORS content and improves the performance of the system as a whole , especially to enhance the performance of QoS , in addition to that point arrays load network and the loss of packets to the prefix content classified proposed check values less compared to prefix content default used in ICN Traditional .

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