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THE OPTIMIZATION OF COMPUTE RESOURCES SCHEDULING IN CLOUD COMPUTING ENVIRONMENTS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Compute resources scheduling is an essential aspect of any computing paradigm and it becomes a decisive feature for cloud computing model given the new service delivery model proposed by this innovative computing technology. To the extent of our knowledge, one of the most used scheduling algorithms, up to this moment, is Round Robin scheduling considering its time-shared design, which assigns a time slice (time quantum) to each task or job scheduled for execution on the Core Processing Unit (CPU). Mostly, all computer platforms using Round Robin scheduling, comprised the ones used on Cloud Computing environments, adopts a fixed value for time quantum that usually causes processor thrashing. In this paper, a new compute resources scheduling algorithm is proposed, in which it uses the Round Robin time-shared design with a dynamic time quantum extracted from scheduled tasks characteristics. Moreover, Artificial Neural Networks capabilities of prediction and classification are used in order to automatically select the finest time quantum calculation method that would optimize the average waiting and turnaround time of the compute resources scheduler intended for cloud computing environments. Additionally, a comparison of the proposed algorithm with the First Come First Served and the simple Round Robin algorithms is discussed in order to highlight the significance of our proposed method.

Keywords: *Cloud Computing, Task Scheduling, Neural Networks, Multilayer Perceptron, Round Robin*

1. INTRODUCTION

Scheduling in computer science is the correct allocation of computer resources to the correct job or task that request it, where Compute resources scheduling is the procedure used by computer platforms in order to execute a set of tasks or jobs, taking into account the availability of resources. Until now, almost every computer platform (Operating systems, Hypervisors, Middleware, Provisioning platforms…) are still using scheduling algorithms that were designed on the past decades with some minor adjustments [1]. Nevertheless, every particular scheduling algorithm can give significant or insignificant results under specific conditions, because of the unknown nature, amount and complexity of tasks or jobs submitted to the scheduler.

Many researchers discussed the optimization of the existing scheduling algorithms from a general perspective that aims to accelerate the scheduler response time. Round Robin algorithm is no exception; this algorithm has drawn attention of many researchers, namely because of its time-shared design, where the most important aspect is the time quantum computation. For example, N. Srilatha et al [2] proposed a Round Robin algorithm using Manhattan distance as a calculation method for the time quantum value. The time quantum computation is done by calculating the difference between the highest burst time and lowest burst time of tasks or jobs on the ready queue. Similarly, Y. Berhano et al [3] manipulated the time quantum in order to be equal to the first task or job burst time on the ready queue, where tasks or jobs are arranged on ascending order of their remaining burst time. Compute resources is allocated to the first task from the ready queue for one-time quantum. After completion of currently running task, the remaining burst time is checked, if it is less than one-time quantum, CPU is allocated again to the same task for the remaining burst time. Equivalently, A. Abdulrazaq et al [4] proposed a

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Round Robin based algorithm which calculates a dynamic time quantum based on the average burst time of tasks on a queue list and then allocates the time quantum to every task on the queue. The algorithm introduces a test to verify if the time quantum was enough for task termination and reallocate the necessary time to complete the task execution in the opposite case. In the same context, several other investigators explored the enhancement of Round Robin algorithm by manipulating the calculation method of time quantum. However, all of these optimized algorithms founded their effort on changing the value of the time quantum to a dynamic value that changes every time the ready queue changes using only one calculation method. Nevertheless, the most important characteristic that needs to be tackled with recent Information Technology (IT) shift (Cloud Computing, Big Data, IoT…) is intelligence, and that is by incorporating several calculation methods that suits various conditions and technologies.

The originality introduced here is the improvement of the Round Robin algorithm by the employment of the dynamic time quantum calculation perceptive method, proposed by several researchers and academics, combined with Artificial Neural Networks that has strong classification and predication capabilities that can help diversify the time quantum calculation method taking into consideration the changes occurring on the processor tasks ready queue and the Cloud Computing requirements.

This paper is organized as follows: Section 2 introduces Cloud Computing and the existing scheduling algorithms. Section 3 describes the Round Robin algorithm and its importance. Section 4 presents Artificial neural networks and their abilities to better solve the scheduling problematic for cloud computing. Section 5 defines the proposed algorithm and its functioning mechanism. Section 6 is an overview of the evaluation metrics, environments and experimentation used to assess the proposed algorithm. Section 7 demonstrates results, comparison and analysis of the experimentation defined on section 6.

2. CLOUD COMPUTING AND SCHEDULING ALGORITHMS

Cloud Computing model consists of a new service delivery model that aims to supply diverse services on-demand over the internet. These services can be paid for specific time periods or by subscriptions. This new service delivery exhibits a lot of advantages, particularly in the infrastructures costs reduction side.

While most of cloud providers are investing more and more on their infrastructures in order to respond to the growing demand of this new computing model, few of them are taking action into the optimization of their existing infrastructures.

One of the major factors that affects cloud computing response is the compute resources scheduling that is mostly orchestrated by the operating systems used as a platform to host different services. Despite the fact that most of the existing platforms are still giving remarkable results using old compute resources scheduling algorithms, they still lack the required intelligence for this innovative computing model that is growing every year in term of users and services.

The most significant scheduling algorithms used up to this moment are:

- First Come First Served: as stated by its name, this algorithm executes tasks/jobs on the same order they came in to the Core Processing Unit (CPU) queue.
- Round Robin: This algorithm uses a time fraction called “quantum” to be allotted to each task/job that was submitted for execution. Once this time fraction is elapsed the CPU switches to the next task/job and the first one is sent to the waiting queue. This procedure is repeated until all the tasks/jobs are executed.
- Priority scheduling: The logic of this algorithm resembles to the First Come First Served algorithm, but in this case, tasks/jobs are assigned a priority, and task with the higher priority is the one to be executed first.
- Min-Max and Max-Min: The purpose of this algorithms is to select the task/job that needs to be executed first (the smallest in case of Min-Max and the largest in case of Max-Min).
- Genetics: This algorithm simulate the human genetics process in order to execute the submitted tasks/jobs. It starts with a population of random individuals

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(tasks/jobs), each corresponding to a particular candidate solution to the problem. Then, the best individuals survive, mate, and create offspring, originating a new population of individuals. In the scheduler, the best candidates are the ones that produces the best response time.

3. ROUND ROBIN SCHEDULING ALGORITHM

Round Robin scheduling algorithm [2] enables the Core Processing Unit (CPU) scheduler to go around the ready queue allocating the CPU to each task for a time interval of up to one-time quantum (time portion). The time quantum is a fundamental characteristic of Round Robin algorithm, where its value is generally a constant calculated from the CPU frequency and explained in Million Instructions Per Second (MIPS). If the time quantum is too large, the response time of the processes is too considerable, which may not be tolerated in interactive environments such as Cloud Computing. If the time quantum is too small, it causes unnecessarily frequent context switch leading to more overheads resulting in less throughput and long waiting time.

4. MACHINE LEARNING AND ARTIFICIAL NEURAL NETWORKS

4.1 Machine learning:

Machine learning is a field of "Artificial Intelligence", that tackles modeling of procedures in the aim of making machines (computer devices) more intelligent and capable of making strategic decisions.

Generally, in machine learning there are three learning algorithms types, which are "supervised", "unsupervised" [5] and reinforcement learning [5], used to train several models in order to resolve various sorts of issues e.g. "pattern recognition, classification, regression, clustering, etc.".

The supervised learning [7] is a task of interpreting a function from labeled training data sets which is composed of several training instances. More specifically, the supervised learning algorithm analyzes the training data and produces an interpreted function, which can be used to map new instances, wherein two techniques "Classification and regression [8]" are used to train the models.

Classification technique is a systematic approach to building classification models for training and testing data sets. In the same context, there are several classification models such as decision tree, logistic regression, neural networks [1], and others. Classification divides data samples into target classes/labels; then, it can predict the target class for each data point. By cons, the regression consists on generating a model capable of predicting continuous valued outputs.

4.2 Artificial neural networks:

The concept of artificial neural networks is inspired from the subject of biology [9], where the neural network plays the main role in a human body; where those interconnected neurons can granite all the parallel processing.

The basic element of this network is the neuron, which is a special biological cell that process information from one neuron to another neuron with the help of some electrical and chemical changes. It is composed of a cell body and two types of outreaching tree like branches: the axon and the dendrites (Figure 1); the cell body has a nucleus that contains information about genetic traits and plasma that holds the molecular equipment's or producing material needed by the neurons [10].

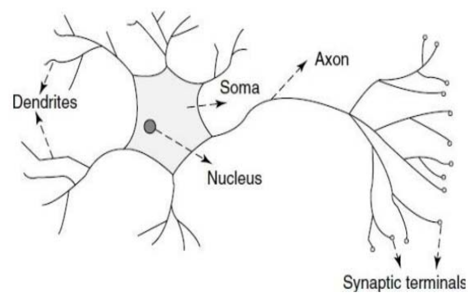

Figure 1. Human neurons.

Therefore, the artificial neuron is basically an engineering approach of biological neuron. It has a device with many inputs and one output (Figure 2).

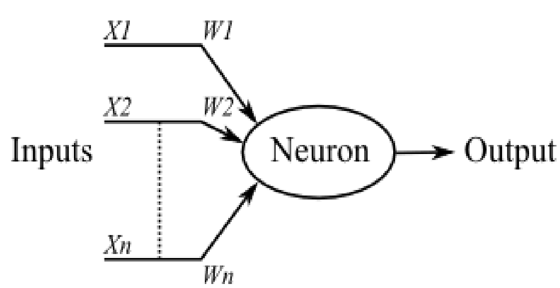

Figure 2. Artificial neuron.

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The structure of the interconnected artificial neurons called multilayered artificial neural network (Figure 3).

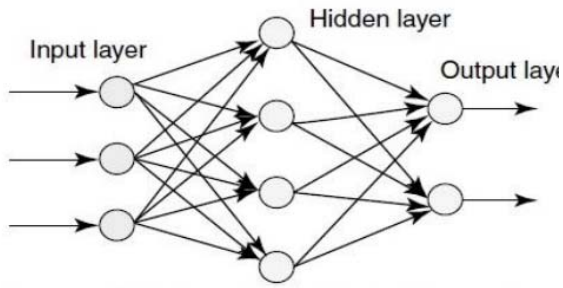

Figure 3. Multilayered artificial neural network.

The Artificial Neural Network characteristics are basic and important for this technology:

- Network Structures
- Parallel Processing
- Fault Tolerance
- Distributed Memory
- Parallel Processing
- Collective Solution
- Learning Ability

Among the neural networks categories that can be used for classification task, there is the Multilayer Perceptron (MLP) [11]; MLP is a class of feedforward artificial neural networks. An MLP consists of at least three layers of nodes. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training, that has proven its capacity on resolving CPU scheduling following our recent research [1] and will be evaluated on the upcoming sections.

Each neuron from the multi-layer Perceptron has an activation function, in most cases a sigmoid [12] function, which is a mathematical function having a characteristic "S", shaped curve or sigmoid curve. Frequently, sigmoid function refers to the logistic function special case shown on the fourth figure and defined by the formula:

$$S(x) = \frac{1}{1+e^{-x}} = \frac{e^{x}}{e^{x}+1}$$

Finally, the Backpropagation is an abbreviation of backward propagation of error algorithm [13] that was originally introduced in 1970s. It is a method of training artificial neural networks based on the gradient descent [14]. This method calculates the gradient of a loss function with respect to all the weights in the current network.

5. THE PROPOSED SCHEDULING ALGORITHM FOR CLOUD COMPUTING

The proposed scheduling algorithm design uses the Round Robin time-shared logic in the aim of creating an interactive algorithm mostly suited for Cloud Computing environments. While the entire existing Round Robin scheduling algorithms used on most computer platforms are using a static/constant time quantum for compute resources allocation, the proposed scheduling algorithm introduces a new concept of dynamic time quantum that was discussed in various occasions, however, it was never considered as a solution for Cloud Computing platforms.

The time quantum calculation methodology in the proposed algorithm exploits the list of tasks submitted for execution in the pursuance of calculating the best time quantum that would reduce the average response time, the average waiting time and the context switches. Although the nature of submitted tasks is hard to identify, several calculation methods exists for time quantum extraction, where each calculation method has proven its validity under specific circumstances. It is at this point, where the Artificial Neural Networks steps in to classify the calculation methods and predicts the best one for each presented situation. To the extent of our knowledge, the following are the foremost used calculation methods for improved Round Robin algorithms [15]:

- Tasks burst time average of tasks on the “Ready Queue”.
- (The average of tasks burst time + Burst Time of task with highest burst time) / 2.
- The square root of the task with highest burst time + the average burst time of all tasks.
- The burst time median of tasks on the “Ready Queue”.
- (The median of tasks burst time + Burst Time of task with highest burst time) / 2.
- The square root of the task with highest burst time + the median of all tasks.
- The burst time of the task with real time priority. (If there are more than one then calculate the average, if there isn’t, then calculate the burst time average of all tasks)
- The burst time of the task with lowest Burst Time on the ready queue.
- Tasks Amount / (∑ 1 / Task Burst time)
- (Task with highest burst time + Task with smallest burst time) / 2

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- Ceil of ((Square root ((mean * task with highest burst time) + (median * task with smallest burst time)))/2)
- Ceil of ((Square root ((median * task with highest burst time) + (mean * task with smallest burst time)))/2)

Here is an illustration of the proposed scheduling algorithm:

First, all the processes are sorted on descending manner based on their priority (1 to 6), If there are more than one task with the same priority, then sort them on ascending manner based on their burst Time,

1. nt → number of tasks
2. sbt → sum of all tasks burst time
3. spt → sum of all tasks priorities
4. Normalize(nt, sbt, spt) using Max-Min Normalization method.

Second, Load the Artificial Neural Networks training model and predict the accurate time quantum calculation method,

// i: Method position

5. Get(i) → the Artificial Neural Networks predicted classification of the case

// TQ: time quantum

6. TQ → CalculationMethod(i)

Third, Assign the time quantum to each submitted task,

7. For j=1 to nt
   BT [j] = BT [j] – TQ
   If BT[j] = 0
      Send task to finish list
   Else
      Send task to waiting list

Fourth, Get the tasks on the waiting list and send them to Ready list and dynamically recalculate the TQ for tasks on the new list,

8. Go back to step 5.
9. Continue until all tasks are finished

6. THE PROPOSED SCHEDULING ALGORITHM EVALUATION

The proposed scheduling algorithm evaluation consists of a set of experiments that were tested and implemented on CloudSim simulation toolkit and compared to the existing algorithms, which are the simple Round Robin (RR) and First Come First Served (FCFS). The artificial neural networks implementation was managed by "NEUROPH" which is a java open source framework.

6.1. Simulation Environment and Assumptions

The simulation environment consists of CloudSim, which is a java based, generalized, and extensible simulation framework that allows seamless modeling, simulation, and experimentation of emerging Cloud computing infrastructures and application services [16].

CloudSIM simulator uses Million Instructions Per Second (MIPS) to determine the processor speed or performance [17]:

$$MIPS = \frac{Processor\ Clock\ Frequency\ (MCLK)}{Average\ Cycles\ Per\ Instruction\ (CPI) \times 1\ 000\ 000}$$

$$= \frac{\frac{Cycles}{Second}}{\frac{Cycles}{Insctruction} \times 1\ 000\ 000} = \frac{Million\ Instructions}{Second}$$

The first experiment executed on the proposed scheduling algorithm considered the following assumptions:

- 1 datacenter with one host,
- The host physical configuration is:
  - o 1 processor with the capacity of 2000 MIPS,
  - o 2048 MB of RAM (Random Access Memory),
  - o 100 GB of storage.
- One testing Virtual Machine was created on the host with the following configuration:
  - o 1 processor with the capacity of 1000 MIPS,
  - o 1024 MB of RAM (Random Access Memory),
  - o 10 GB of storage.

These configurations were considered in the aim of testing the algorithm performance at first, in which if proven would be correct in any form of platforms (Uniprocessor or Multiprocessor with different MIPS capacities).

The second experiment carried on the proposed algorithm considered the following model to create a cloud like environment:

- 1 datacenter with 100 hosts,
- The host physical configuration is:
  - o 16 processors with the capacity of 96900 MIPS (The equivalent of an Intel E7-x870 processor according to Cisco Industry Benchmarks Performance [18]),
  - o 65 536 MB of RAM (Random Access Memory),
  - o 1 TB of storage.

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- 200 testing Virtual Machines were created on the different hosts:
  - 8 processors with the capacity of 96900 MIPS,
  - 16 384 MB of RAM (Random Access Memory),
  - 10 GB of storage.

This second experimentation aims to evaluate the proposed algorithm performance on a Cloud Computing like environment and its contribution for large scale infrastructures.

6.2. Artificial Neural Networks Implementation

As discussed on section "5", the multilayer perceptron algorithm will be used in combination with Round Robin in order to classify and predict the best calculation method that suits various conditions. The implementation was done through the "NEUROPH" framework, which is a set of open source java libraries completely embeddable with any type of integrated development environments.

The multi-layer perceptron settings used for the proposed algorithm evaluations are the following (Table 1):

Table 1. The ANN settings.

ANN Type	Feed Forward
Learning algorithm	Backpropagation
Input Layer	3 nodes
Hidden layer	6 nodes
Output Layer	12 nodes
Learning rate	0.2
Learning error	0.01
Max Iteration	10 000
Activation function	Sigmoid

The proposed multilayer perceptron architecture is detailed on figure 4.

6.3. Data Generation and ANN Training

The proposed artificial neural network was trained on data generated from ten thousands of simulations that consists of numerous tasks ranging from 1 to 300, with random burst time (from 1 to 1000 seconds) and priority (1 to 6).

The simulations were automated and scored in order to create an operational data for the proposed artificial neural network algorithm training, which comprises the task amount, task burst time summation, task priority summation and the best-scored method. Afterwards, Max-Min normalization has been used on the generated data in order to provide the multilayer perceptron algorithm with expressive information for classification:

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

6.4. Evaluation Metrics

The evaluation metrics that will be used to assess the proposed algorithm are the following:

- **Average Turnaround Time:** The average time amount necessary to carry out the execution of tasks:

$$ATT = \frac{\sum_i^n FTi}{n}$$

  - FTi: Task finish time
  - n: Tasks Amount
- **Average Waiting Time:** The average time amount spent by tasks on the waiting queue:

$$AWT = \frac{\sum_i^n (FTi - BTi)}{n}$$

  - FTi: Task finish time
  - BTi: Task Burst time
  - n: Tasks Amount
- **Number of Context Switches:** The number of switches from one task to another on the ready queue, this metric can be decisive in order to calculate the processor lifetime.

7. RESULTS AND ANALYSIS

In this section, the proposed neural network algorithm was used to predict the optimal time quantum calculation method that gives minimum turnaround time, waiting time and context switches. Accordingly, the proposed algorithm was tested offline with several sets of random inputs and following are the findings:

7.1. The first experiment:

Figure 5 represents the performance of the proposed algorithm in regards to the average waiting time. The proposed algorithm proved a remarkable output in regards to the simple Round Robin algorithm which produced longer waiting periods associated with the usage of a constant time quantum, which is in general considered as one processor cycle (one MIPS in CloudSim giving the assumptions used in section "6.1."). On the other hand, the First Come First Served algorithm showed a poor performance in contrast with the proposed algorithm that proved its value and gave good performances in all presented cases that can be seen on Figure 5. In the same context, First Come First Served algorithm caused shorter tasks to wait for longer tasks before getting the chance to get the processor, hence longer periods of waiting.

Figure 6 illustrates the efficiency of the proposed algorithm relevant to the average turnaround time that demonstrates the algorithm task processing celerity. The Round Robin algorithm showed deprived performances because of the minor quantum given to each task, consequently, once presented with heavy tasks the algorithm lost a lot of time switching from task to task and produced lateness in term of response. The First Come First Served algorithm can be very notable when the tasks are organized on ascending way (The case of Shorter Job First). However, once a time-consuming task get on the head of the list all the other task will have to wait for the first one to finish, therefore the response time can be very poor and this is how the proposed algorithm demonstrated its significance and surpassed the FCFS algorithm.

Figure 7 is an evaluation of the context switches used to compare the proposed algorithm and the existing most used algorithms until now. The proposed algorithm confirmed its prominence compared to the Round Robin algorithm, which surpasses a thousand context switches even for small amount of tasks, which on most cases causes the processor thrashing. Furthermore, the proposed algorithm gave an approximate number of context switches to the First Come First Served algorithm that ranks the best on this last evaluation.

7.2. The Second experiment:

Figure 8 shows the proposed algorithm performance in regards to the average waiting time of tasks/processes in a cloud like environment. On the one hand RR and FCFS displayed a good output when presented with small amount of tasks, however, both algorithms became deficient when the task amount climbed to higher extents which is the case for cloud computing model. On the other hand, the proposed algorithm had a steady output which continues even when presented with high amounts of tasks, thing that proves its dominance.

Figure 9 exposes the average turnaround time of the compared algorithms. The proposed ANN based algorithm contributed clearly to the celerity of tasks/processes execution and that is for all presented cases on this second experimentation. The RR and the FCFS still gives good performances, nevertheless, their design is not suited for large scale computing.

7.3. Analysis and discussions

As reported by the simulations results obtained on the previous sub-sections, one can clearly observe the proposed algorithm added value, especially when compared with the simple Round Robin and First Come First Served algorithms that are still being used by all operating systems and cloud computing orchestration platforms. This accomplishment certainly pinpoints the Artificial Neural Networks role and its benefits in solving the scheduling problematic in its general term and exclusively for Cloud Computing environments. Artificial Intelligence (AI) is the upcoming technology that is revolutionizing our world. This computer science field is being considered as solution for several problematics, principally to promote autonomy. From this perspective, our research is amid other studies that encourages artificial intelligence integration within the Cloud Computing platforms scheduler in pursuance of an autonomous system capable of scheduling resources based on experience.

O. AlHeyasat et al [19] investigated the integration of artificial intelligence (Artificial Neural Networks, Multilayer Perceptron) with the Round Robin algorithm in approximately the same way we did, nevertheless, their proposed algorithm used the artificial neural networks prediction capability to estimate a linear static time quantum value that would be allotted for each task submitted for execution. Furthermore, their proposed algorithm uses an input layer (Neural Networks input) composed of tasks submitted for execution. This input layer is then fixed to ten (10) tasks during their simulation, while the system was trained with only data composed of several cases of the ten tasks with a burst time from 1 to 10. Although the authors of this paper produced several results, it wasn't tested or compared with other scheduling algorithms. On our side, the proposed algorithm used the artificial neural networks capability of classification in order to find the best calculation method that would produce a dynamic time quantum that changes every time the ready queue characteristics changes (tasks amount, tasks priority, tasks order) and the results obtained were compared to two of the most used scheduling algorithms.

In brief, the proposed scheduling algorithm displays the importance of artificial neural networks on solving the scheduling issue for cloud computing environments. The data used to

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assess and evaluate the algorithm is produced on a simulation environment which can prove the proposed algorithm significance in theoretical manner. However, more accurate results would consider many other criteria such as: the number of cloud users, network bandwidth, storage, datacenter location…

8. CONCLUSION

In this paper, a compute resources scheduling algorithm has been developed using the Multilayer Perceptron which is a category of Artificial Neural Network. The proposed scheduling algorithm used the Round Robin algorithm logic to schedule tasks in a time-shared manner using dynamically calculated time quantum that was extracted from the tasks characteristics submitted for execution. Accordingly, the proposed algorithm produced balanced time quantum that suits various situations with the help of supervised learning capability that comes with the Artificial Neural Networks.

The proposed algorithm was trained using thousands and thousands of data sets. Additionally, the proposed algorithm was evaluated and tested offline using CloudSim Simulator. The analysis performed on the evaluation section of this paper demonstrated the efficiency of the proposed algorithm in regards to the existing most used algorithms, which are the Round Robin and First Come First Served algorithms.

In conclusion, an implementation of the proposed algorithm is planned to test the performance of this accomplishment in one of cloud computing real world platforms, wherein this implementation can prove the simulation results and brings an innovative solution to the scheduling problematic.

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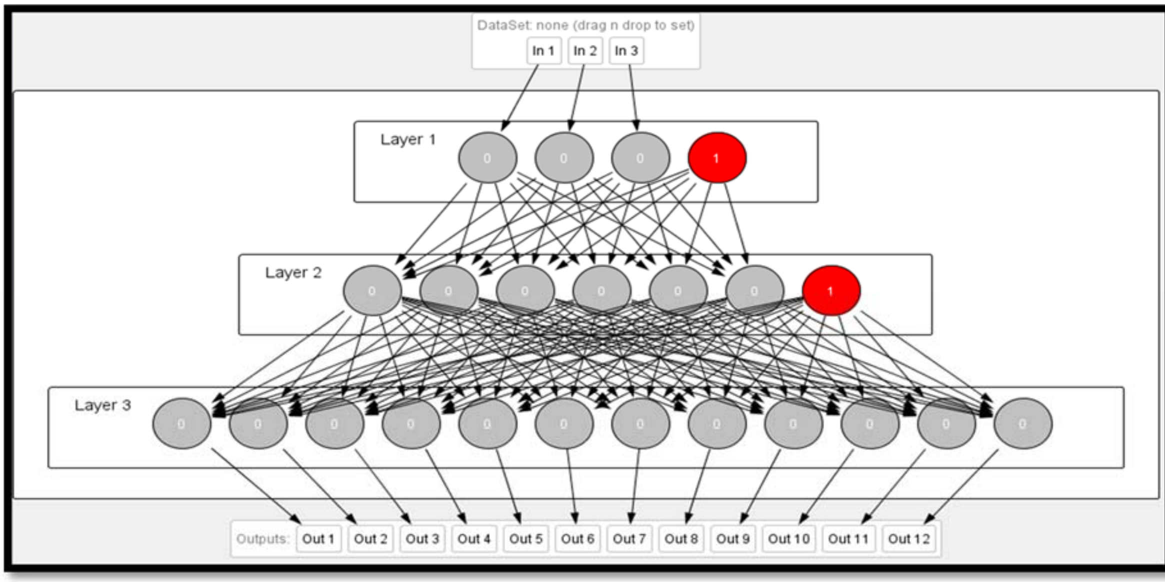

Figure 4. Architecture of the proposed Multi-Layer Perceptron

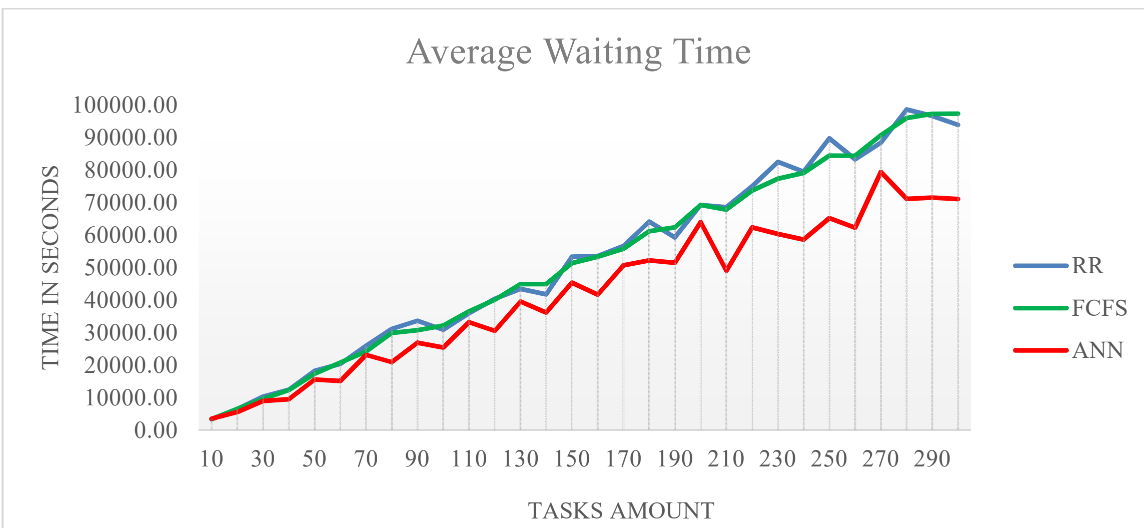

Figure 5. Average Waiting Time

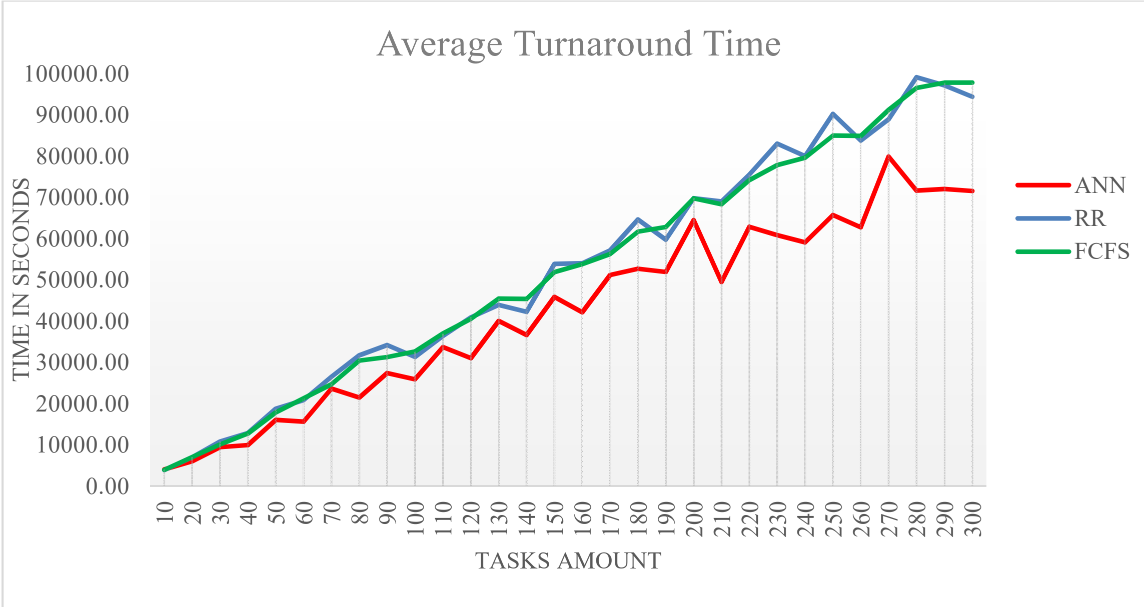

Figure 6. Average Turnaround Time

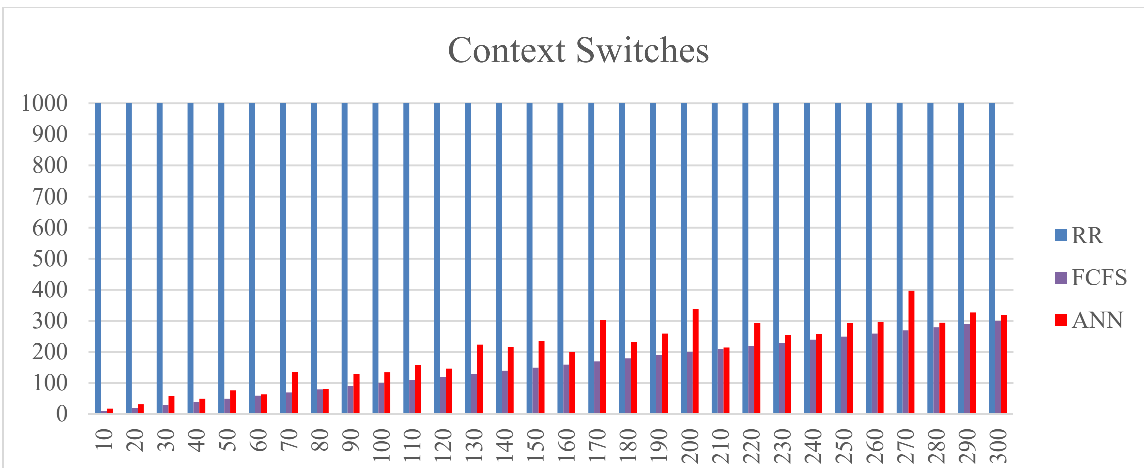

Figure 7. Context Switches

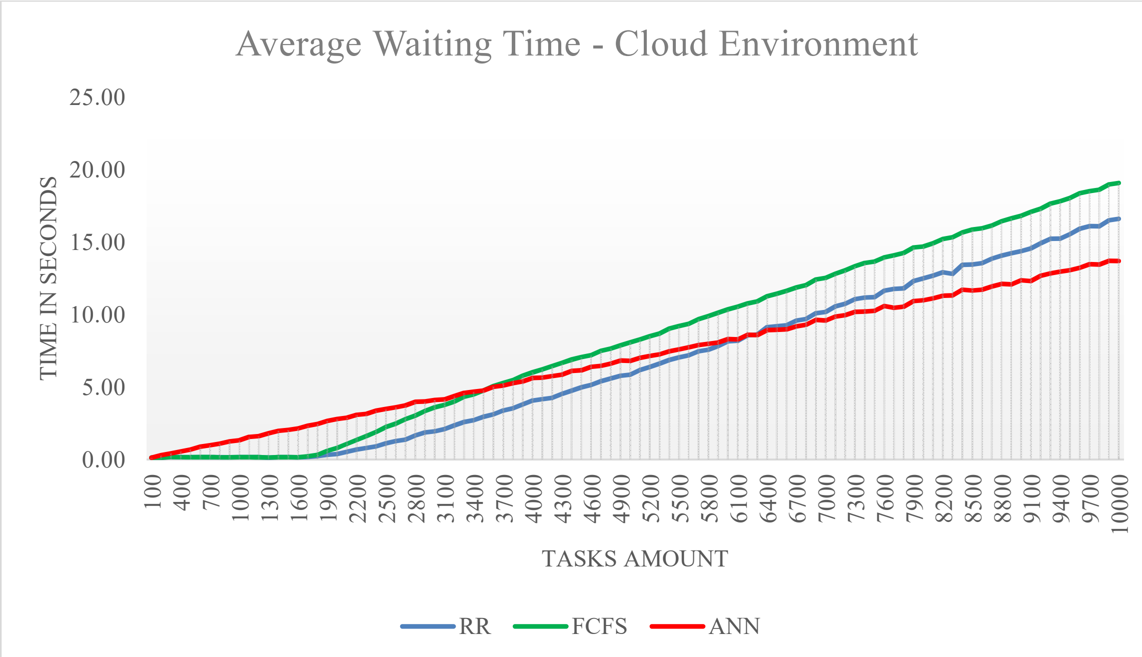

Figure 8. Average Waiting Time in a Cloud Environment

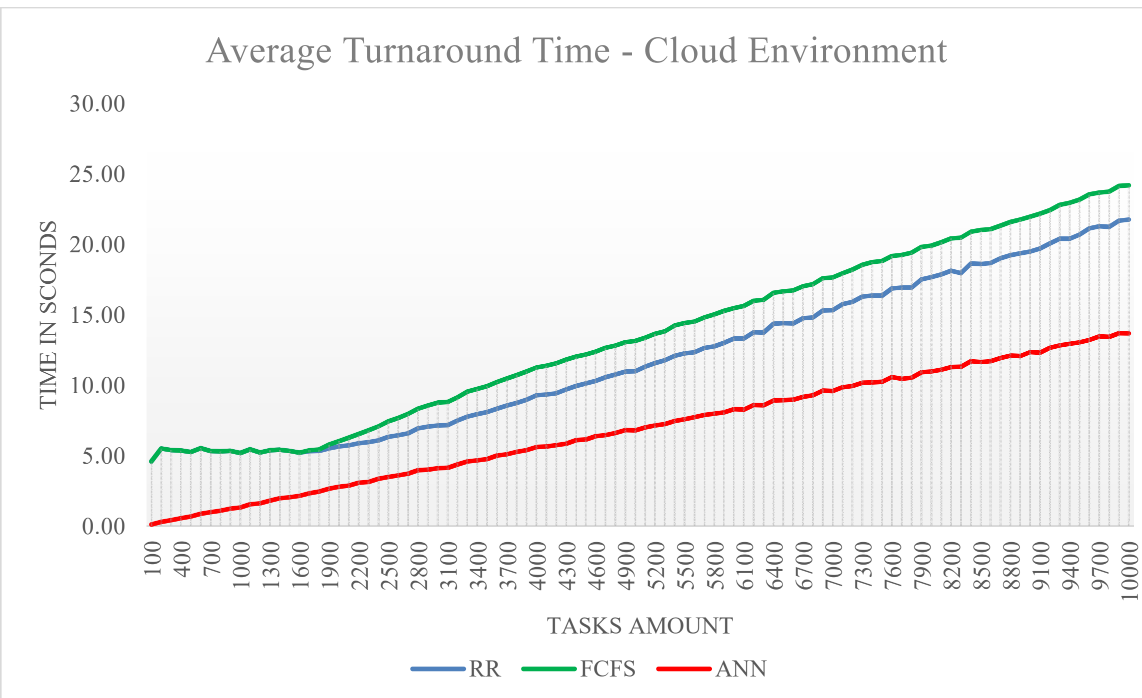

Figure 9. Average Turnaround Time in a Cloud Environment