3rd National Level Students' Research Conference on "Innovative Ideas and Inventions in Computer Science & IT with Its Sustainability"
In association with International Journal of Scientific Research in Computer Science, Engineering and Information Technology | ISSN : 2456-3307 (www.ijsrcseit.com)

Optimal VM Placement Approach Analysis Using FSRL and RLVMP in Cloud Computing

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ABSTRACT
The environmental sustainability and energy cost extant an important challenge for cloud computing practitioners and the growth of next generation data centers. Today, RM (Resource Management) contributes to significant energy usage in data center operations. The deployment of virtual machines (VMs) is used to reduce energy and improve resource management. Due to the energetic nature of cloud application, VM (Virtual Machine) Placement algorithm faces a challenge to exactly forecast upcoming resource difficulties. This paper presents and compares a FSLR (FUZZYBASED SARSA (STATE-ACTION REWARD-STATE-ACTION) REINFORCEMENT LEARNING) algorithm with a RLVMP (REINFORCEMENT LEARNING BASED VIRTUAL MACHINE PLACEMENT) strategy for energy savings in cloud data centers to address VM placement problem. This paper proposed a relative study of commonly used prediction models and introduces a predictive VMP approach based on workload traces.
Keywords: Cloud Computing, FSLR, SARSA, RLVMP Resources Management, Virtual Machine, Virtual Machine Placement.

I. INTRODUCTION

Around the world, advances in virtualization technologies and commercial computing are powering a large portion of internet applications and enabling the low-cost implementation of large-scale data centers. Cloud data centers offer several benefits including mobility, elasticity, disaster recovery, flexibility and on-demand resources [1-3]. One of the most important features of the cloud paradigm is elasticity. Elasticity enables an application to scale its resource requirements at any time[4], [5]. It has enabled the trend of renting of hardware, software and network resources rather than buying and managing computation resources. User can leverage complete computation infrastructure with an internet connection. It has wide range of applications like financial management, manufacturing, marketing, business management, academia, hospital management and many more [6], [7], [8].

The goal of this research is to find a way for minimizing energy usage in cloud computing for resource provision and development, but it may also be used to edge computing. Other alternative technologies, like edge computing, can significantly lower energy use be owing to their nature. As a result, Virtual Machines are regarded as allocatable resources in data centers. The distribution of Virtual Machines (VMs) is deemed critical in order to regulate the data center's energy consumption over time.

The main contribution of this study is as follows.

- Proposed a model for getting result VMR
- The aim of this study is to equivalence technique for energy-aware VM scheduling while taking resource constraints into account.
- Comparative Analysis have done for both algorithm

This Paper work flow organized as follows

- Related study
- Methodology
- Discussion

II. RELATED WORK

Son et al. [9], To increase both energy efficiency and performance, an energetic resource overbooking technique based on previous resource consumption data was implemented. In [10], For requests for VM allocation, no time beginning points were considered. The hill-climbing technique was also used to resolve optimization complications. This approach's convergence speed is slow when dealing with high-dimensional issues. lt's also more prone than meta- heuristic techniques like ant colony optimization, which is also examined in this paper, to get trapped in the local optimum.

In [11], The idea of a limit wasn’t examined, and VM beginning ideas were assumed to be constant. The greedy heuristic methods were employed to reduce the overall busy time f servers and resolve the energy-aware scheduling of virtual machines, which may not have found the ideal answer. In [12 - 14], Approximate heuristic approaches were provided to handle the challenge of reducing overall busy time in real-time task scheduling while taking resource restrictions into account.

Li et al. [15] propose Pareto-based MOVMrB (Multi-Object Virtual Machine Rebalance Solution), a new VMP method that aims to maintain load balance between machine loads of hosts.

Guddeti et al. [16] advise an algorithm that outperforms both the benchmark and the ant colony algorithms. The performance loss of PMs in comparison to Virtual Machines is not examined in most of the associated work, although limits like that threshold values are applied.

Zhao et al. [17] Evaluate the Performance Loss (PL) and solve it with the ant colony algorithm. However, their algorithm's solution is very intricate, and the pace with which it is solved is poor.

III. METHODOLOGY

The first technique for analysis is the RLVMP algorithm, which treats the early virtual machine placement as a continuous decision problem and then solves it using the enhancedRLtechnique.

This model defines the set of PMs as PMS= {PM1, …,PMj,...,PMN},

N -Number of PMs.
This model defines the set of VMs as VMS = {VM1,...,VMi,...,VMM},
M –Number of VMs.
S- State Space
V (Sij) and R(Sij) indicate the state value and the return of placing V Mi on PMj for each state Sij in the State Space, respectively. Each VM may only be allocated to one PM. Each PM must meet the memory requirements of the Virtual Machines (VMs) running on it. This model doesn't take into account central processing unit restrictions, but rather restricts the central processing unit in terms of performance loss.

A. RLVMP MODEL

To develop a placement approach that reduces real energy consumption while accounting for recognized State Values and Performance Loss gained through extensive learning. Then, to resolve the goal problem, the RL (Reinforcement Learning) approach is applied. In order to arrive at a final answer for Reinforcement Learning, we must first define state values before exploring and evaluating techniques.

Steps of RLVMP model

- The parameters are set to zero during the initialization phase, and initialized the Q value matrix.
- The Greedy–After the last update ε algorithm is used in the exploration strategy iteration, and respectively plan choice is only connected to the SV (State Values).
- When the placement is finished, the Number of States and Status Values are updated.
- Once the iteration termination condition is fulfilled, the F Greedy algorithm is used to execute the final placement. The row strategy is chosen mostly by the greedy algorithm based on the SV (State Values). Because of the nature of virtual machine placement, we employ the Greedy algorithm as the VM's decision-making method.

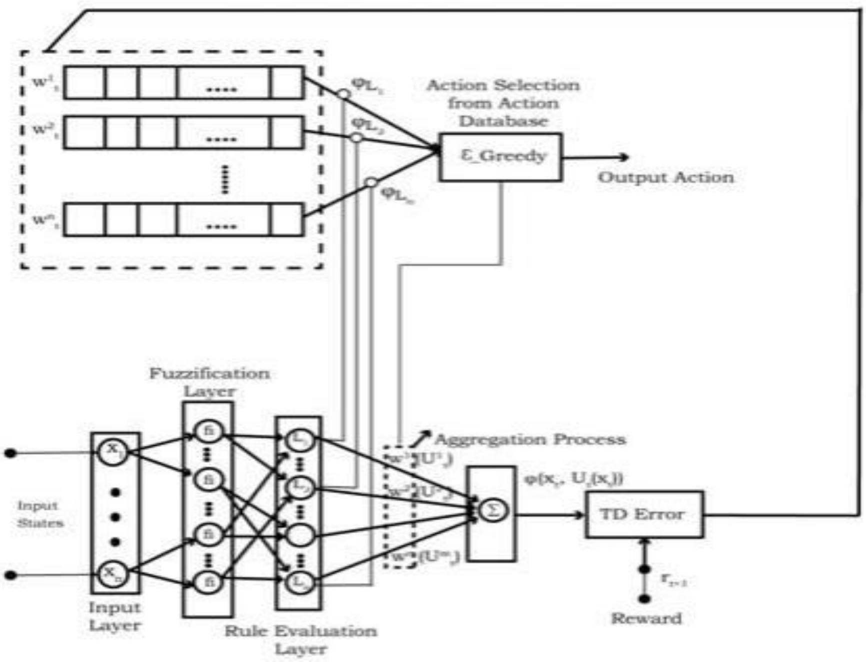
B. FSRL (FUZZY SARSA LEARNIG) ALGORITHM

The research expands the well-known reinforcement learning technique SARSA by incorporating a fuzzy controller for dynamic VM placement. SARSA has an advantage over other RL techniques in these techniques compares that the current state to the next state. SARSA is an on-strategy learning environment in which strategy is optimized and learning is accelerated as a result of carrying out the action one stage to next stage. In general, RL approaches are hampered by the Q-table and the table is used to accumulate the SAV (State Action Value). The FUZZY algorithm provides an excellent result to reinforcement learning by dropping its state-space and allowing it to study closer. During mapping of fuzzy algorithm that true state level to a set of FUZZY labels, and also.
In this work, the set X = x1, x2, xk
xk-The set of resource consumption of active hosts
t-time slot
t= 1, 2, ….,k
k- Number of Time Slots.
n+1 – The maximum Time Slot
The Number of time slots(k) is set to the maximum time slots(n+1)

Where n – Number of virtual machines

When the agent reaches the xn+1 state, all VMs are put. It is sometimes referred to as the ending stage of the learning process.

Fig 1: Architecture diagram of FSRL method



Steps of Fuzzy SARSA Learning Method:

1) Fuzzy Membership: A fuzzy is a subjective regular of the rules' repercussions

$$a = \sum_{l=1}^{p} \mu_l(x) \times a_l$$

μl(x)) - the degree of membership

x -Input State and

p -Number of Rules

2) Quality Function Calculation: The calculation of state x and reference rule1 as follows:

$$\mathbb{Q}(x, a) = \sum_{l=1}^{p} \left(\mu_l(x) \times q[l, a_l]\right)$$

3) Error estimation:

$$\Delta\mathbb{Q} = r + \gamma \times \mathbb{Q}(x', a') - \mathbb{Q}(x, a)$$

r-Reward of New State level
$\gamma \in (0, 1)$- Discount Rate
Above parameter affects the significance of upcoming benefits in relation to present rewards.

4) Updating q-values with each iteration:

$$q[l, a_l] = q[l, a_l] + \varphi \times \mu_l(x) \times \Delta\mathbb{Q}$$

Where [0, 1] -Learning Rate

Table 1: Comparison of simulation parameters

Parameters	RLVMP	FSRL
Learning rate	0.85	0.1
number of VM's	500	300
Energy Efficiency	18%	24%
Discount factor	0.5	0.8

IV. RESULTS AND DISCUSSION

The simulation is used to develop the FSRL method, and the results are contrasted with the RLVMP approach, which has a single target for the VM placement problem in terms of energy use and resource waste across different scenarios. For VM placement, the CloudSim is utilized to execute both the fuzzy SARSA RL technique and the RLVMP model. The discount factor is the parameter that influences the learning impact of the reinforcement learning algorithm. The closer to Discount Factor is (1), the more weight is placed on future returns, and the further away it is from one, the less importance is placed on imminent returns. As a result, adjusting the magnitude of the discount factor is required to make learning simpler to converge or to become improved outcomes. The FSRL on-policy absorbs fast and progresses to the process of controlled examination-manipulation, that is, it completes the learning stage of virtual machine placement rapidly in accord with the features of both virtual machine and host and arrives at the last examination level, preventing further examination while selecting action.

Overall, the FSRL approach outperforms the RLVMP in terms of energy usage and resource waste.

Advantages of FSRL algorithm

1) FSRL algorithm for virtual machine placement.
2) The usage of a FUZZY inference system to construct a collection of FUZZY sets based on the quantity of virtual machines and host utilization helps to reduce the Exploration Rate and speed up Convergence.
3) FSRL's on-policy learning method, which aids in system learning and action selection, yielded improved results in relationships of Energy and Resource use.

Figure 2 depicts the percentage of energy consumed by FSRL and RLVMP.

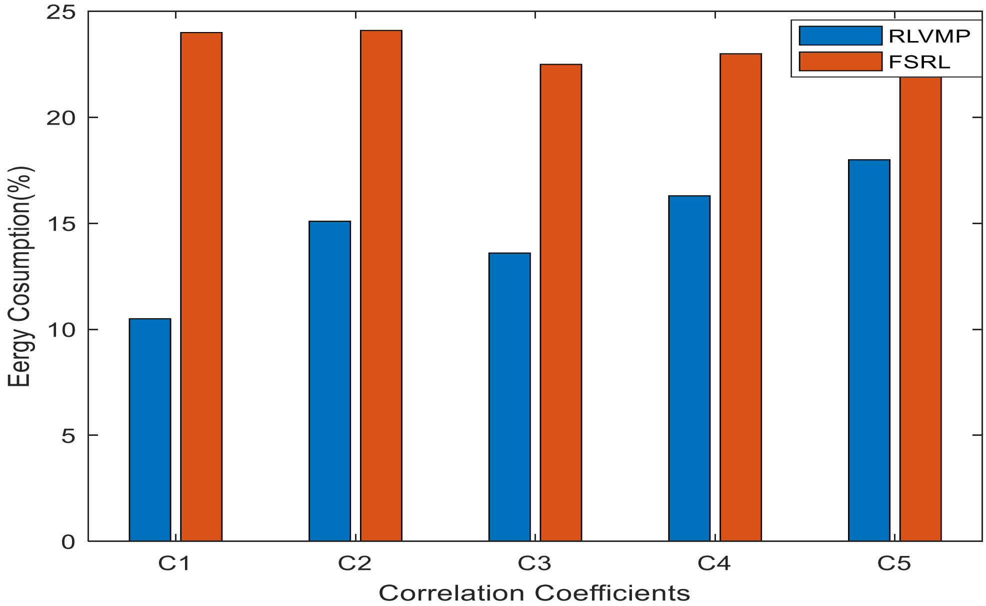


Fig 2: Comparison of energy consumption

V. CONCLUSION

In cloud data centers, energy usage accounts for the lion's share. Modern data center is energy costs and environmental sustainability have emerged as key considerations for cloud computing practitioners and the creation of next-generation data centers. In this study, we give a comparison of the FSRL and RLVMP algorithms for VM placement. The experimental findings reveal that FSRL efficiently uses energy, which is a major difficulty for virtual machine placement algorithms. FSRL is also accomplished of attaining better energy efficiency of at least 24 percent, demonstrating that it outperforms RLVMP. Furthermore, when compared to certain well-known VM placement algorithms, it reduces service violations by more than 45 percent, boosting practitioners' capacity to accomplish considerable improvements in the quality of service offered.

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