An Improved Metaheuristic based Node Localization Technique for Wireless Sensor Networks

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Abstract

Cloud computing (CC) becomes a familiar topic in offering unlimited access to services as well as resources via the Internet. A comprehensive CC management system is needed to collect details of the task processing and ensure proper resource allocation with the accomplishment of Quality of Service (QoS). At the same time, virtual machine (VM) migration is a crucial problem in the CC platform which contributes to energy utilization and resource usage. Therefore, this paper presents a new energy-aware elephant herd optimization-based VM migration (EAEHO-VMM) scheme. The EAEHO-VMM algorithm aims to migrate the VMs and prediction failure VMs. At the initial stage, the EHO algorithm is executed to minimize the energy utilization of the VM migration process in the CC environment. In addition, a support vector machine (SVM) model is applied to identify the failure VMs and allows relocation in an effective way. In order to make sure the better performance of the EAEHO-VMM algorithm, a series of simulations take place, and the results are investigated in terms of different aspects. The experimental outcomes ensured the enhanced VM migration performance of the EAEHO-VMM algorithm over the other techniques.

Keywords: Cloud computing, Energy utilization, VM migration, Failure prediction, Machine learning.

1. Introduction

Cloud computing has revolutionized industry and academia by the provisioning of on-demand computing resources. These on-demand resources are based on pay-as-you-use [1]. Organizations and individuals outsource Cloud services for the diverse nature of tasks that demand high-performance computing, large memory instances, licensed software applications, large-scale simulations [2, 3] and development platforms, etc. Specifically, organizations prefer to outsource Cloud services rather than designing their own private data centers for their business needs due to the huge investment, maintenance, and management cost. The high demands of organizations for Cloud service result in the development of largescale CDC. In CC environments, the major foundation in virtualization [4-6]. All the PMs or host hardware resource is divided to several implementation platforms i.e., refereed to a VMs. In PM, the processing requests from the client are controlled using the VM by satisfying the computation resources constraint like CPU resource, memory size, and computational time [7-9]. Fig. 1 shows the overview of VM migration in CC.

Generally, the cloud gathers information from VM, resource, host, data center, etc. [10]. Cloud service is given to the datacenters in cloud environment. But, a huge number of energies are used for this datacenter in their task. The annual power utilization of datacenters in the US is 91 billion kWh, i.e., considered to increase by 140 billion kWh by 2020. Similarly, in the datacenter, a rapid increase in energy utilization leading to a fundamental financial problem as well as environmental troubles. Together with, the power

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costs of amazon datacenters are nearly 42% of overall functioning costs [11, 12]. If a host experiences an under-loaded problem in the CDC, all Virtual Machines (VMs) of that host are migrated to other hosts using live migration [13], and concerned under-loaded hosts are then powered off accordingly. In this way, the number of active hosts is reduced across the CDCs which ultimately leads to reduced energy consumption. However, aggressive consolidation of VMs can cause performance degradation due to the high demands of resources.

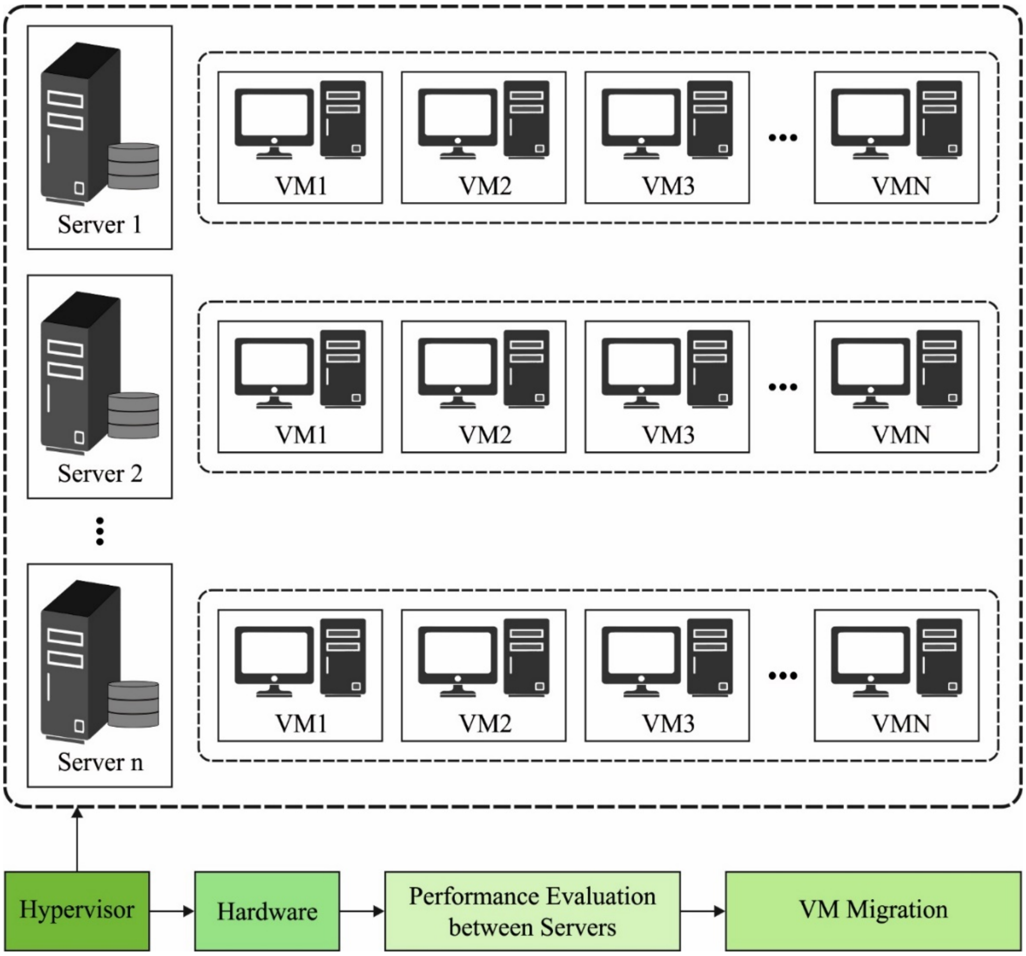

Fig. 1. Overview of VM migration in CC platform

Moreover, if the required resources are not available to the application for its processing, it will ultimately lead to an increased response time, which may result in application failure or late response. Numerous approaches have been proposed by researchers to improve resources consumption with reduced power utilization in CDCs. After this, power consumption is increasing over 80% as anticipated and the datacenters are a major cause for this improvement. Related to the older office system, hundred times extra energies were employed in the datacenters. These statements are depending on the reports of the Environment Protection Agency [14]. Depending on the computation capability of PM and computation need of assigned VM, the energy utilization of certain PMs is district. For physical servers i.e., idle, the energy consumption is exceeded two-third of the utilized servers [15]. In order to beat this energy ineffectiveness, effective utilization of PM resources with virtualization is a significant solution.

In [16], the NB classifiers using hybrid optimization with ABC–BA method have been executed for reducing the power utilization in VM migrations. The presented approach has been calculated in CloudSim. Jiang et al. [17] proposed a VMM-3WD approach to save cloud hosts' energy consumption while considering the network correlation between virtual machines. The strategy first is to classify hosts into overloaded hosts, regular load hosts, and under-loaded hosts based on their load situation. Then, different migration strategies are targeted developed for these three types of cloud hosts. Specifically, the approach migrates the VMs in under-loaded hosts to regular load hosts.

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In [18], an EAMA method is presented to an efficient placement and migration of VM on the PM vigorously. The presented method contains 2 different characteristics: firstly, election of PM location through optimal accessing delay where the VM is needed to be migrated, and next, reduce the numbers of VM migration. In [19], multi-objective EPO algorithms were presented for allocating the VMs through energy consumption in a heterogeneous cloud environment. The presented technique is explored for making it appropriate to VMs in the datacenter via BGSA, ACO, and PSO models. In [20], new solutions have been presented to the assignment of VMs to physical hosts in cloud datacenters by means of the Krill Herd model, i.e., the fast collective intelligence approach presented newly.

This paper presents a new energy aware elephant herd optimization based VM migration (EAEHO-VMM) scheme. The EAEHO-VMM algorithm aims to migrate the VMs and prediction failure VMs. At the initial stage, the EHO algorithm is executed to minimize the energy utilization of the VM migration process in CC environment. In addition, support vector machine (SVM) model is applied to identify the failure VMs and allows relocation in an effective way. In order to make sure the better performance of the EAEHO-VMM algorithm, a series of simulations take place and the results are investigated in terms of different aspects

2. The Proposed EAEHO-VMM Model

The EAEHO-VMM algorithm involves two major processes namely EHO based VM migration and SVM based VM failure prediction. At the initial stage, the EHO algorithm is applied to effectively migrate the VMs in the cloud environment. Besides, in the second stage, the SVM model is used for the prediction of failure VMs in the cloud platform.

2.1 VM Migration Scheme

EHO technique [21] was mostly dependent upon nature of elephants that are lately projected to global optimization. The EHO technique does not employ the earlier separate in the following upgrade procedure. If the meaningful data in the preceding separate are completely employed in the optimized procedure, the solution quality is significantly improved. The main influence of this work is for enhancing the EHO upgrading procedure where EHO upgrading operator was implemented. According to the EHO separating operator, the compared processes are determined subsequently. The upgrading rule of basic EHO was established. Let us elephant clan that was applied as ci. Afterward, the upcoming place of elephant j, in the clan is maximization by the application of (1), as demonstrated under:

$$x_{new,ci,j} = x_{ci,j} + \alpha \times \left(x_{best,ci} - x_{ci,j}\right) \times r, \tag{1}$$

where $x_{new,ci,j}$ implies the upgraded place, and $x_{ci,j}$ represented the preceding place of elephant j in clan ci. $x_{best,ci}$ signifies to the matriarch of clan ci; she refers the fittest elephant from the clan. The scale factor $\alpha \in [0,1]$ has been implemented to measure the matriarch of ci on $x_{ci,j}$. $r \in [0, 1]$ that goes to stochastic distribution which is able of given that enhancement in the diversity of population. A uniform distribution was implemented in this works.

It can be noted that $x_{ci,j} = x_{best,ci}$ that signifies the matriarch from the clan may not be maximization by (1). This condition is eliminated by upgrading the place of fittest elephant utilizing the provided function:

$$x_{new,ci,j} = \beta \times x_{center,ci}, \tag{2}$$

where $x_{center,ci}$ on $x_{new,ci}$, refers the taken by $\beta \in [0,1]$.

The data attained in every individual from the clan ci has been implemented to develop a new individual $x_{new,ci,j}$. The intermediate portion of clan ci, $x_{center,ci}$ has been defined to d-th dimensional by D computations where D defines the whole dimensional as depicted under:

$$x_{center,ci,d} = \frac{1}{n_{ci}} \times \sum_{j=1}^{n_{ci}} x_{ci,j,d} \tag{3}$$

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During this technique, $1 \leq d \leq D$ illustrates the d dimensional, n_{ci} refers the individuals in ci, and $x_{ci,j,d}$ represents the d-th dimensional of individuals $x_{ci,j}$.

Algorithm 1 depicts the pseudo-code to update the operator.

Algorithm 1: Clan updating operator

Initialize
for $ci = 1$ to $nClan$ (to all clans from elephant population) do
for $j = 1$ to n_{ci}(to all the elephants individual in clan ci) do
Upgrade $x_{ci,j}$and make $x_{new,ci,j}$ based on (1).
if $x_{ci,j} = x_{best,ci}$then
Upgrade$x_{ci,j}$and generate $x_{new,ci,j}$.
endif
end for $\boldsymbol{j}$
end for ci
End

Essentially, the ME leaves the family member and lives alone once it is matured. The procedure of isolation has been labelled as separate operators that are appropriate for solving the optimized problem. In order to improve the searching capability of EHO technique, consider elephants with reduced fitness to execute the separate operator to every generation as demonstrated in (4).

$$x_{worst,ci} = x_{min} + (x_{max} - x_{min} + 1) \times rand \tag{4}$$

where x_{max} and x_{min} represents the upper as well as lower bound correspondingly. $x_{worst,ci}$ refers the worse individual's elephant from the clan ci. $rand \in [0, 1]$ refers the kind of stochastic as well as uniform distribution in 0 and 1 that has been implemented in the present research.

The energy utilization has been typical energy utilized with hubs which contribute in message that is after approved on a vital hub to an objective hub. An objective of utility capability is for boosting the VM arrangement by minimized the energy utilization explained in the formula under. The lower evaluations of energy utilization use in reduced usage. This represents that lesser the measure of energy devoured, the optimum the task will be.

$$EC_i = min\{energy_{ideal\ machine,i} + energy_{running\ machine,i}\} \tag{5}$$

2.2 VM Failure Prediction Scheme

In order to determine the failure VMs in the cloud environment, the SVM model is used [22]. SVM is real-world use of statistical learning concepts in multi-dimensional functions. It is a learning machine determined to classify as optical character recognition (OCR) and established for regression objectives. SVM is currently utilized in several engineering regions and presented methods with better accuracy. For simple example input data $x \in R^d$ are regressed by hyper plane f(x):

$$f(x) = \langle w, x\rangle + b \ with\ x \in X, \qquad b \in R \tag{6}$$

Where $\langle w, x\rangle$ denotes inner product among x and w. A flat solution can be achieved when w is smaller. Specifically, its norm $||w||^2 = \langle w, w\rangle$ must be minimal. For regression cases, a loss function that permits few errors in specific field epsilon and few slack parameters can be away from marginal area by few penalties.

$$\xi = |y_i - f(w, x_i)|$$

$$|\xi|_\varepsilon := \begin{cases} 0 & if\ |\xi| \leq \varepsilon \\ |\xi| - \varepsilon & otherwise \end{cases} \tag{7}$$

Loss function determination provides more adaptability for supporting vector machine regression techniques. By assuming positive slack parameters (ξ_i, ξ_i^*) optimization problem is equated as:

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$$minimize\ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{\ell}(\xi_i + \xi_i^*)$$

$$subject\ to \begin{cases} y_i - \langle w, x_i\rangle - b \le \varepsilon + \xi_i \\ \langle w, x_i\rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{8}$$

Where C represents positive constant and penalizes factor for the information that derives from f are ξ_i unit greater than ε.

3. Result Analysis

A brief VM migration analysis of the EAEHO-VMM technique takes place in terms of Table 1 and Fig. 2. The figure denoted that the fuzzy model has showcased worse outcomes with the least accuracy of 77.74% and specificity of 79.06%. In addition, the KNN model has gained slightly improvised outcomes with an accuracy of 78.80% and specificity of 80.92% Moreover, the NB model has resulted in certainly effective results with an accuracy of 97.10% and specificity of 95.24%. However, the EAEHO-VMM technique has accomplished maximum performance with an accuracy of 99.49% and specificity of 97.90%.

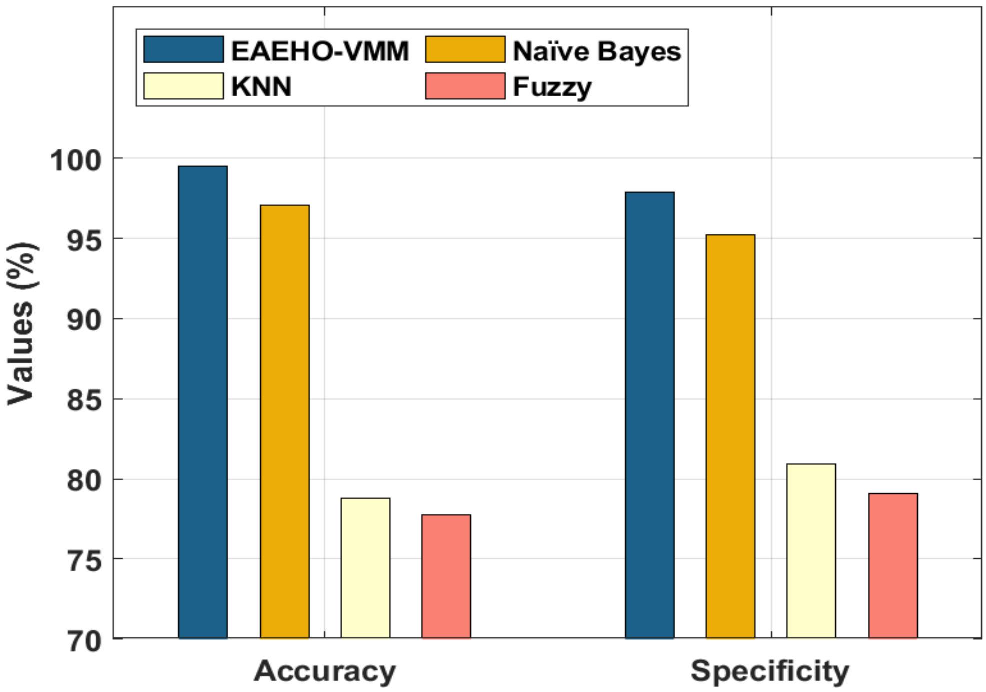

Fig. 2. Results analysis of EAEHO-VMM technique

Table 1 Results analysis of EAEHO-VMM technique

Performance (%)		
Methods	**Accuracy**	**Specificity**
EAEHO-VMM	99.49	97.90
Naïve Bayes	97.10	95.24
KNN	78.80	80.92
Fuzzy	77.74	79.06

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Table 2 and Fig. 3 demonstrates the VM migration results of the EAEHO-VM technique under varying number of failure VMs. The results demonstrated that the migration level gets raised with an increase in failure VMs. For instance, with 10VMs, the EAEHO-VM technique has obtained a migration level of 2. Also, with 20VMs, the EAEHO-VM approach has reached a migration level of 4. Besides, with 30VMs, the EAEHO-VM algorithm has gained a migration level of 7. In addition, with 40VMs, the EAEHO-VM methodology has obtained a migration level of 8. Additionally, with 50VMs, the EAEHO-VM approach has achieved a migration level of 9.

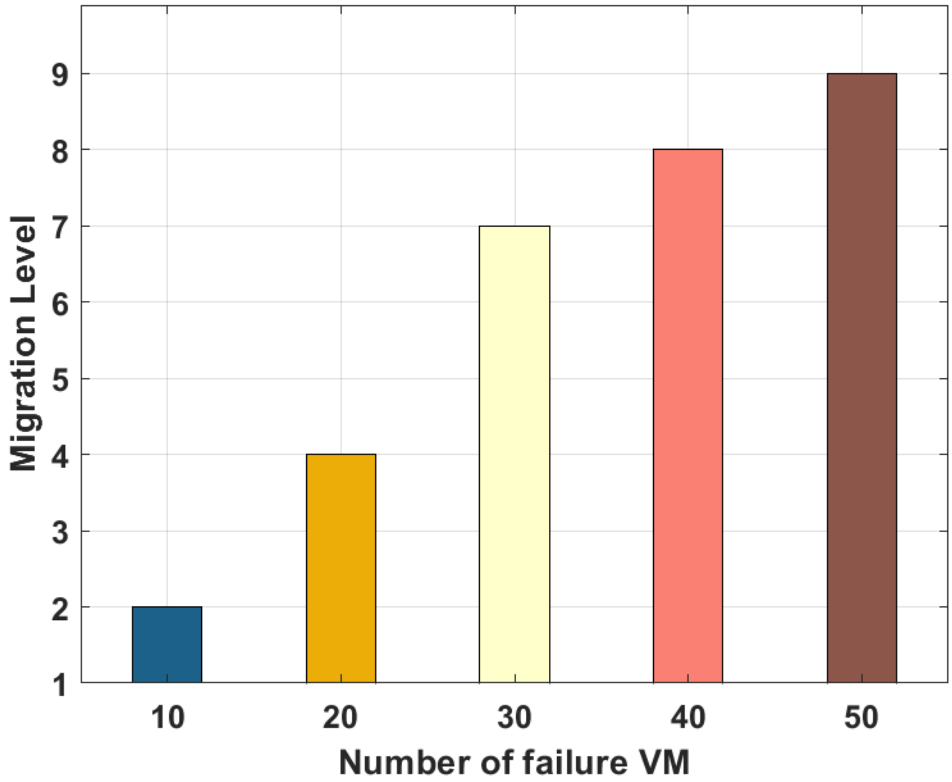

Fig. Migration level analysis of EAEHO-VM Technique

Table 2 VM migration results of EAEHO-VM technique

Number of failure VM	Migration Level
10	2
20	4
30	7
40	8
50	9

Table 3 and Fig. 4 illustrate the energy consumption (EC) analysis of the EAEHO-VM technique under distinct failure VMs. The results demonstrated that the EAEHO-VM technique has accomplished lower EC under all failure VMs. For instance, with 5 failure VMs, the EAEHO-VM technique has resulted in a lower EC of 909KWh whereas the ABC-BA(Hybrid), ABC, BA, PSO, and DAPSO techniques have obtained a higher EC of 1148KWh, 1227KWh, 2357KWh, 2453KWh, and 1546KWh respectively. Likewise, with 10 failure VMs, the EAEHO-VM algorithm has resulted in a lesser EC of 1052KWh whereas the ABC-BA(Hybrid), ABC, BA, PSO, and DAPSO manners have obtained a superior EC of 1259KWh, 2357KWh, 3630KWh, 4267KWh, and 2532KWh correspondingly.

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Table 3 Energy efficiency analysis of EAEHO-VM technique under varying failure VMs

Energy Consumption (KWh)						
Number of failure VM	**EAEHO-VMM**	**ABC-BA(Hybrid)**	**ABC**	**BA**	**PSO**	**DAPSO**
5	909	1148	1227	2357	2453	1546
10	1052	1259	2357	3630	4267	2532
15	1989	2182	2453	3773	4871	2468
20	2134	2532	3455	4569	3566	2707
25	1036	1323	2309	2819	3519	2516
30	2532	3025	4601	3216	4219	3630
35	2453	2898	3901	4378	4935	4601
40	1546	1927	4394	3360	4808	4442

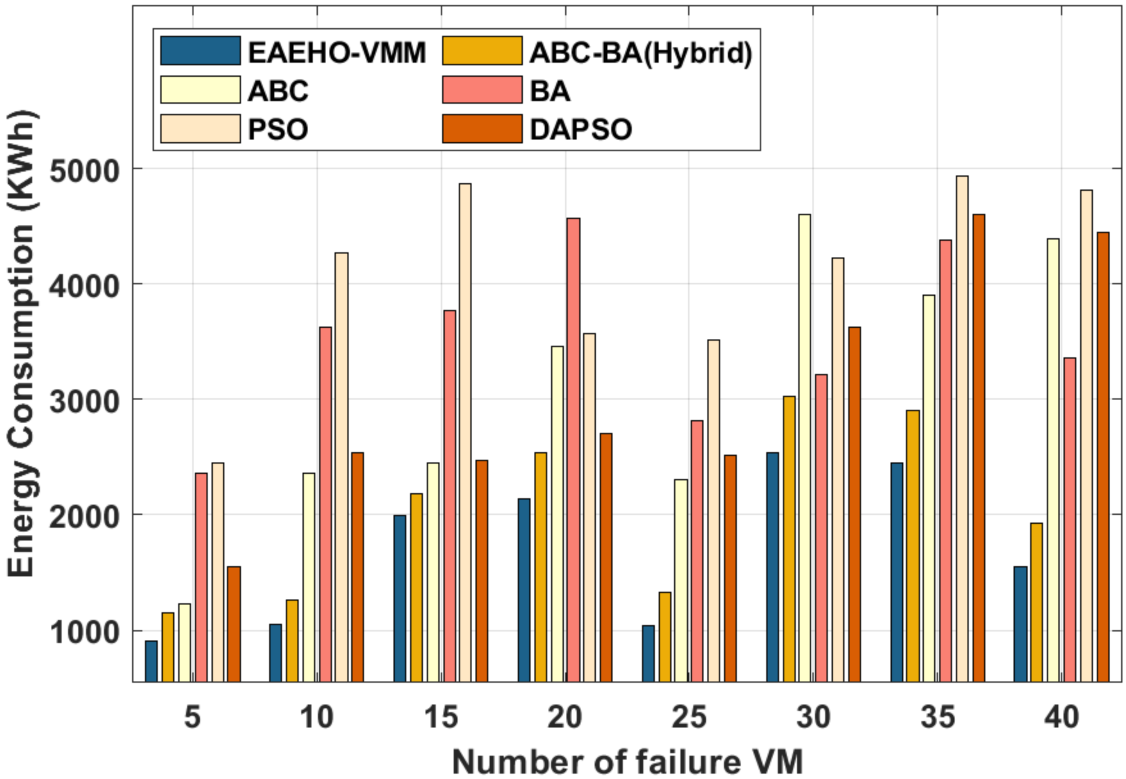

Fig. 4. EC analysis of EAEHO-VMM technique under distinct failure VMs

Similarly, with 15 failure VMs, the EAEHO-VM method has resulted in a minimum EC of 1989KWh whereas the ABC-BA(Hybrid), ABC, BA, PSO, and DAPSO manners have obtained a maximum EC of 2182KWh, 2453KWh, 3773KWh, 4871KWh, and 2468KWh respectively. Simultaneously, with 25 failure VMs, the EAEHO-VM method has resulted in a lower EC of 1036KWh whereas the ABC-BA(Hybrid), ABC, BA, PSO, and DAPSO techniques have obtained a higher EC of 1323KWh, 2309KWh, 2819KWh, 3519KWh, and 2516KWh correspondingly. Concurrently, with 30 failure VMs, the EAEHO-VM algorithm has resulted in a reduced EC of 2532KWh whereas the ABC-BA(Hybrid), ABC, BA, PSO, and DAPSO manners have gained an increased EC of 3025KWh, 4601KWh, 3216KWh, 4219KWh, and 3630KWh respectively. At last, with 40 failure VMs, the EAEHO-VM methodology has resulted in the least EC of 1546KWh whereas the ABC-BA(Hybrid), ABC, BA, PSO, and DAPSO techniques have obtained an improved EC of 1927KWh, 4394KWh, 3360KWh, 4808KWh, and 4442KWh correspondingly.

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4. Conclusion

This paper has developed a novel EAEHO-VMM scheme to migrate VMs in CC platform. The EAEHO-VMM algorithm aims to migrate the VMs and prediction failure VMs. At the initial stage, the EHO algorithm is executed to minimize the energy utilization of the VM migration process in CC environment. In addition, SVM model is applied to identify the failure VMs and allows relocation in an effective way. In order to make sure the better performance of the EAEHO-VMM algorithm, a series of simulations take place, and the results are investigated in terms of different aspects. The experimental outcomes ensured the enhanced VM migration performance of the EAEHO-VMM algorithm over the other techniques. In future, hybrid metaheuristic algorithms and deep learning models can be utilized for VM migration process in the cloud environment.

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