

A proposed learning model based on fog computing technology

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Abstract— These days, e-learning has become indispensable as it facilitates the learning process and enables the students to obtain educational resources faster. With the increase in the number of learners and the number of requests on the e-learning frameworks, the e-learning framework has become suffering from some shortcomings, which prompted to search for a model that could facilitate students' access to educational resources. Therefore, in this research, a model based on fog computing was proposed, in which the e-learning resources are closer to the end-users. A test of the proposed model was conducted on a sample of students to measure the response time. Result data are collected and analyzed. The response time resulting from the proposed model compared with that resulting from the current model based on cloud computing. It founded that the proposed model has advantages as the number of students is divided on the fog computing nodes, unlike what happens in the cloud-based model in which the students did not split in the required way, as dividing students reduces the response time of the learning framework.

Finally, using fog computing in a learning environment makes the learning resources closer to the end-user at the edge layer as described in the results of this paper.

Keywords: fog computing, fog nodes, latency, learning model, learning performance

I. INTRODUCTION

The Internet of Things (IoT) speeds up mindfulness and reaction to a lot of fields. It is changing entire ventures, including producing oil, gas, and nearby government [1-2]. So this exploration centers around utilizing IoT in learning frameworks to give a decent climate to the learning environment and learning resources. Nonetheless, the IoT requires another sort of framework. The cloud without a standalone provider can't provide an environment for learners over huge regions. Catching the force of the IoT requires an answer that can interface new sorts of shrewd gadgets to the educational organization, secure the sources that produce information, and secure the data as it goes from the organization's edge to the cloud [3].

As a few instructive foundations depend on the utilization of the Virtual Learning Environments (VLEs), primarily supported by the development in the

correspondence transmission capacity and the expanded accessibility of fog computing and IoT [4], they are ready to give an association anyplace and whenever. Subsequently, both customary and e-learning-based colleges are developing towards virtual and versatile learning (m-learning) structures.

This research presents a practical model design empowering time-productive investigation of learning system resources through a successful utilization of fog computing processing innovations and cloud computing joined with it. The model design actualized in a fundamental variant which gives a great outcome in the analysis for users utilizing distance learning framework [5].

Thus fog computing is gaining an increase in research and development momentums, but it stills in an early stage. And, according to [6] end-devices such as smartphones and WiFi access points which used for data analysis. However, they expected to take only simple time-sensitive data processing tasks. Less time-sensitive analysis and big data analytics that performed in the cloud layer [7].

The remainder of this article is organized as follows: Section2 shows the related works, Section3 describes the problem definition. Section4 describes the proposed approach and its architecture. Section5 discusses the study's findings. Finally, section6 shows the conclusion of the paper.

II. RELATED WORK

According to Pecori, R. (2018) [8]. The article presents an overview of distance learning environments and their limitations, as well as the explanation of the main ideas behind the paradigms of cloud computing and fog computing, to introduce an e-learning model integrating both of them. Such an action aims to enhance the ability of the virtual learning environment to meet the demands of all the users in an educational scenario, as explained by a preliminary implementation of the mentioned architecture. The main unresolved issues The cloud solution need a simple solution rather than the complicated one, even if more simple and lightweight and always closer to the end-user, as they cannot be

instantaneous and the uncertain degree of savings in operational costs, in case student's devices, are not usable or compatible.

Another paper B. Ottenwalder et al. [9] The article presents a placement and movement method for Cloud and Fog resources suppliers. It ensures application-defined end-to-end latency restrictions and reduces network utilization by planning the migration in the future. They also show how the application knowledge of the events processing system can be used to decrease the required bandwidth of fog nodes during their movement. Network-intensive agents are placed on distributed fog nodes, while computationally intensive agents are in the cloud model. Finally, this offers an overview of the possible benefits of a model based on fog computing techniques applied to learning systems and benefits that could be obtained from using fog computing in the learning field.

III. PROBLEM DEFINITION

In Learning Management System (LMS) environments, the presentation and proficiency occur to give a great of the learning climate [10]. The LMS that depend on cloud computing frameworks could be suitable and utilized for getting to learning resources. The cloud computing frameworks still required a significant expense to handle a large number of requests. If this large number of clients access it simultaneously will cause high traffic and leads to service failure. So that, the learning model needs to be enhanced and avoid the latency of services which affects the learning process [11]. There are some cons when using cloud architecture (as a stand-alone service) described as follows:

A. *Reliable connection required for cloud based:*

To get the benefits of cloud hosting, reliable internet connection and device(s) must exist that are required to make sense. If the internet connection goes down, the learner will not access the learning environment [12]. Thus, organizations that lack a reliable connection may want to use another LMS solution.

B. *Cost fluctuation and localization:*

From the finance perspective, a cloud-based LMS indeed avoids the potentially high costs of installation, set up, and staff training [13-15]. So that, it is not recommended to install more than one cloud hosting service. As the cloud services are centralized and that makes the data sources far away from some users. So, it is preferred to use fog nodes to avoid latency or delay in response time.

C. *Services provider issues:*

The idea to consider when moving to cloud computing is the LMS providers themselves. In the fact that cloud architecture e-learning relies on the quality of host platforms, their members, and their servers.

Another issue that affects the learning environment is the size of data of the learning resources that could be a large size which will affect the performance of the learning process as well [16].

IV. PROPOSED APPROACH

Normally, the users of learning system access the learning environment to get data or send data. So, with a huge number of users the system performance is affected and this will lead to latency in the services.

This paper introduces a model based on fog computing to improve the learning framework performance and decrease response time for users requests. Fog computing has emerged to enhance the performance and avoid the latency of the learning process that needs to be more efficient with the increase of the number of learners.

The fog computing applied in several applications like the smart electrical grid, Smart transportation networks, and Linked vehicles has encouraged to use it in the learning field as it may serve to enhance the learning environments and improve its performance. The fog computing models include everything you need to do this like:

- Connect any kind of IoT devices.
- Secure the IoT devices and protect the produced data.
- Quickly develop and deploy fog applications.
- Direct data to the best place for analysis: fog nodes or the data center cloud platform. The request depends on how time-sensitive the request is as well as data privacy state.
- Automate operational and management of large numbers of fog nodes spread out over large locations.

For instance, suppose that there are n^{th} of users connected to cloud service which contains the learning framework. The n^{th} number of users will be divided over the fog nodes according to the location of each user when using the proposed model while this did not happen when using the cloud service.

To illustrate the work of the proposed model let's take an example. Suppose that there are 1500 learners who need to access the learning environment and it is already available on the cloud data center. So, when the 1500

learners are connected to the cloud it will take a long time to serve this number of users which delays the learning process. In the proposed model, the sample is divided into small parts that each part will connect to the nearest fog node. The fog nodes by nature are decentralized. So, it will handle the requests and resend the data later on to the cloud data center.

Table 1 shows the sample consists of 1500 users and how it is distributed on the cloud model and the proposed model as follow:

TABLE 1: SHOWS THE SAMPLE USED IN THE EXPERIMENTS.

# of Connection	Cloud Model	Proposed Model
1500 users	1500 connected	1500 Available fog nodes

From the previous example, the connection of 1500 users on the cloud model will take more time than the connection on the proposed model. The proposed model receives less number of requests based on the fog nodes location. So, it leads to improving the learning environment.

A. Proposed Architectural Design

This section describes the design approach of the proposed model in a general view. The proposed model is consists of three layers. The cloud layer, the fog layer, and the edge layer. The figure below shows the layers for the proposed model:

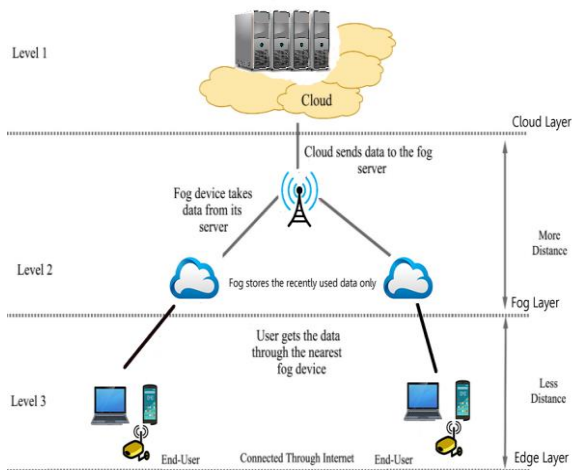


Figure 1: Architecture Design for proposed model

To demonstrate the model in more detail. Let's see it from different types of views as follow.

B. Layered view:

Figure 1 shows the layered view of the proposed model. This type of view helps to understand the components of the approach defined in the proposed model. Each layer has a task to do as follow:

- *Cloud Layer*: This layer is responsible for storing the complete set of records, the proprietary data application information, and the records of authorization, and the main data resources.
- *Fog Layer*: This layer is responsible for providing compute, storage, and application services closer to edge devices producing the data.
- *Edge Layer*: This is the layer at which the end-users can access the learning resources from their devices.

C. Architecture's layer decomposition view [17]:

To understand how the proposed model work, it must be decomposed into small parts. In this section, the layers of the proposed model will be described in detail, as each layer has its job during the data processing.

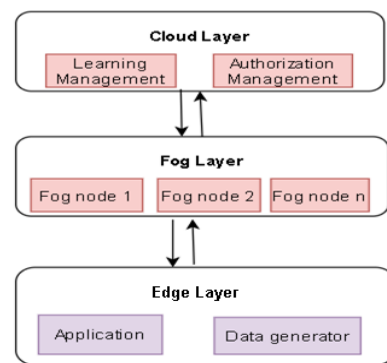


Figure 2: Architecture's layer decomposition view

Figure 2 shows the components of each layer that can be as follow:

- The *Cloud Layer*: This layer is composed of two modules, the *learning management module* and the *authorization management module*. The first one is a software component responsible for storing the entire set of learner information in JSON format in a relational database and responsible for receiving new data from the *fog layer* and making access to the data available at any time.

The *authorization management module* is a software component responsible for validating and authenticating a user who uses the system and validates it in the fog nodes.

- The *fog layer*: this layer composes of a set of components called fog nodes. The Fog nodes may be either physical or virtual elements and tightly coupled with the smart end-devices or access networks. Fog nodes provide some types of data management and communication service between the model layer where smart end-devices reside and the Cloud model.

- The *Edge Layer*: this layer composes of two modules. The first module is the application module, which is a

software component that allows end-users to deal with learning resources, and the second module is the data generator module, which is a software component that receives the raw data and converts it to JSON format then sends it to the Fog Layer.

The fog layer is composed of multi parts. Each part is called a fog node. Each fog node is consists of modules. The decomposition of the fog node is demonstrated in figure 3 as follow:

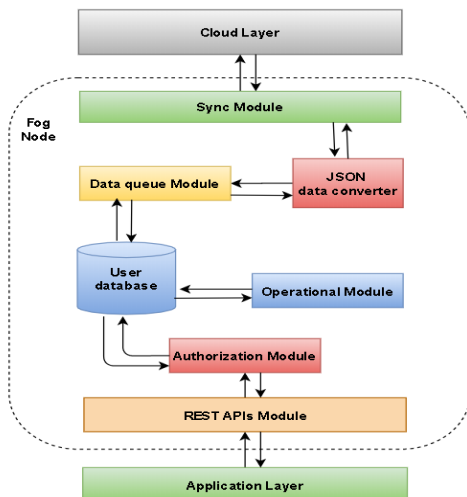


Figure 3: Decomposition of a fog node

Each fog node consists of modules. Each module has a job to do as follow:

1. REST APIs module: is a software component responsible for communication with (IoT) devices connected to the *fog node*. This module provides a REST interface for exchanging learning objects with the edge layer.
2. The authorization module is a software component responsible for authorizing and authenticating the learner's information. And it validates the authorizations for the end-users and gateway to manipulate learning system resources.
3. Operational module: is a software component responsible for managing a subset of the learner's record data and store it in a relational database.
4. Data Queue module: is a software component responsible for organizing data objects in the *fog node* to replicate them on the cloud layer.
5. JSON module: is a software component that manages information related to the data stored in the *fog node* as an object of the JSON format. This information is used to decide which data should be released first from Fog Layer, and which should be stay.

6. Synchronization module: is a software component responsible for synchronizing the data stored in the fog layer with the data stored in the cloud layer. It is also responsible for updating the edge layer data.

D. Repositories View:

This view for the proposed model display one or more components called repositories. Each one contains extensive collections of fog nodes shown in figure 4. This view gives an imagination of using a collection of fog nodes to serve in the learning environment.

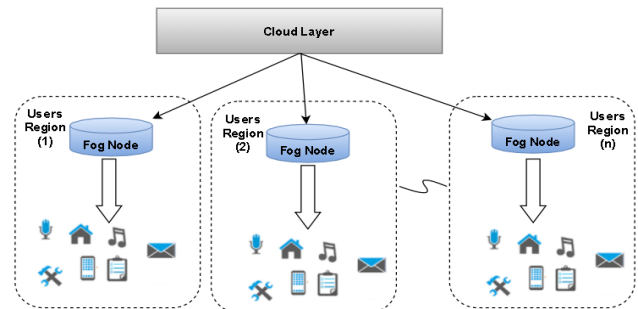


Figure 4: Architecture's repositories view

In figure 4, the architecture's repositories view on multi-fog nodes connected to the end-users according to their geographical location. The fog nodes are distributed over a wide area of regions to provide learning resources to the end-users at the edge.

V. RESULTS:

The results of this paper are from experiments done on fog nodes and cloud based services. The algorithm used to do this experiment is:

Algorithm 1 users distribution over fog nodes

```

1: Function distribute_Users()
2:   Input: geo-location database.
3:   // Define locations arrays
4:   // Fog nodes locations
5:   Let FogLocs[FnLoc1,FnLoc2,FnLoc3
6:   // Users Locations
7:   Let UsersLocs[Loc1,Loc2,...,Loc1500]
8:   // Results of the distributions
9:   Let Results[BF[1][], BF[2][], BF[3][]]
10:
11:  // Loop to find nearest node and assign user to it
12:  For Loc in UsersLocs
13:    Let Distances[]
14:    For FnLoc in FogLocs
15:      // get distance by location latitude and longitude
16:      Distances[FnLoc] = FnLoc - Loc
17:    End for
18:    // find minimum value
19:    locVal = getMinVal(Distances)
20:    // find key of minimum value to assign it
21:    locKey = getMinKey(Distances)
22:    Results[locKey][locVal]
23:  End for
24:  // Loop on users requests for each node
25:  For node in Results
26:    For url in node

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27:     ResponseTime = makeUrlRequest(url)
28:     Saveinfile(ResponseTime)
29:     End for
30: End for
31: Output: Graph for the response time
32: End function

```

The fog nodes used in the experiments are not virtual machines. The fog nodes are decentralized and serve users according to their locations. The previous algorithm shows how the requests (users) split into small requests and spread over the fog nodes.

The experiment is consists of two samples. The first sample comprises 500 learners. The second sample consists of 1500 learners, which connected to the proposed model according to the algorithm described above.

In the first sample, the learners make requests on the cloud model then the responses time is recorded. On the other hand, the learners make requests on the proposed model, and the responses time is recorded. In a close look at this experiment, the 500 learners are connected to the cloud directly while the same number are connected to the proposed model but divided based on users' location as explained in the algorithm.

The results from both tests are plotted in figure 5 as response time in the y-axis and elapsed time in the x-axis as follows:

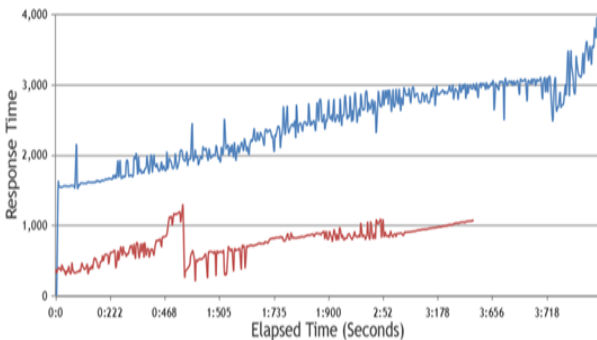


Figure 5: Latency time for 500 learners

The red curve represents the proposed model and, the blue one represents the cloud model. The data transactions between the proposed model and the existing model have been computed. After the data was processed, the results were projected in the figure, and the standard deviation and mean were noted as follows:

TABLE 2: STATISTICAL DATA FOR PROPOSED MODEL AND EXISTING MODEL SAMPLE OF 500 LEARNERS

Model	Proposed	Existing
Mean	476.4	2718.16
Variance	72427	240926
S. deviation	269.12	490.84

In table 2, comparison done between the existing model and the proposed model, it becomes clear from the results above that the current model suffers from slow communication and response time while the proposed model gives high performance than the current model. So, this leads to that the proposed model improves the performance of the learning system. The proposed model used in the experiment is consists of three fog nodes which represented in figure 6:

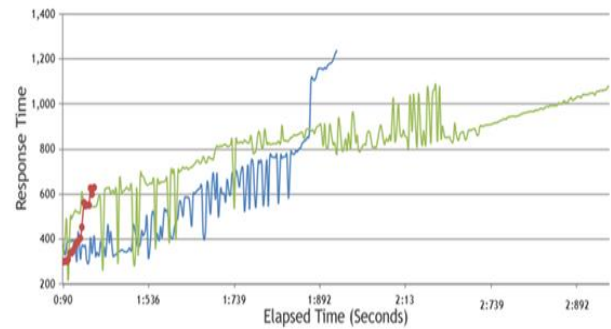


Figure 6: Proposed model latency time for 500 learners

Although, from the results of fog nodes the statistical data like mean, variance and, standard deviation noted in table 3, as follow:

TABLE 3: STATISTICAL DATA FOR PROPOSED MODEL ONLY SAMPLE OF 500 LEARNERS.

Nodes	Fog 1	Fog 2	Fog 3
Mean	596.03	435.58	816.41
Variance	59155	14658	27732
S. deviation	243.22	121.07	166.53

The loading of 500 learn shown in the previous experiment is not enough to check out the response time of the proposed model. So that, more load on the proposed system conducted with the following sample that compromised of 1500 learners connected to both models at the same time. The results obtained from the cloud model and from the proposed model are plotted below:

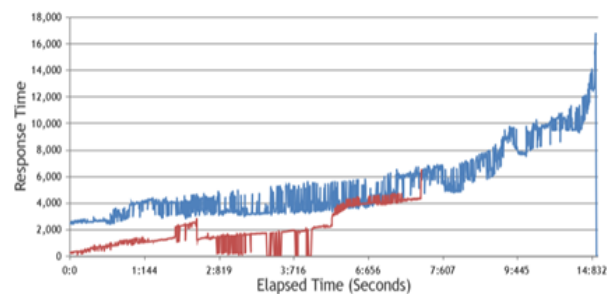


Figure 7: Latency time for 1500 learners

In the previous figure, the cloud model represented by the blue line taking a lot of response time to serve the second sample, while the proposed model represented by the red color did not take the same time to serve the same number of learners. The statistical data for the experiment like mean, variance, and standard deviation are in table 4.

TABLE 4: STATISTICAL DATA FOR PROPOSED MODEL AND EXISTING MODEL SAMPLE OF 1500 LEARNERS.

Model	Proposed	Existing
Mean	1965.94	5307.9
Variance	1847903	6461091
S. deviation	1359.38	2541.87

The response time for the proposed model alone is plotted in figure 8, as the proposed model also consists of three fog nodes. Each node serves the local learners according to geographical location as stated before:

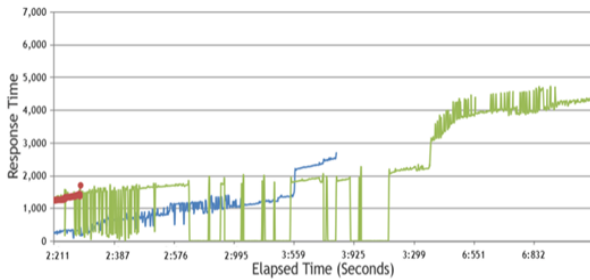


Figure 8: Proposed model latency time for 1500 learners

The statistical data for the fog nodes in the proposed model like mean, variance, and standard deviation for the previous experiment noted in table 5.

TABLE 5: STATISTICAL DATA FOR PROPOSED MODEL AND EXISTING MODEL SAMPLE OF 1500 LEARNERS.

Nodes	Fog 1	Fog 2	Fog 3
Mean	1081	1330.6	1925.22
Variance	38890	6424	2534500
S. deviation	623	80.15	1592.01

From the above results for both experiments, it becomes clear that the proposed model in the learning environment can make a difference in this field when comparing the results between the cloud model and the proposed model. The learners will be divided based on their location into small blocks rather than all are connected to the cloud data center directly.

VI. CONCLUSION

This paper describes a model designed to enhance the management of learning system resources and avoid delay and latency. The proposed model is based on the Fog Computing paradigm, providing the availability and performance processing by allowing the service for the end-users depending on their geo-location. And emerging the internet of things (IoT) and fog computing with cloud computing architecture in the learning field will provide a good environment for learning system.

In this paper, the proposed model consists of three layers. The first layer is the cloud layer that contains a learning management module and an authorization module, and the second layer is the fog layer that consists of fog nodes each node has a set of modules. And the last

layer is the application layer which represents the end-users and smart devices connected to the model.

The decentralization of fog computing gives the proposed model high ability to avoid latency and connection failure that can occur on a large number of smart devices connected to the educational environment.

As shown in the experiments done on the proposed model the learners are divided based on their location and the huge bulk of learners split into small parts that connect to the nearest fog node. This will serve to increase the performance of the learning environment instead of using cloud data center directly with the bulk of learners as shown in the results section.

Finally, the scalability of the proposed model makes it open for future improvements and further research to make a leading model for automated learning systems.

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