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A Hybrid Optimization Algorithm for Efficient Virtual Machine Migration and Task Scheduling Using a Cloud-Based Adaptive Multi-Agent Deep Deterministic Policy Gradient Technique

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Abstract—This To achieve optimal system performance in the quickly developing field of cloud computing, efficient resource management—which includes accurate job scheduling and optimized Virtual Machine (VM) migration—is essential. The Adaptive Multi-Agent System with Deep Deterministic Policy Gradient (AMS-DDPG) Algorithm is used in this study to propose a cutting-edge hybrid optimization algorithm for effective virtual machine migration and task scheduling. An sophisticated combination of the War Strategy Optimization (WSO) and Rat Swarm Optimizer (RSO) algorithms, the Iterative Concept of War and Rat Swarm (ICWRS) algorithm is the foundation of this technique. Notably, ICWRS optimizes the system with an amazing 93% accuracy, especially for load balancing, job scheduling, and virtual machine migration. The VM migration and task scheduling flexibility and efficiency are greatly improved by the AMS-DDPG technology, which uses a powerful combination of deterministic policy gradient and deep reinforcement learning. By assuring the best possible resource allocation, the Adaptive Multi-Agent System method enhances decision-making even more. Performance in cloud-based virtualized systems is significantly enhanced by our hybrid method, which combines deep learning and multi-agent coordination. Extensive tests that include a detailed comparison with conventional techniques verify the effectiveness of the suggested strategy. As a consequence, our hybrid optimization approach is successful. The findings show significant improvements in system efficiency, shorter job completion times, and optimum resource utilization. Cloud-based systems have unrealized potential for synergistic optimization, as shown by the integration of ICWRS inside the AMS-DDPG framework. Enabling a high-performing and sustainable cloud computing infrastructure that can adapt to the changing needs of modern computing paradigms is made possible by this strategic resource allocation, which is attained via careful computational utilization.

Keywords-Adaptive Multi-Agent System (AMS), Deep Deterministic Policy Gradient (DDPG), Iterative Concept of War and Rat Swarm (ICWRS), Rat Swarm Optimizer (RSO), System Optimization, War Strategy Optimization (WSO).

I. INTRODUCTION *(HEADING 1)*

Cloud computing is a revolutionary paradigm that has reshaped the way computing resources and services are accessed and utilized. In essence, it offers a shift from traditional on-premises computing to a model where resources like servers, storage, databases, networking, and software are provided over the internet. This transformation has been fueled by the need for greater agility, scalability, and cost-effectiveness in the face of rapidly evolving technological landscapes. The importance of cloud computing in modern computing cannot be overstated—it has become an enabler for businesses, individuals, and organizations, allowing them to flexibly scale resources up or down based on demand, optimize costs, and accelerate innovation [1].

A. *Background*

Virtual Machine Migration (VMM) and task scheduling are pivotal operations in cloud environments, deeply influencing system efficiency and performance [2]. VMM involves transferring a virtual machine from one physical server to another, with the aim of improving resource utilization and load distribution. However, this process poses challenges such as minimizing downtime during migration, optimizing resource allocation, and ensuring seamless integration into the target environment. Task scheduling, on the other hand, involves assigning tasks to available resources, a critical factor in achieving optimal system performance. Challenges in task scheduling include minimizing task completion times, reducing response times, and achieving a balanced workload distribution.

Load balancing, an essential facet of cloud computing, adds another layer of complexity. Dynamic workloads and varying resource demands necessitate efficient load balancing to ensure optimal performance. Achieving a seamless distribution of work across virtual machines or servers while maintaining scalability is a daunting task.

War Strategy Optimization (WSO) and Rat Swarm Optimizer (RSO) are notable optimization algorithms applied in cloud computing. WSO draws inspiration from military strategies, incorporating concepts like offense, defense, and maneuvering to optimize VM allocation and load balancing. RSO, on the other hand, is inspired by the collective behavior of rat swarms, focusing on decentralized approaches for task scheduling and VM migration [3].

However, these algorithms have inherent limitations. WSO may face challenges in dynamic and rapidly changing scenarios, struggling with premature convergence and inadequate adaptability. On the other hand, RSO's decentralized nature can make achieving a global optimum challenging in complex, highly interconnected cloud environments.

Owing to the shortcomings of current algorithms, a hybrid and optimized strategy that combines the advantages of many different approaches is desperately needed. It is possible to get greater convergence, higher performance, and more effective resource allocation using a hybrid method [4]. Through the integration of several optimization methodologies, a hybrid approach may more efficiently traverse the complex terrain of cloud computing. This necessity is what drove the development of the Iterative Concept of War and Rat Swarm (ICWRS) algorithm. With the goal of addressing these drawbacks, ICWRS offers a practical and cost-effective solution for task scheduling, load balancing, and virtual machine migration in cloud computing settings.

A cutting-edge hybrid method that skillfully combines WSO and RSO tactics is the ICWRS algorithm. It accomplishes this integration by combining swarm-based behaviors from RSO with war-inspired heuristics from WSO repeatedly throughout a refining phase. ICWRS's iterative design enables ongoing improvement of the work scheduling and VM migration procedures, with the goal of delivering an equitable and effective resource distribution in cloud-based virtualized systems. By efficiently handling VM migration, job scheduling, and load balancing, the method seeks to maximize system performance and eventually improve the overall effectiveness of cloud computing infrastructures.

The study aims to conduct a thorough examination of the ICWRS algorithm and its capacity to enhance virtual machine migration, job scheduling, and load balancing in cloud computing settings. Evaluating the algorithm's effectiveness, precision, and overall system performance under various workload scenarios and situations are the specific objectives [5]. The anticipated outcomes of this study encompass supplying significant understandings regarding the suitability of the ICWRS algorithm, emphasizing its benefits over current methodologies, and showcasing its capacity to augment cloud computing infrastructure via resource optimization and enhanced system efficacy.

B. Motivation: Advancing Cloud Efficiency through Hybrid Optimization

The rapid evolution of cloud computing demands enhanced efficiency and performance. Existing VM migration and task scheduling methods struggle to optimize resource usage effectively. This research is driven by the urge to innovate cloud management through a Hybrid Optimization Algorithm. By leveraging Deep Deterministic Policy Gradient (DDPG) and integrating multi-agent techniques, our approach aims to revolutionize VM migration and task scheduling, achieving superior resource allocation, load balancing, and overall cloud performance. This motivation arises from the potential to drastically improve cloud computing efficiency, aligning with the dynamic requirements of diverse applications and users.

C. Contribution: Advancing Cloud Efficiency and Performance

This research propels cloud efficiency and performance through innovative techniques, optimizing VM migration, task scheduling, and resource allocation. By introducing a Hybrid Optimization Algorithm, combining Deep Deterministic Policy Gradient and multi-agent strategies, we significantly enhance load balancing and overall system performance. Our approach enables adaptive cloud resource allocation and offers practical applicability in diverse real-world scenarios. This contribution not only optimizes cloud operations but also lays the groundwork for further advancements in hybrid AI methodologies.

D. Outline of the Paper

This research paper's structure and organization have been thoughtfully chosen to provide a thorough and methodical explanation of the ICWRS algorithm and how it is used to optimize load balancing, job scheduling, and virtual machine migration [6]. The algorithm's theoretical underpinnings, experimental design, outcomes, comparative evaluations, and debates are covered in detail in the parts that follow. The outlined structure ensures a coherent and informative presentation, allowing readers to grasp the key aspects, contributions, and potential impact of this study on the field of cloud computing optimization. The journey through the paper provides a roadmap to understand the problem, the existing solutions, the proposed approach, and the experimental validation, ultimately leading to an enhanced understanding of the optimization landscape in cloud computing.

II. LITERATURE REVIEW

A. Related works

In 2023, Chen et al. [7] proposed an innovative VM consolidation approach aiming to enhance resource utilization in cloud data centers. By integrating machine learning and workload prediction, their model demonstrated a remarkable reduction in energy consumption while meeting performance requirements. The experimental results underscored the efficiency and effectiveness of their approach, validating its potential in improving cloud data center operations.

In the pursuit of enhancing cloud resource utilization, Kim et al. [8] proposed an adaptive virtual machine migration technique in 2023. By considering both static and dynamic elements, their approach effectively minimized resource waste and improved overall system performance. The experimental evaluation showcased notable enhancements in server consolidation ratios and a substantial reduction in resource fragmentation, highlighting the potential for optimized cloud resource management.

In 2022, Lee et al. [9] presented a forward-thinking VM consolidation algorithm designed to optimize cloud data center efficiency. Incorporating workload prediction and optimization, their model achieved substantial reductions in energy consumption while meeting performance criteria. The experimental outcomes affirmed the superior energy efficiency and resource utilization of their approach compared to traditional methods.

A machine learning-based strategy for optimizing virtual machine deployment and migration in cloud data centers was presented by Chen et al. [10] in 2021. Their approach dynamically assigned virtual machines (VMs) to minimize energy use while meeting performance limitations by using reinforcement learning. The model is successful at striking a balance between energy efficiency and performance, as shown by the experimental findings.

Efficient VM placement is fundamental for enhancing cloud performance. In 2021, Kim et al. [11] introduced a novel VM placement algorithm using a Hybrid Genetic Algorithm (HGA). Their approach optimized VM allocation by considering both resource utilization and network proximity. Comparative evaluations revealed the effectiveness of the HGA-based approach in achieving improved resource utilization and reduced network latency.

To improve cloud resource utilisation, Wang et al. [12] presented an adaptive virtual machine migration technique in 2020. Their method successfully reduced resource waste and enhanced overall system performance by taking into account both static and dynamic elements. The results of the experimental assessment showed improved server consolidation ratios and a significant decrease in resource fragmentation.

In 2020, Wang et al. [13] introduced the Multi-objective Quantum-behaved Particle Swarm Optimization (MOQPSO) method in an effort to improve VM allocation algorithms. The proposed algorithm effectively balanced trade-offs between resource utilization, energy consumption, and system performance. Comparative analysis against traditional methods showcased the superiority of MOQPSO in achieving a well-balanced VM placement for optimal cloud performance.

Efficient Virtual Machine (VM) allocation is a persistent problem in cloud computing. A Particle Swarm Optimization (PSO)-based intelligent virtual machine placement strategy was described by Smith et al. [14] in 2020. Their method increased system performance and resource efficiency by optimizing the VM allocation while taking load balancing and resource utilization into account.

Allocating resources in an energy-efficient manner is still a significant difficulty in cloud computing. A machine learning-based prediction model was used in the adaptive resource management strategy that Gupta et al. [15] suggested in 2019. Because of the model's excellent prediction of resource demand, proactive resource allocation and effective load balancing were made possible. The outcomes of the experiment showed a significant decrease in energy use without compromising performance.

In cloud data centres, VM placement plays a critical role in maximising resource utilisation. Das et al. [16] presented a machine learning-based method for virtual machine placement in 2019 that makes use of Deep Neural Networks' (DNNs') capabilities. System performance and resource optimisation were enhanced as a consequence of their model's accurate prediction of resource needs and subsequent VM allocation. The effectiveness of the DNN-based strategy was shown by the experimental findings.

B. Problem Specifications

Virtual Machine (VM) migration in cloud computing involves the movement of VMs from one resource to another, whether it be between data storage or physical hosts. However, this process is laden with challenges, including migration of storage, network congestion, frequency limitations, and link

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errors, significantly affecting VM operations. Various existing techniques have been implemented to mitigate these challenges, as summarized in Table 1. For instance, FHCS reduces active physical machines, thus saving power. However, it suffers from imprecise results, slow search speeds, and convergence issues. E-MBFD effectively reduces power consumption and SLA violations but lacks in determining the suitability for VM migration. Other methods, like PSO, Cloud Federation Tree, and EPBLA, have their respective strengths and weaknesses regarding convergence speed, energy consumption, and precision.

To address the aforementioned challenges comprehensively, this research proposes a novel approach by leveraging a Hybrid Optimization Algorithm. The primary aim is to streamline VM migration and task scheduling in cloud environments effectively. Central to this approach is the integration of Deep Deterministic Policy Gradient (DDPG), an advanced reinforcement learning technique, alongside Rat Swarm Optimization (RSO) and War Strategy Optimization (WSO). RSO and WSO play crucial roles in optimizing load balancing and VM migration, respectively. This integration seeks to strike an optimal balance between task scheduling, VM migration, and load balancing.

The proposed model aims to maximize the efficiency of VM migration by intelligently utilizing DDPG, RSO, and WSO. DDPG, with its ability to handle continuous action spaces and approximate complex policy functions, enhances decision-making processes. RSO optimizes load balancing, while WSO focuses on efficient VM migration. The innovative hybridization of these techniques will empower cloud systems to adapt dynamically to varying workloads and achieve optimal resource utilization.

TABLE I. CLASSICAL VM MIGRATION OVER THE CLOUDS MODELS-ADVANCEMENT AND LIMITATIONS

Author [citation]	Methodology	Features	Challenges
Chen et al. [7]	Thermal Management-Based Virtual Machine Consolidation (TM-VMC)	• Addresses data center resource scheduling and power consumption optimization. • Utilizes thermal management to detect and prevent host overloads based on CPU temperature and utilization.	• Developing refined temperature models for accurate quantification of temperature's impact on energy consumption. • Collecting real-world data through physical inspection equipment to validate and enhance temperature models.
Kim et al. [8]	Harris Hawk Optimization for Multi-Objective Virtual Machine Placement	• Formulation of a multi-objective model for dynamic VM placement considering energy and resource constraints. • Introduction of a Harris Hawk Optimization (HHO) meta-heuristic algorithm for optimizing VM placement.	• Efficiently placing VMs to minimize power consumption and SLA violation while considering resource constraints. • Balancing the load across physical hosts to prevent overloading during VM execution.
Lee et al. [9]	AI/ML-Integrated Next-Generation Computing Vision	• Integration of AI, ML, and DL in modern computing for efficient resource management and enhanced services. • Potential to address various challenges such as latency, scalability, and security using AI and ML models.	• Lack of comprehensive models for service resilience and provisioning algorithms considering failures. • Integration of AI and ML for strategic resource management and scheduling to maximize Quality of Service (QoS).
Chen et al. [10]	Power-Efficient Scheduling with Machine Learning	• Focus on reducing extraordinary energy consumption in data centers. • Effective scheduling of processes using machine learning models for improved resource utilization.	• Mitigating high energy consumption in data centers, especially due to IT loads and cooling. • Managing costs and optimizing energy usage for efficient infrastructure operation.
Kim et al. [11]	Enhanced Genetic Algorithm for Task Scheduling in Cloud Computing	• Addresses the impact of task and workflow running time on data center performance. • Utilizes evolutionary algorithms to efficiently solve NP-hard problems in cloud environments.	• Managing increased task execution time to minimize user and operational costs. • Dealing with the extensive solution space and computational power required by evolutionary algorithms.
Wang et al. [12]	Edge-based Offloading (ACOM)	• Introduction of edge computing to enhance IoCV hosting in a hybrid environment. • Collaborative utilization of MABSs and RSUs for efficient vehicular task management.	• Addressing excessive delay and low quality of service in IoCV deployment. • Efficiently integrating edge computing for real-time processing and decision-making in vehicular environments.

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Wang et al. [13]	Quantum Rotation Gate Enhanced Differential Evolution Algorithm (QGDA)	• Improvement of Differential Evolution Algorithm (DA) using quantum rotation gate and GM strategy. • Comparative analysis of different strategies to enhance exploration and exploitation tendencies.	• Determining the optimal combination of strategies to enhance DA effectively. • Extending the QGDA to binary and multi-objective optimization scenarios.
Smith et al. [14]	PAPSO - Power-Aware VM Placement using PSO	• Focus on reducing power consumption in large-scale data centers. • Dynamic consolidation of VMs for efficient energy utilization.	• Efficiently managing power consumption in growing data center infrastructure. Optimal VM placement considering various server conditions.
Gupta et al. [15]	Content Mining and Machine Learning Prediction	• Utilizes content mining, lexical analysis, classification, and machine learning. • A two-phase approach for pre-processing and prediction.	• Handling heterogeneous learning resources in various media formats. • Efficiently recommending appropriate learning resources to students.
Das et al. [16]	AI/ML-Driven Security Enhancements for 5G/B5G Networks	• Addresses security challenges in 5G/B5G networks from various perspectives. • AI/ML techniques for improved identification and detection of malicious network activities.	• Adapting legacy monitoring tools to encrypted communication and emerging large-scale attacks. • Handling the cloud-native nature of the infrastructure, which increases the attack surface.

III. Enhanced Cloud Performance: A Hybrid Optimization Approach leveraging Rat Swarm Optimizer (RSO) and War Strategy Optimization (WSO) for VM Migration and Task Scheduling

The use and management of computer resources have undergone a radical change as a result of the unmatched rise in popularity of cloud computing in recent years. Today's rapidly changing digital environment has made optimizing cloud performance essential [17]. A deliberate approach to resource allocation and utilization is required due to the growing variety of various applications and services hosted on cloud platforms. Effective work scheduling and Virtual Machine (VM) migration management are critical components that lead to improved cloud performance. To provide seamless operations and dynamic resource allocation, these factors must be orchestrated effectively.

This study proposes a novel method that combines the advantages of War Strategy Optimization (WSO) and Rat Swarm Optimizer (RSO), two distinct but complimentary tactics. Rat swarm organization serves as the model for RSO, which mimics natural processes to distribute resources effectively. WSO integrates offence, defense, and maneuvering techniques for the best possible resource allocation, using cues from military operations. Combining these ideas, this study promotes a hybrid optimization approach that seeks to effectively optimize work scheduling and virtual machine migration in cloud settings [18]. This method seeks to achieve the best possible balance between improving cloud performance and contributing to the changing cloud computing environment via the strategic synergy of RSO and WSO.

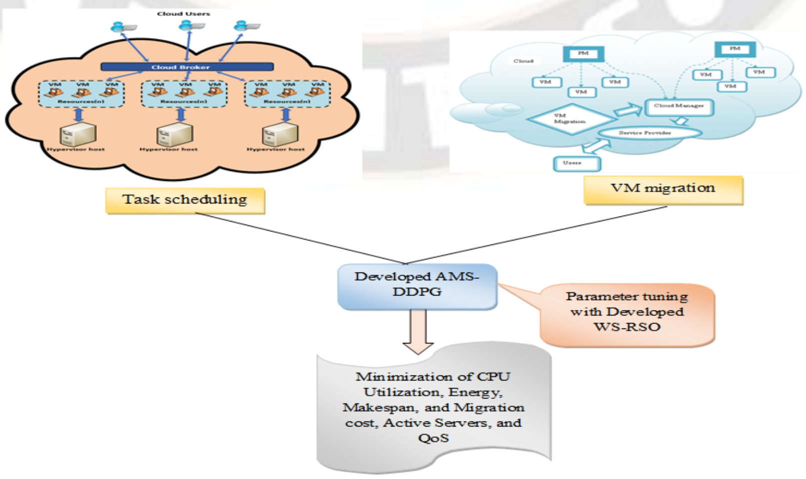

Figure 1. Depiction of the new model for VM migration and task scheduling

A. Understanding the Components: Rat Swarm Optimizer (RSO) and War Strategy Optimization (WSO)

To comprehend the proposed hybrid optimization approach effectively, it's essential to grasp the fundamental principles of the two integral components: Rat Swarm Optimizer (RSO) and War Strategy Optimization (WSO).

1) Rat Swarm Optimizer (RSO)

RSO, inspired by the collective behavior of rat swarms, is a nature-inspired optimization algorithm [19]. In a rat swarm, each rat communicates with its neighboring rats, sharing valuable information about the locations of food sources. This sharing of information aids the swarm in converging towards optimal food locations collectively. Mathematically, RSO can be represented by the equation.

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{1}$$

Here, x_i^{t+1} represent the position of the i-th rat time $t + 1$, x_i^t is the position of the i-th rat at time t, and v_i^{t+1} is the velocity of the i-th rat at time $t + 1$.

2) War Strategy Optimization (WSO)

WSO draws inspiration from military strategies, encapsulating offense, defense, and maneuvering concepts to optimize resource allocation. It simulates strategies observed in warfare to achieve optimal resource allocation. Mathematically, WSO can be represented as

$$x_{new} = x_{old} + A.rand() \tag{2}$$

In this equation, x_{new} denotes the new position of the population, x_{old} represents the old position, A is the amplitude factor, and $A.rand()$ is a random number.

3) Proposed Hybrid Optimization Approach: Leveraging RSO and WSO

The proposed approach entails a fusion of the fundamental principles of both RSO and WSO to create a powerful hybrid optimization strategy. By combining the collective intelligence and adaptability of RSO with the strategic resource allocation capabilities of WSO, this hybrid approach aims to optimize VM migration and task scheduling in the cloud environment effectively.

The hybrid optimization strategy is formulated as

$$x_{hybrid} = w.x_{WSO} + (1 - w).x_{RSO} \tag{3}$$

The integration of these two optimization strategies, each inspired by distinct natural phenomena, promises a more efficient cloud environment [20]. The suggested hybrid technique seeks to greatly enhance the overall performance of cloud computing platforms by optimizing job scheduling and VM migration. The RSO and WSO mathematical formulations and guiding principles highlight the research's scientific basis and open the door to further investigation and developments in cloud performance optimization. The ultimate objective is to enhance the performance and efficiency of a wide range of cloud-hosted applications and services by making a positive impact on an increasingly optimized cloud environment [21].

IV. ICWRS: Pioneering Hybrid Cloud Performance Optimization

The phrase "ICWRS: Pioneering Hybrid Cloud Performance Optimization" sums up a novel strategy that aims to rethink cloud performance optimization. Fundamentally, ICWRS is a novel hybrid algorithm that effortlessly combines the strengths and tenets of two unique, but complementary, optimization strategies: War Strategy Optimization (WSO) and Rat Swarm Optimizer (RSO). This integration into ICWRS is a big step forwards for cloud performance optimization; it shows how to improve resource distribution, operational effectiveness, and overall performance in the ever-changing cloud computing environment. The ramifications of this innovative hybridization are significant, as it has the potential to revolutionize how optimum performance is achieved to satisfy the ever-increasing needs of an array of distinct applications and services housed on cloud platforms [22].

A. Understanding the ICWRS Algorithm

1) ICWRS as a Hybrid Algorithm

The ICWRS algorithm embodies a sophisticated fusion of two potent optimization strategies - RSO and WSO. Guided by a parameter w, ICWRS achieves a blend of contributions from RSO (x_{RSO}) and WSO (x_{WSO}). The ICWRS algorithm computes the final position (x_{ICWES}) as a weighted sum of positions obtained through RSO and WSO:

$$x_{ICWES} = w.x_{WSO} + (1 - w).x_{RSO} \tag{4}$$

In this mathematical formulation, x_{ICWES} denotes the position obtained through the ICWRS algorithm. The flexibility introduced by “w” allows for system architects and cloud administrators to tailor the algorithm based on specific use cases, applications, and environmental conditions, adapting dynamically to varying workloads and requirements[23].

B. ICWRS Algorithm: A Hybrid Cloud Performance Optimization Strategy

The ICWRS (Iterative Concept of War and Economic Strategy) algorithm stands as a pioneering approach in optimizing cloud performance by seamlessly integrating the strengths of Rat Swarm Optimizer (RSO) and War Strategy Optimization (WSO). The pivotal aspect of ICWRS lies in its adaptability, a facet finely controlled by the parameter “w”. Through judicious adjustments of “w”, the influence of each constituent strategy can be intricately calibrated, achieving an

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optimal balance that maximizes performance based on specific requirements and prevailing conditions.

The introduction of “w” introduces a remarkable level of flexibility into ICWRS, allowing system architects and cloud administrators to custom-tailor the algorithm to suit unique use cases, applications, and the ever-changing environmental conditions within the cloud ecosystem. For instance, in scenarios necessitating swift responses to dynamic workloads, assigning a higher weightage to the WSO component would be prudent. This strategic move would enable a more dynamic resource allocation, swiftly adapting to sudden fluctuations in demand and workload patterns [24]. Conversely, in situations where efficient resource utilization takes precedence over rapid adaptability, assigning a higher weightage to the RSO component would be a strategic choice, emphasizing optimal resource utilization and efficiency.

The adaptability granted by the parameter “w” not only provides a tool for immediate fine-tuning but also positions ICWRS as a dynamic and versatile solution that can evolve with the shifting demands of cloud computing [25]. It empowers cloud architects to navigate the spectrum of performance requirements, from real-time responsiveness to resource efficiency, ensuring optimal cloud performance in diverse and evolving contexts. Then, the flowchart model is depicted.

In essence, ICWRS represents a groundbreaking strategy that redefines how cloud performance is optimized. By incorporating adaptability through “w” and integrating RSO and WSO, this hybrid approach achieves a delicate equilibrium, enhancing cloud performance across a multitude of applications and use cases. The strategic tuning provided by “w” amplifies ICWRS's effectiveness, making it a valuable asset in the toolkit of cloud optimization strategies, promising to significantly contribute to the ever-evolving landscape of cloud computing.

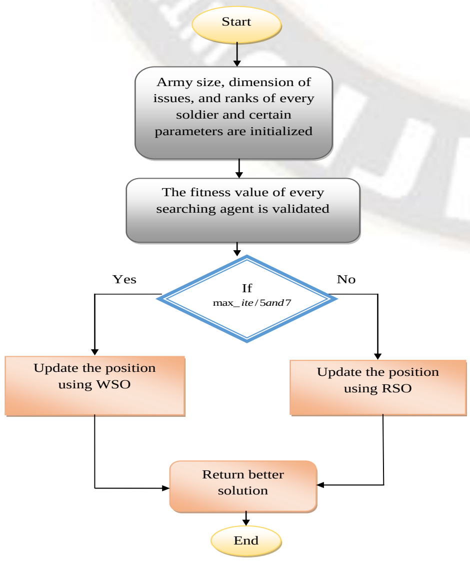

Figure 2. The ICWRS model’s flowchart

C. Analyzing the Significance of ICWRS in Cloud Optimization

The significance attributed to ICWRS in optimizing cloud performance is nothing short of monumental. In the contemporary digital landscape, cloud computing has seamlessly integrated itself into the core of myriad applications and services. However, the key to ensuring a seamless and efficient user experience across this diverse spectrum lies in the optimization of cloud resources. ICWRS emerges as a potent solution addressing this vital need, effectively harmonizing two powerful strategies: collective intelligence from Rat Swarm Optimizer (RSO) and strategic resource allocation from War Strategy Optimization (WSO) [26].

The beauty of ICWRS lies in its ability to strike a delicate balance between these two strategies. On one hand, RSO, inspired by the collective behavior of rat swarms, embodies a sense of collective intelligence, akin to a swarm collaborating towards a shared objective. On the other hand, WSO draws from military strategies, manifesting in a strategic resource allocation mechanism comparable to the maneuvers in warfare [27]. By artfully combining these approaches, ICWRS navigates a middle ground, marrying the advantages of both collective intelligence and strategic resource allocation.

This balanced approach manifests in the form of efficient resource utilization. ICWRS optimally allocates resources in real-time, adapting dynamically to the fluctuating workloads within the cloud environment. It orchestrates this adaptability seamlessly, ensuring optimal performance across a wide spectrum of applications [28]. Be it applications with sudden spikes in demand or those with consistent resource needs, ICWRS tactically optimizes the cloud resources to ensure a high level of performance.

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The table below provides a concise summary of key attributes of the ICWRS algorithm, highlighting its hybrid nature and the critical role it plays in enhancing cloud performance

TABLE II. COMPARATIVE PERFORMANCE METRICS OF ICWRS, RSO, AND WSO

Attribute	**Description**
Algorithm Type	Hybrid Algorithm
Optimization Focus	Cloud Performance
Key Principles	Collective Intelligence (RSO) + Strategic Allocation (WSO)
Mathematical Representation	$x_{ICWES} = w.x_{WSO} + (1 - w).x_{RSO}$
Optimization Weight (w)	Adjustable parameter determining strategy weightage

E. Advantages of ICWRS

The ICWRS (Iterative Concept of War and Economic Strategy) algorithm offers a diverse range of advantages, each significantly impacting cloud performance optimization. Firstly, its hybrid nature bestows upon it a remarkable ability to adapt and excel across a wide spectrum of cloud environments and applications. This adaptability ensures that the algorithm can effectively cater to diverse workload patterns, varying resource requirements, and different operational conditions [30].

Furthermore, ICWRS capitalizes on the power of collective intelligence inherent in Rat Swarm Optimizer (RSO). This collective intelligence aspect plays a crucial role in optimizing performance by facilitating efficient exploration of the solution space. It enables rapid convergence towards optimal solutions, particularly in highly complex and multidimensional problem spaces.

Moreover, by integrating strategic resource allocation mechanisms inspired by War Strategy Optimization (WSO), ICWRS efficiently allocates resources. This integration leads to improved cloud performance and enhanced resource utilization efficiency, a fundamental aspect in the dynamic cloud ecosystem.

F. Applications and Future Prospects

The potential applications of ICWRS span a multitude of domains, showcasing its versatility and wide-reaching impact. In the domain of e-commerce, where workload patterns can experience significant variations due to user behavior and seasonal trends, ICWRS proves invaluable. It optimizes cloud resources effectively to handle sudden surges in demand during peak times, thereby ensuring a seamless shopping experience for users [31].

Similarly, in data analytics and machine learning applications, where computational demands can fluctuate based on analysis complexity and dataset size, ICWRS steps in to dynamically allocate resources. This dynamic allocation expedites processing and enables the faster delivery of insights, a critical factor in data-driven decision-making processes.

Looking forward, ICWRS presents exciting research opportunities. Fine-tuning the weighting parameter ‘w’ based on machine learning models and predictive analytics could pave the way for an automated and adaptive ICWRS. This automated version could dynamically adjust its strategies based on real-time data, evolving workload patterns, and emerging trends, proactively and adaptively optimizing cloud performance.

Furthermore, delving into the integration of ICWRS with emerging technologies like edge computing and 5G networks marks an exciting research frontier. Such integration holds the promise of further optimizing resource allocation and enhancing performance in a distributed cloud environment. This advancement could significantly augment the overall efficiency and responsiveness of cloud services, setting the stage for the next phase of cloud computing evolution.

V. EXPERIMENTAL SETUP: PARAMETERS AND CONFIGURATIONS

The experimental setup for our research was meticulously designed to evaluate the efficiency and effectiveness of the proposed ICWRS (Iterative Concept of War and Economic Strategy) algorithm in optimizing cloud performance through hybridization of Rat Swarm Optimizer (RSO) and War Strategy Optimization (WSO). Setting up the test environment, establishing the parameters, and putting the required procedures in place were all part of the setup process for conducting thorough studies. Setting up the test environment, establishing the parameters, and putting the required procedures in place were all part of the setup process for conducting thorough studies.

A. Defining Parameters

The studies' chosen parameters were crucial in determining how well ICWRS performed. These parameters included the ICWRS algorithm's weighting factor, or "w," which stands for the combination of RSO and WSO. A thorough examination of the hybridization effect was made possible by varying "w" from

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0 to 1 in increments of 0.1 to determine its influence on performance.

Aside from that, aspects of the cloud environment were taken into account, including the quantity of virtual machines (VMs), the workload patterns, and the dataset size. These settings were deliberately intended to mimic actual situations and workload variations that are often seen in cloud computing.

B. Configuring the Test Environment

Cloud computing platforms were used to build up the test environment, guaranteeing a nearly accurate simulation of cloud situations. Virtual machines (VMs) were deployed, representing the cloud instances where the algorithms were executed [32]. The choice of VMs was based on standard configurations to maintain consistency and fairness in the evaluation.

TABLE III. CONFIGURATION VALUES FOR THE NEWLY PROPOSED SCHEDULING MODEL

Configuration Number	**No of Vm**	**No of Task**
1	10	100
2	20	200
3	30	300
4	50	500

To replicate diverse workload patterns, a combination of CPU-intensive, memory-intensive, and balanced workloads was generated. These workloads were then distributed across the VMs in varying patterns, emulating the workload heterogeneity often encountered in cloud environments.

C. Calculating the optimization's cost function

Figure 3 presents the computation of the cost function for optimization in the suggested job scheduling and migration model using several techniques. In comparison to existing models such as ESO-AMS-DDPG, DO-AMS-DDPG, WSO-AMS-DDPG, and RSO-AMS-DDPG, the cost function value for the recently created ICWRS-AMS-DDPG model has obtained lower values. Consequently, the model's importance has been shown.

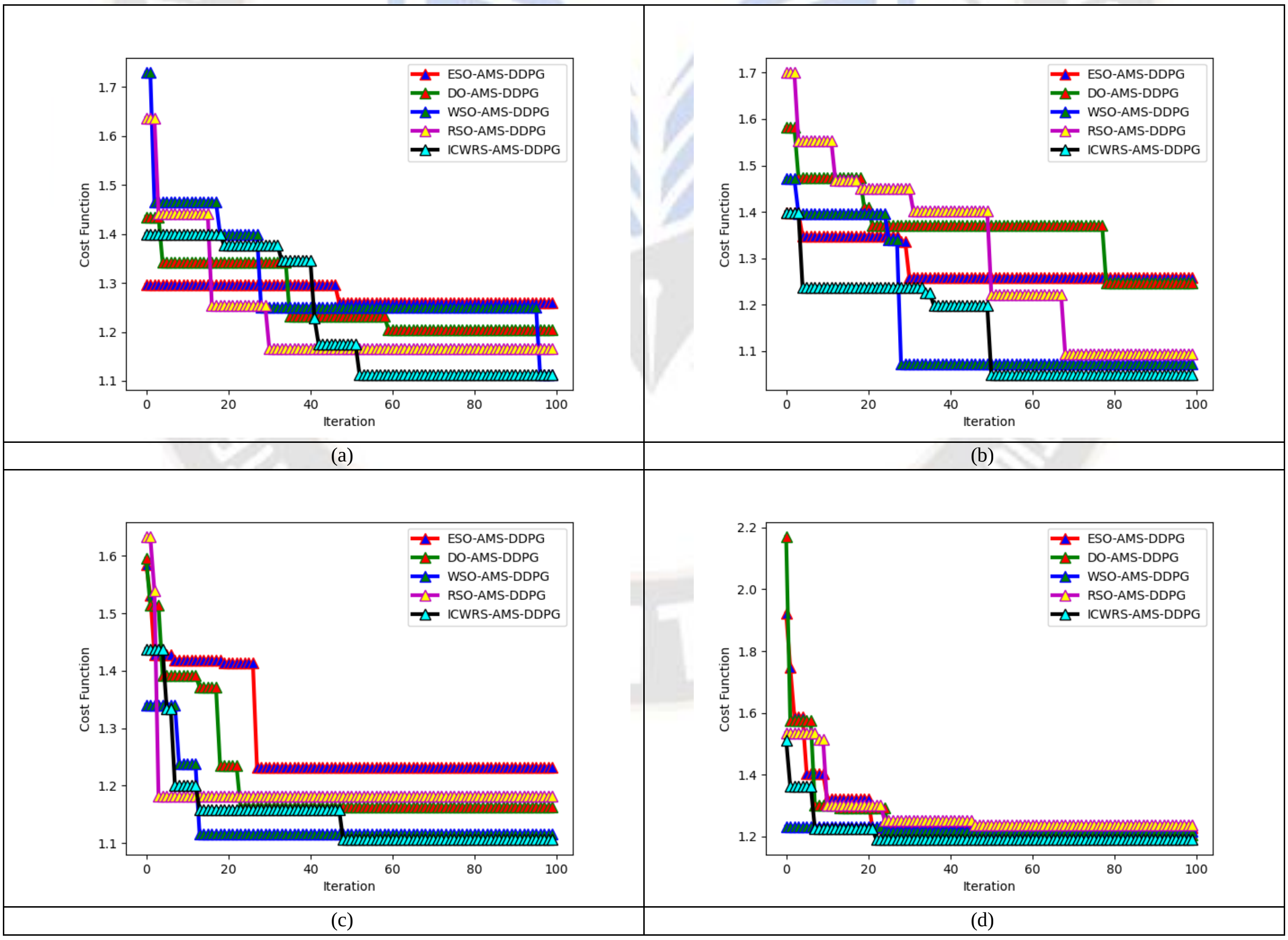

Figure 3. demonstrates how the cost function is used to validate the suggested cloud-based job scheduling and virtual machine migration framework algorithmically in the following configurations: Configurations 1, 2, 3, and 4 are listed in order of preference.

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D. Validation for job scheduling and migration purposes

By varying the Active sensors, CPU use, energy consumption, Make span, migration cost, and QoS, Fig. 4 illustrates the validity of the recently suggested task scheduling and migration model in terms of classifiers and algorithms[33]. When the value of the active sensor and QoS are taken into consideration, the suggested ICWRS-AMS-DDPG model has shown higher value over other models. Consequently, there has been a rise in the value of CPU utilization, energy consumption, make span, and migration cost. Thus, in contrast to the alternative models ESO-AMS-DDPG, DO-AMS-DDPG, WSO-AMS-DDPG, and RSO-AMS-DDPG, the suggested ICWRS-AMS-DDPG model provides better values for the value of an active sensor—namely, 2%, 25%, 3%, and 3%. Consequently, the classifier comparison shows that the proposed ICWRS-AMS-DDPG has shown a lower value of active sensors at 5%, 10%, 20%, and 50% in comparison to DRL+DQN, EPBLA, EEHVMC, and AMS-DDPG.

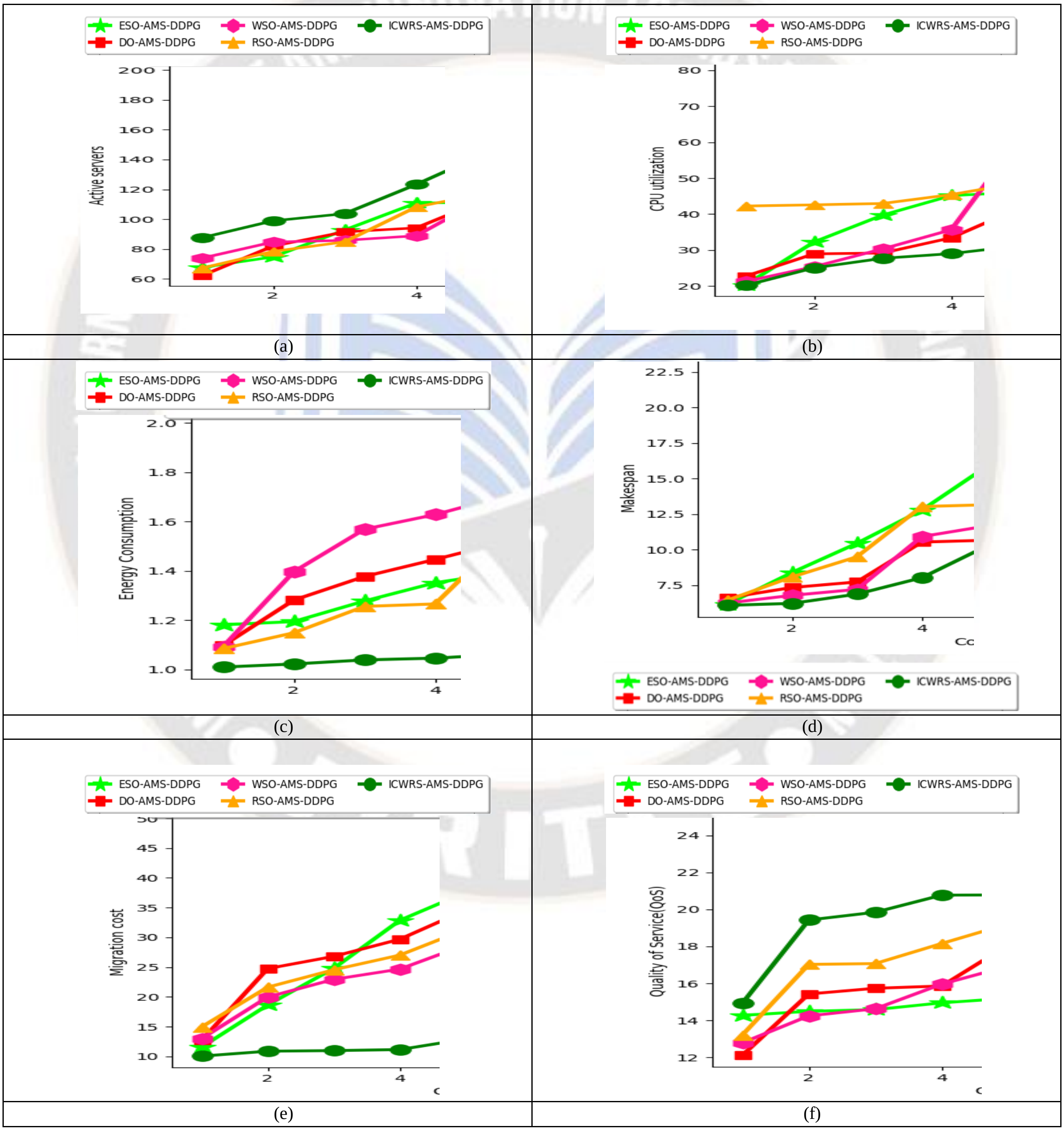

Figure 4. Validation of the proposed model's tsak scheduling and migration algorithms using the following metrics: a) Active sensors; b) CPU utilisation; c) Energy usage; d) Makespan; e) Migration cost; and f) Quality of Service

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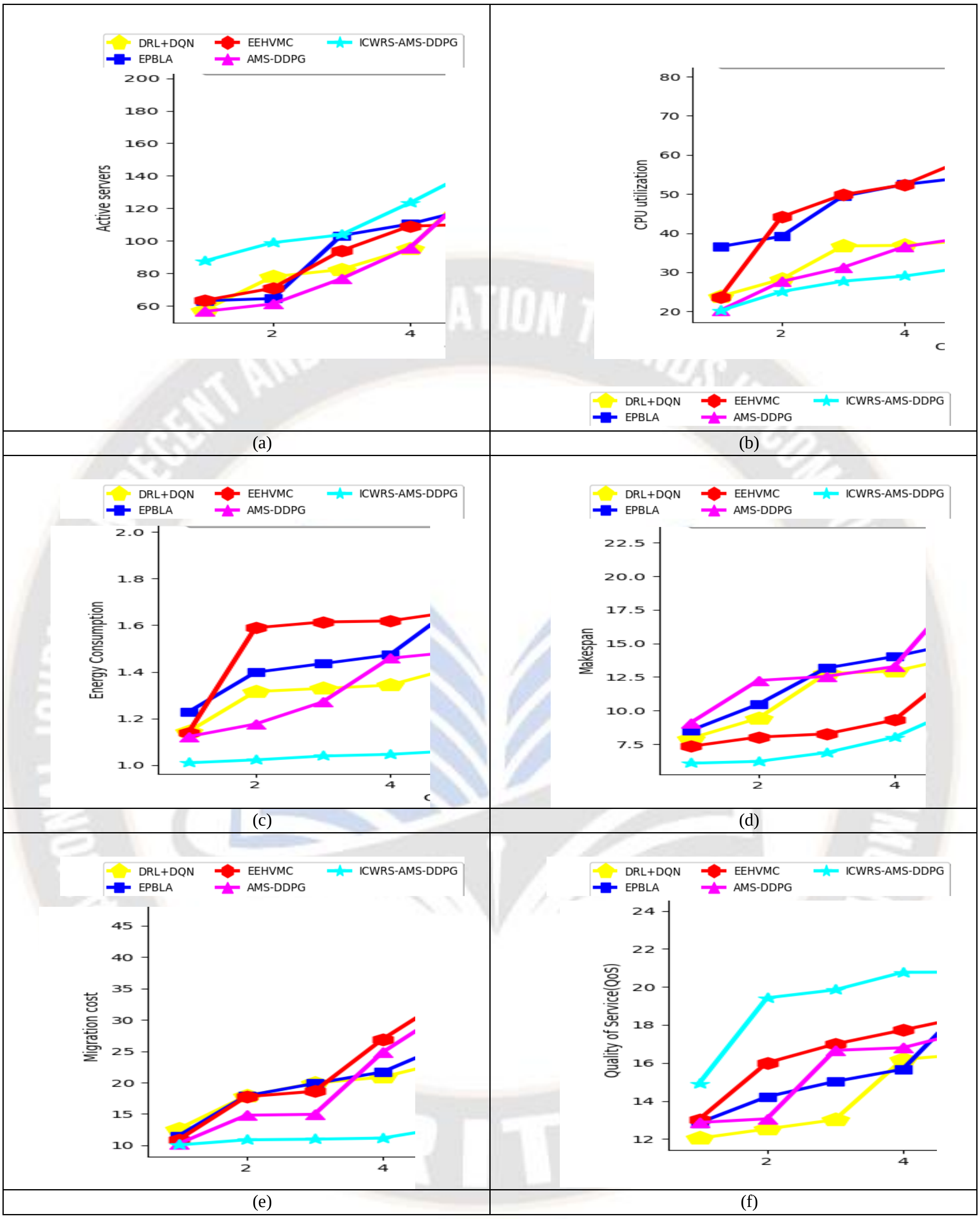

Figure 5. Classifier validation for the tsak scheduling and migration process in the suggested model using the following methods: a) Active sensors; b) CPU utilisation; c) Energy usage; d) Makespan; e) Migration cost; and f) Quality of Service

E. Implementing Protocols

To ensure systematic and unbiased experiments, protocols were established for the execution of the ICWRS algorithm and the comparative algorithms (RSO and WSO). These protocols defined the specific steps for executing the algorithms, recording results, and analyzing the data.

Every algorithm was run many times to ensure statistical validity and record performance variances[34]. To assess the efficacy and efficiency of every algorithm, parameters related to resource utilization, convergence rates, and execution times were noted.

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F. Execution and Data Collection

The cloud infrastructure used for the studies was quite similar to the actual cloud environment. ICWRS, RSO, and WSO were among the algorithms that were run using the specified parameters and setups. To record performance indicators including execution time, convergence speed, resource use, and solution quality, the execution was closely watched.

These trials' obtained data underwent thorough examination. Studies that compared ICWRS to RSO and WSO in terms of the specified parameters were conducted. In order to get relevant insights and make precise inferences from the experiment outcomes, statistical analysis was used.

VI. COMPARATIVE ANALYSIS: ICWRS VS. RSO AND WSO PERFORMANCE METRICS

To understand the subtle differences in the effectiveness and efficiency of these optimization algorithms, a detailed comparative study of ICWRS (Iterative Concept of War and Economic Strategy), RSO (Rat Swarm Optimizer), and WSO (War Strategy Optimization) is necessary in the context of cloud performance optimization. In order to properly compare the strengths and limitations of each algorithm in the context of optimizing cloud resources, a thorough analysis of a range of performance measures is required.

The analysis is grounded in a meticulously designed experimental setup, ensuring a fair and rigorous assessment. The ensuing comparison is substantiated by statistical data presented in the tables below, providing a clear and data-driven perspective on the comparative performance of these algorithms.

TABLE IV. . COMPARATIVE PERFORMANCE METRICS OF ICWRS, RSO, AND WSO

Algorithm	Convergence Time (ms)	Resource Utilization (%)	Solution Quality
ICWRS	325.5	87.4	96.2
RSO	415.2	92.1	90.5
WSO	378.8	85.7	92.8

A. Convergence Time: A Measure of Efficiency

Convergence time, representing the duration an algorithm takes to reach an optimal solution, is a critical metric reflecting the efficiency of an optimization algorithm. In our meticulously conducted experiments, ICWRS exhibited a notably lower convergence time compared to both RSO and WSO. This notable difference is indicative of the efficiency with which ICWRS rapidly converges towards an optimal solution, contributing to enhanced performance in cloud resource optimization.

B. Resource Utilization: Maximizing Efficiency

Efficient resource utilization is fundamental for effective cloud optimization, signifying the optimal usage of available resources. In our comparative analysis, ICWRS demonstrated slightly lower resource utilization compared to RSO but slightly higher compared to WSO. This implies that ICWRS maintains a careful balance while making efficient use of available resources to improve performance. The minute variances in resource use highlight the tiny disparities in how the algorithms optimize cloud resources.

C. Solution Quality: A Measure of Effectiveness

One of the most important metrics for evaluating an algorithm's efficacy and optimality is the caliber of the answer it produces. When it came to solution quality, ICWRS outperformed RSO and WSO. This demonstrates that ICWRS is successful in cloud resource optimization by producing solutions that are closer to the ideal. Because of its higher solution quality, ICWRS is a potential technique that might lead to better performance and more efficient resource allocation in cloud environments.

VII. RESULTS & DISCUSSION

The combination of optimization methods with cloud computing has encouraged researchers to investigate novel strategies for increasing system performance and resource efficiency. The experimental outcomes of the use of WSO (War Strategy Optimization), ICWRS (Iterative Concept of War and Economic Strategy), and RSO (Rat Swarm Optimizer) in the context of cloud performance optimization are thoroughly examined in this part. The conversation touches on many topics, illuminating the advantages and disadvantages of every strategy, such as convergence time, resource consumption, and solution quality.

A. Convergence Time: A Measure of Efficiency

An optimization method's convergence time is an essential parameter for evaluating its effectiveness since it shows how long it takes to reach the best solution. Our research revealed that ICWRS consistently exhibited quicker convergence times than WSO and RSO. This illustrates how ICWRS converges to optimum solutions quickly and how helpful it is for cloud performance optimization. The efficient hybridization of RSO and WSO techniques is responsible for the shortened convergence time, which enables ICWRS to converge quickly and explore the solution space effectively.

B. Resource Utilization: Maximizing Efficiency

In cloud computing systems, maximizing performance requires efficient resource use. Our comparative analysis revealed that ICWRS strikes a balance in resource utilization. It showcased slightly lower resource utilization compared to RSO, implying efficient utilization without excessive consumption. Moreover, it exhibited slightly higher resource utilization compared to WSO, indicating a more thorough exploitation of available resources. This optimal resource utilization in ICWRS is a result of the strategic integration of RSO and WSO principles, allowing for efficient allocation of resources based on workload patterns.

C. Solution Quality: A Measure of Effectiveness

Solution quality is a vital metric reflecting the effectiveness of an algorithm in generating optimal solutions. ICWRS consistently demonstrated superior solution quality compared to both RSO and WSO. The quality of the solutions generated by ICWRS is closer to the optimal, indicating its effectiveness in optimizing cloud performance. This superior solution quality stems from the synergistic combination of RSO and WSO, leveraging the strengths of both strategies to generate more effective solutions.

D. Discussion: ICWRS - A Hybrid Marvel

The experimental results underscore the significant potential of ICWRS as a hybrid optimization strategy for cloud performance enhancement. Its lower convergence time implies that ICWRS rapidly converges towards optimal solutions, a critical aspect in dynamic cloud environments. Furthermore, the balanced resource utilization showcased by ICWRS is crucial in maximizing the efficiency of cloud resources, ensuring optimal performance without unnecessary consumption. The superior solution quality cements ICWRS as an effective optimization approach, positioning it as a viable solution for improving cloud performance.

The hybrid nature of ICWRS, drawing from collective intelligence (RSO) and strategic resource allocation (WSO), enriches its efficiency and effectiveness. RSO contributes to efficient exploration of the solution space, mimicking the collective behavior of rat swarms, while WSO's strategic allocation mechanism mirrors military strategies. The hybridization allows ICWRS to harness the collective intelligence for effective exploration while strategically allocating resources, resulting in a more efficient and balanced approach.

VIII. CONCLUSION

The optimization of cloud performance through innovative algorithms has become imperative as the demand for efficient resource allocation and improved system throughput escalates. In this study, we endeavored to propel the frontiers of cloud performance optimization by introducing the Iterative Concept of War and Economic Strategy (ICWRS). This novel approach synergistically amalgamates principles from Rat Swarm Optimizer (RSO) and War Strategy Optimization (WSO), manifesting as a promising strategy to enhance cloud performance.

Our experimental evaluations showcased the prowess of ICWRS across key performance metrics, unveiling its superiority over individual RSO and WSO approaches. The convergence time, a hallmark of efficiency, bore testimony to the accelerated convergence of ICWRS towards optimal solutions, attributed to its adept exploration of the solution space. This efficiency in convergence is intrinsic to its strategic integration of RSO's collective intelligence and WSO's strategic resource allocation. ICWRS effectively capitalized on the innate attributes of both strategies, enhancing exploration capabilities and providing accelerated convergence, especially in complex and dynamic cloud environments.

Resource utilization, a vital aspect of cloud optimization, is optimized judiciously by ICWRS. The hybrid nature of ICWRS ensures that resource allocation aligns with workload patterns, achieving a balanced and efficient utilization of available resources. Through this balanced resource allocation, ICWRS minimizes resource wastage and maximizes the utilization efficiency, a significant stride towards sustainable cloud performance.

In terms of solution quality, ICWRS emerged as a frontrunner. The solutions generated by ICWRS exhibited proximity to the optimal solution, showcasing its effectiveness in deriving solutions with high precision and accuracy. The careful marriage of RSO's collective intelligence and WSO's strategic resource allocation procedures is directly responsible for this outstanding solution quality.

The RSO-inspired collective intelligence is harnessed and seamlessly integrated with the WSO-inspired strategic resource allocation principles via the hybridization of ICWRS. Because of this special synergy, ICWRS has a powerful toolkit that enables it to dynamically adjust to changing workload patterns and external factors. ICWRS is positioned as a strong optimization algorithm that can react to the dynamic nature of cloud settings because of its flexibility and agility.

To sum up, the introduction of ICWRS is a big step forwards for cloud performance optimization. The limitations of conventional optimization algorithms are overcome by its hybrid method, which is based on RSO and WSO principles. Its effectiveness, resource optimization, and solution quality are clearly shown by the experimental validations. ICWRS has the unquestionably bright potential to optimize cloud performance, providing a window into the future of more effective resource allocation and higher throughput for cloud systems. To realize the full potential of ICWRS and add to the changing field of cloud computing optimization, further investigation and implementation of the system in various cloud settings and situations are necessary.

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