Sustainable Virtual Machine Migration in Cloud Data Centers Using Cuckoo Search Algorithm with Knowledge Acquisition

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Abstract. In the context of optimizing cloud sustainability using virtual machine migration across cloud data centers, this paper explores the integration of knowledge acquisition with the Cuckoo Search Algorithm. Given the increasing demand for efficient and sustainable resource allocation in cloud environments, the study examines how knowledge acquisition mechanisms can enhance the system performance using a bio-inspired algorithm to optimize energy sustainability in this domain. Specifically, the paper compares the effectiveness of the Cuckoo Search Algorithm augmented with knowledge acquisition against the traditional Pittsburgh Algorithm and Knowledge Acquisition with a Swarm Intelligence Approach for Virtual Machine (VM) migration tasks seeking a higher percentage of renewable energy over total energy consumed by the cloud environment. Through a series of experiments conducted in simulated cloud scenarios using a CloudSim-based simulator, the paper evaluates the proposed method's ability to achieve higher renewable energy rates and reduced overall energy consumption. The findings highlight the potential of incorporating knowledge-driven enhancements into an evolutionary algorithm such as Cuckoo Search Algorithm to tackle the complex optimization challenges in cloud computing, particularly regarding VM migration.

Keywords: Knowledge acquisition · VM migration · Cuckoo Search Algorithm · Sustainability · Cloud Computing .

1 Introduction

Cloud computing has revolutionized the way organizations manage and utilize computational resources, offering scalability, flexibility, and cost-effectiveness.

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Central to the efficient operation of cloud infrastructures is the dynamic migration of virtual machines across data centers to optimize resource utilization, enhance performance, and minimize operational costs [1]. However, the process of Virtual Machine (VM) migration presents complex optimization challenges, including the need to balance factors such as resource availability, network latency, and energy consumption [2, 3].

In recent years, nature-inspired optimization algorithms have emerged as powerful tools for addressing such challenges [4–6]. Among these, the Cuckoo Search Algorithm (CSA) has garnered attention for its ability to efficiently navigate complex search spaces and find optimal solutions [7]. CSA, inspired by the brood parasitism of some cuckoo species, mimics the reproductive behavior of these birds to iteratively refine candidate solutions through a process of local search and randomization.

To further improve the efficacy of CSA in the context of VM migration, this study proposes the integration of knowledge acquisition mechanisms, aimed at enhancing the algorithm's ability to exploit domain-specific knowledge and adapt to dynamic cloud environments [8]. Knowledge acquisition techniques encompass various methods for acquiring, representing, and utilizing domain knowledge, including expert systems, machine learning, and data mining. By leveraging domain knowledge, CSA can better navigate the search space, identify promising regions, and expedite convergence towards high-quality solutions.

The application of a knowledge acquisition based on an expert system to CSA for optimizing VM migration across cloud data centers is investigated in this paper. Specifically, how leveraging cloud knowledge can augment CSA's performance compared to conventional approaches, such as the Pittsburgh Algorithm or Knowledge Acquisition with a Swarm Intelligence Approach (KASIA) [9], is explored. The Pittsburgh Algorithm, a traditional heuristic-based approach [10], has been widely used in cloud environments but may struggle to adapt to changing conditions and exploit domain-specific knowledge effectively [11, 12].

The effectiveness of the proposed method in optimizing the renewable energy percentage of the cloud environment is assessed through empirical evaluations conducted in simulated cloud-based environments [13, 14]. By comparing the performance of knowledge-aided CSA against traditional approaches, the potential of knowledge-driven optimizations for enhancing the renewable energy percentage of VM migration in cloud data centers is aimed to be demonstrated.

The findings of this research contribute to advancing the state-of-the-art in cloud resource management, offering insights into the potential of knowledge-driven optimizations for addressing the complex optimization challenges inherent in VM migration. By harnessing the power of nature-inspired algorithms and domain-specific knowledge, efforts are made to facilitate more efficient and intelligent VM migration strategies, ultimately enhancing cloud sustainability and performance.

The subsequent section presents the CSA with Knowledge Acquisition, aimed at optimizing virtual machine migration across cloud data centers. In this approach, domain-specific knowledge is encoded through a fuzzy expert system to

enhance performance in addressing the complex optimization inherent in cloud computing environments. In Section 3, the proposed model is compared against a traditional approach, such as the Pittsburgh Algorithm and KASIA, to evaluate its effectiveness in achieving superior migration outcomes regarding sustainability. Finally, conclusions are drawn, and potential avenues for future research in this domain are outlined.

2 Cuckoo Search Algorithm with Knowledge Acquisition

The CSA is a nature-inspired optimization algorithm that simulates the reproductive behavior of cuckoo species to iteratively refine candidate solutions. Developed by Yang and Deb in 2009 [7], CSA has gained popularity for its simplicity, efficiency, and ability to find near-optimal solutions in complex search spaces. The algorithm is based on the obligate brood parasitism behavior exhibited by some cuckoo species, where they lay their eggs in the nests of other host bird species, relying on the hosts to incubate their eggs and rear their offspring [15, 16].

In the context of optimization, CSA operates on a population of candidate solutions represented as nests. Each nest X_i corresponds to a potential solution to the optimization problem, and the quality of a nest is evaluated based on an objective function, in this paper renewable energy percentage over total energy consumed by the cloud environment. During each iteration, the algorithm iteratively updates the nests by performing a combination of local search and randomization. The global exploration is facilitated by the randomization process, which mimics the random selection of host nests by cuckoos, while the local search mechanism enables the algorithm to exploit promising regions of the search space using Lévy flight, which is a key component of the local search in CSA: a random walk characterized by step lengths that follow a heavy-tailed probability distribution. Lévy flights enable the algorithm to make large jumps, which helps in exploring the search space more effectively and escaping local optima. The mathematical representation of the update process for a nest X_i is defined as follows:

In the context of multi-objective optimization, CSA operates over a population matrix $\mathbf{X} \in \mathbb{R}^{m \times n}$ representing m candidate nests in an n-dimensional search space:

$$\mathbf{X} = \left[X_1^T \; X_2^T \; \cdots \; X_m^T\right]^T \tag{1}$$

where each row vector $X_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,n}]$ encodes a specific virtual machine placement layout. The evolutionary optimization trajectory balances localized exploitation and randomized global exploration.

Localized search is governed by non-Gaussian random walks whose step lengths follow a heavy-tailed power-law distribution. The position update of the i-th nest at generation $t+1$ is modeled as:

$$X_i^{(t+1)} = X_i^{(t)} + \alpha \cdot \mathcal{L}(\beta) \odot (X_{best} - X_i^{(t)}) \tag{2}$$

where $\alpha > 0$ represents the dynamic step size scaling factor, $\odot$ denotes the Hadamard entry-wise product, and X_{best} is the current global optimum vector. The stochastic step sequence $\mathcal{L}(\beta)$ is drawn from a stable symmetric Lévy distribution via Mantegna's algorithm:

$$\mathcal{L}(\beta) \sim \frac{u}{|v|^{1/\beta}}, \quad u \sim \mathcal{N}(0, \sigma_u^2), \quad v \sim \mathcal{N}(0, 1) \tag{3}$$

where the distribution parameters obey $1 < \beta \leq 2$ (typically set to $\beta = 1.5$), and the standard deviation σ_u is defined through Euler's gamma functions:

$$\sigma_u = \left[\frac{\Gamma(1+\beta) \cdot \sin(\pi\beta/2)}{\Gamma\left(\frac{1+\beta}{2}\right) \cdot \beta \cdot 2^{(\beta-1)/2}} \right]^{1/\beta} \tag{4}$$

This heavy-tailed distribution allows $\mathcal{L}(\beta)$ to yield occasional large jumps, preventing the population from trapping in local minima during host suitability mapping.

Conversely, global exploration models the host bird's awareness, where a fraction $p_a \in [0, 1]$ of sub-optimal nests are discovered and abandoned. The replacement mechanism introduces structured diversification:

$$X_i^{(t+1)} = X_i^{(t)} + H(p_a - \epsilon) \cdot r \cdot (X_j^{(t)} - X_k^{(t)}) \tag{5}$$

where $H(\cdot)$ is the Heaviside step function, $\epsilon, r \sim \mathcal{U}(0, 1)$ are uniform random numbers, and $j, k \in \{1, \ldots, m\}$ are mutually exclusive random nest indices ($j \neq k \neq i$).

The fitness assessment maps the algorithmic boundaries to cloud sustainability goals. The objective function evaluates the environmental efficiency by maximizing the renewable energy share over the aggregated consumption profile:

$$\max_{X_i} \text{Fitness}(X_i) = \frac{\sum_\tau E_{\text{ren}}(X_i, \tau)}{\sum_\tau E_{\text{total}}(X_i, \tau)} \tag{6}$$

where E_{ren} and E_{total} represent the renewable energy utilized and total energy consumed by the infrastructure during the scheduling interval τ, respectively.

To enhance the performance of CSA for VM migration in cloud data centers, the proposal is the integration of a knowledge acquisition mechanism: Cuckoo Search Algorithm with Knowledge Acquisition (CSAKA). Knowledge acquisition encompasses various techniques for acquiring, representing, and utilizing domain-specific knowledge to guide the optimization process. In the context of CSA, knowledge acquisition can be employed to provide insights into the characteristics of the optimization problem, such as the features related to cloud data centers, hosts and virtual machines as shown in Table 1.

One approach to incorporating knowledge acquisition into the CSA is through the utilization of expert systems, which encode domain expertise into a set of rules or heuristics [17, 18]. These rules serve as the foundation for guiding the

algorithm's behavior by leveraging insights from expert knowledge about the problem domain. In this sense, in the context of optimizing cloud sustainability through virtual machine migration, a fuzzy expert system can be employed. Following this idea, in this paper, a fuzzy expert system utilizes rule bases to represent each "cuckoo's nest" in CSA, with rules constructed based on features extracted from the cloud system description (Table 1).

Table 1. Features for cloud system description.

Variable	**Description**
Renewable Availability (CDC-RA)	Renewable energy supplied to the CDC
Host Computational Capacity (HCC)	Maximum computational capacity (CC) in MIPS
Host Computational Availability (HCA)	Remaining CC of the host in MIPS after holding other VMs
VM Maximum Computational Needs (VM-MCN)	Maximum needs of the VM in MIPS
VM Current Computational Needs (VM-CCN)	Remaining computational needs in MIPS for the VM

The features outlined in Table 1 provide essential information about the cloud environment, such as renewable energy availability, host computational capacity, and VM computational needs. By incorporating these features into the fuzzy expert system's knowledge base, CSA can make informed decisions during the optimization process. For example, knowledge about renewable energy availability (CDC-RA) can guide CSA to prioritize VM migration to data centers with higher renewable energy supply, thereby enhancing overall sustainability. Similarly, information about host computational availability (HCA) and VM computational needs (VM-CCN) can inform CSA's decision-making regarding VM placement and migration strategies.

This paper utilizes an expert system whose knowledge bases consist of seven rules, adopting an identical rule structure from a previous work [2] to maintain consistency and leverage its proven effectiveness in addressing the problem. The anatomy of the rules within the KBs is illustrated in Table 2, comprising eight variables including five input variables (cloud features), the output of the Fuzzy Rule-Based System (host suitability for migrating the virtual machine), the weight variable, and the logical operator used in the rule. These variables are constrained by specific upper and lower bounds to ensure stability. During the initialization phase, the knowledge bases are randomly created while adhering to the universe of discourse for both input and output variables. Input variables have three possible values along with a complementary operator, resulting in six distinct values per input, while the output variable encompasses five different values and their complementary counterparts, totaling ten possible output values. The weight remains constant at 1 in all rules, indicating equal impor-

tance, and the logical operators for combining input values include AND and OR, allowing for different rule combinations. As additional information, the expert system uses fuzzy Gaussian membership functions. An example of an expert system rule base extracted from the cloud environment is presented in Table 3.

Table 2. Fuzzy rule anatomy.

Parameter	**Value/Description**
Number of Variables	8
Upper Bounds	[3, 3, 3, 3, 3, 5, 1, 2]
Lower Bounds	[1, 1, 1, 1, 1, 1, 1, 1]
Rules per Knowledge Base (KB)	7
Rule Anatomy	Inputs (5), Output, Weight, and Logical Operator

Table 3. Rules base of the expert system.

Rule	**CDC-RA**	**HCC**	**HCA**	**VM-MCN**	**VM-CCN**	**AND/OR**	**OUTPUT**
1		High		Low		AND	Extremely Suitable
2		Low		High		AND	Not Very Suitable
3			High		Low	AND	Extremely Suitable
4			Low		High	AND	Not Very Suitable
5	Low						Not Very Suitable
6	Medium						Suitable
7	High						Extremely Suitable

Incorporating knowledge acquisition into CSA offers several potential benefits for optimizing VM migration in cloud data centers. By leveraging cloud-based information, CSA can make more informed decisions, leading to improved convergence speed, higher-quality solutions, and enhanced overall system performance. Moreover, knowledge-driven optimizations can enable CSA to adapt dynamically to changing conditions and uncertainties in the cloud environment, making it more robust and reliable in future practical deployment scenarios.

3 Experimental Results

To evaluate the performance of CSAKA for VM migration in cloud data centers, a series of experiments in medium-scale scenarios regarding the hosts and virtual machines, and with varying the number of cloudlets were conducted. The experiments were designed to assess CSAKA's effectiveness in optimizing renewable energy compared to the Pittsburgh Algorithm and KASIA, conventional approaches commonly used for VM migration in cloud environments.

For each experiment, a geographically distributed cloud data center environment using an extended version of CloudSim [13] was simulated. The experiments

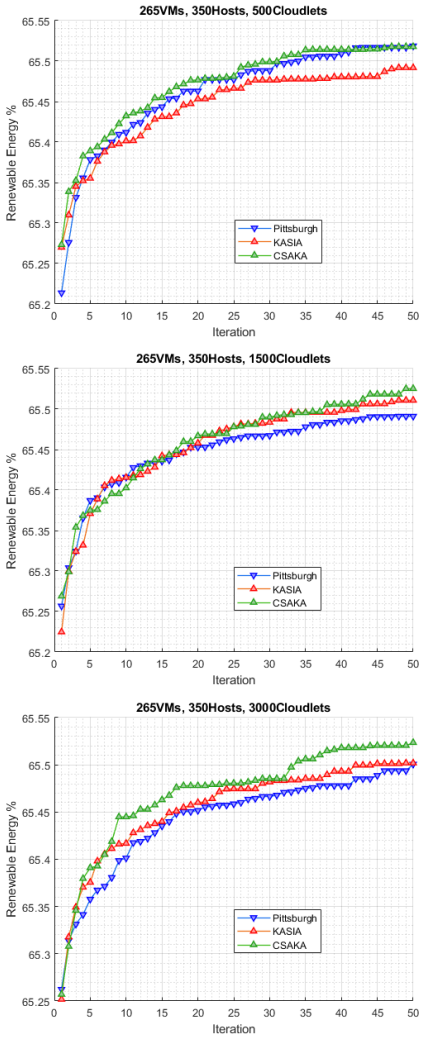


Fig. 1. Performance evolution of Pittsburgh, KASIA and CSAKA in the three scenarios.

were conducted on a server HP ProLiant ML110 G5 (Xeon 3075, dual-core, 2.6 GHz, 4 GB RAM, and 1Gbps of Bandwidth). The simulator enables the simulation of various broker strategies using knowledge bases generated by the knowledge acquisition algorithm. It also accommodates multiple resource architectures and diverse cloud data center builds. The variations encompass different host and VM configurations, as well as various selection and migration policies [3].

For the experiments, three distinct scenarios to assess the performance of the proposed CSAKA were developed in comparison to the Pittsburgh Algorithm and KASIA for renewable energy optimization. Each scenario, counting with 4 geographically distributed cloud data centers, varied in the number of hosts and virtual machines, with a focus on different cloudlet capacities. Specifically, the simulation scenarios encompass 530 hosts and 695 virtual machines, wherein the number of cloudlets varied as follows:

- Scenario 1: Small-scale scenario with 1000 cloudlets.
- Scenario 2: Medium-scale scenario with 2000 cloudlets.
- Scenario 3: Large-scale scenario with 5000 cloudlets.

To evaluate the effectiveness of CSAKA, a comparison is made against the Pittsburgh Algorithm and KASIA in the context of renewable energy optimization. The parameter configuration for both algorithms involved setting 64 individuals, 50 iterations, and 30 repetitions for each simulation run. This setup ensured a comprehensive assessment of the algorithms' performance across multiple iterations and repetitions.

The primary performance metric analyzed in the experiments was renewable energy optimization. By comparing the performance of CSAKA, KASIA and Pittsburgh in terms of their ability to optimize renewable energy usage across the different scenarios, the aim was to assess the efficacy of CSAKA in addressing the complex optimization challenges inherent in cloud computing environments.

From the experimental results shown in Figure 1, it is evident that CSAKA outperforms the Pittsburgh Algorithm and KASIA in all three scenarios. CSAKA demonstrates higher renewable energy rates compared to Pittsburgh Algorithm across different scales of cloud data center environments. This superiority of CSAKA is further corroborated by Table 4, which presents a comparison between Pittsburgh, KASIA and CSAKA in terms of the percentage of renewable energy used. As shown in the table, CSAKA consistently achieves a higher percentage of renewable energy utilization compared to Pittsburgh and KASIA across various configurations of hosts, VMs, and cloudlets. These findings underscore the effectiveness of incorporating knowledge acquisition mechanisms into evolutionary algorithms like CSA for optimizing renewable energy usage in cloud computing environments.

The superior performance of CSAKA can be attributed to its ability to leverage domain-specific knowledge and adapt dynamically to changing conditions in the cloud environment. By incorporating the knowledge acquisition mechanism, CSAKA effectively exploits insights from cloud features to guide the optimization process, resulting in more efficient VM migration strategies.

Table 4. Results comparison between Pittsburgh, KASIA and CSAKA: Percentage of renewable energy used.

Hosts	VMs	Cloudlets	Pittsburgh	KASIA	CSAKA
530	695	1,000	66.70±0.02	66.65±0.02	66.72±0.01
530	695	2,000	66.70±0.02	66.71±0.02	66.72±0.01
530	695	5,000	66.68±0.01	66.67±0.02	66.71±0.01

Overall, the experimental results validate the efficacy of CSAKA for optimizing VM migration in cloud data centers and underscore the importance of knowledge-driven optimizations in enhancing the percentage of renewable energy of cloud computing infrastructures.

3.1 Discussion of Results

The choice of the CSA for the VM migration problem is motivated by its superior ability to maintain a balance between local exploitation and global exploration compared to traditional methods. Unlike the Pittsburgh Algorithm or KASIA, which are often prone to premature convergence in high-dimensional search spaces, Lévy flights are leveraged by CSA to generate a wider, more effective search radius. This mechanism allows the algorithm to escape local optima, a common pitfall encountered in deterministic approaches used in earlier studies. While other metaheuristics, such as Particle Swarm Optimization or Ant Colony Optimization, could theoretically be applied, a lower computational overhead has been demonstrated by CSA in dynamic environments, making it uniquely suited for the energy-intensive demands of cloud data centers.

Regarding the comparison with KASIA and the Pittsburgh Algorithm, a novel fuzzy expert system layer is introduced by the proposed CSAKA approach, which dynamically adjusts the search process based on real-time system states. While numerical improvements over KASIA and Pittsburgh may appear marginal, their significance is underscored by the constraints of cloud sustainability; in large-scale data centers, a marginal increase in renewable energy utilization translates into substantial reductions in carbon emissions and operational costs. These results indicate that a more robust framework for long-term sustainability is provided by CSAKA than by the static structures found in traditional KASIA and Pittsburgh deployments.

The parameters utilized for this study were determined through a sensitivity analysis conducted during the preliminary simulation phases. A population size was selected to ensure diversity across the search space without exceeding the memory limits of the CloudSim environment. Furthermore, these parameters were optimized to ensure that convergence is achieved within a reasonable number of iterations, balancing precision with the execution speed required for real-time VM migration scenarios.

4 Conclusion and Future Work

This paper presented the integration of a knowledge acquisition mechanism based on an expert system with the CSA algorithm to enhance virtual machine migration efficiency and sustainability in cloud data centers. The proposed CSAKA leverages domain-specific knowledge and insights derived from a fuzzy rule-based expert system to improve the optimization process. By incorporating these knowledge-driven elements, CSAKA demonstrated superior performance compared to the traditional Pittsburgh Algorithm and KASIA across various medium-scale scenarios regarding the optimization of renewable energy. The experimental results, conducted in simulated CloudSim environments with different numbers of hosts, virtual machines, and cloudlets, consistently showed that CSAKA outperforms Pittsburgh and KASIA in terms of renewable energy. The significant improvements in this key performance metric validate the efficacy of knowledge acquisition in enhancing the CSA's ability to navigate the complex search space of VM migration problems.

Future work will focus on further refining the knowledge acquisition techniques and exploring their applicability to other optimization problems within cloud computing. Furthermore, the scalability of CSAKA will be investigated in larger and more diverse cloud environments, aiming to ensure its practical applicability and effectiveness in real-world cloud data centers. By continuing to enhance the synergy between evolutionary algorithms and domain-specific knowledge, efforts are made to contribute to the development of more intelligent, sustainable and efficient cloud computing infrastructures.

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