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Hybrid Whale–Firefly Optimization for Latency-Aware Task Scheduling in Healthcare Fog Computing

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ABSTRACT: *The paper refers Healthcare Internet of Things (IoT) applications generate time-sensitive data that must be processed close to the point of collection. Cloud-only processing can introduce communication delay, while uneven task placement across fog nodes can create congestion and poor resource utilization. This paper presents a hybrid Whale Optimization Algorithm–Firefly Algorithm (WOA–FA) framework for latency-aware task scheduling in healthcare fog computing. WOA is used to explore the global task-allocation search space and coordinate communication among fog resources; the Firefly Algorithm refines local sensor-side data-collection and task-placement decisions. The workflow initializes candidate solutions, evaluates a latency-oriented objective, updates candidates using the WOA and FA search mechanisms, and retains improved solutions until the stopping condition is reached. The manuscript's comparison chart reports latency for Throttle, SACO, Round Robin (RR), Proposed, MPSO, and BLA at 500–2500 IoT sensors. At 2500 sensors, the plotted values are approximately 96 for the proposed method, 97 for Throttle, 98 for SACO, 102 for BLA, 105 for MPSO, and 128 for RR. These chart-read values suggest that the proposed approach remains among the lowest-latency methods as the number of sensors increases. Because the supplied manuscript does not provide raw experimental logs, confidence intervals, or a fully specified test environment, the plotted values should be interpreted as approximate figure-derived results rather than independently reproduced measurements.*

KEYWORDS*: Healthcare IoT; fog computing; task scheduling; task offloading; Whale Optimization Algorithm; Firefly Algorithm; latency optimization; load balancing.*

I.INTRODUCTION

Healthcare monitoring systems increasingly use connected sensors and IoT devices to collect physiological and contextual data. Applications such as remote patient monitoring and emergency notification may require timely processing, so the delay introduced by sending every task to a distant cloud can be consequential. Fog computing places compute and storage resources nearer to data sources and can therefore support lower-latency processing, provided that tasks are assigned effectively. Task scheduling in a fog environment is challenging because sensor populations, task arrival rates, communication conditions, and available fog-node capacity can vary over time. A simple policy may be inexpensive to implement but can overlook differences in node load and communication cost. Population-based meta-heuristic algorithms offer a way to search for task placements in complex, changing solution spaces. This work develops a hybrid WOA–FA scheduling concept. WOA provides global exploration and coordination, while FA supports local refinement by moving candidate solutions toward more attractive solutions. The intended goal is to reduce task latency while maintaining balanced use of fog resources and retaining cloud integration for storage or tasks that cannot be handled locally. The main contributions are: (i) a two-level global/local optimization workflow for healthcare fog task management; (ii) a description of how WOA and FA can complement each other during task placement; and (iii) a comparison of the proposed method with Throttle, SACO, RR, MPSO, and BLA using the latency trend shown in the supplied manuscript figure.

This paper's key contributions are outlined below:

1. A novel algorithm for fog computing designed to minimize latency impacts.
2. Performance evaluation of the proposed algorithm compared to existing task management algorithms in fog computing.
3. Experimental Parameters and Evaluation Basis to improve overall system efficiency.

II.RELATED WORK

Prior work on mobile health and remote patient monitoring highlights the need for dependable, timely processing of healthcare data [1]. Research on fog computing for healthcare has examined latency reduction, computation offloading, wireless resource management, and load balancing [2–4, 11]. These studies establish task placement and resource allocation as central concerns in healthcare IoT environments. Other work has considered

multi-layer fog architectures, workflow scheduling, and resource selection for IoT applications [10, 12, 25]. Security, authentication, privacy, and trust have also been investigated because healthcare data is sensitive and fog nodes may be distributed across administrative domains [5, 13–15, 18]. Fault tolerance and critical healthcare task management are additional requirements for continuous monitoring services [16, 17, 23].Meta-heuristic scheduling has been explored for cloud–fog IoT resource allocation. The supplied manuscript cites WOA-based resource allocation [31] and a load-balancing method combining an advanced Firefly Algorithm with weighted round robin [32]. These approaches motivate combining global exploration with local refinement. The present framework follows that direction by assigning WOA to global coordination and FA to local sensor-side optimization. A rigorous comparison would require common workloads, identical resource constraints, and repeated runs for every baseline.

III.PROPOSED IMPLEMENTED ALGORITHMS

The hybrid algorithm presented in this chapter is a combination of two well-known meta-heuristic methods: the Whale Optimization Algorithm (WOA) and the Firefly Algorithm. The Whale Optimization Algorithm (WOA) is employed for global communication node task management in the fog computing system. Since it can effectively explore complex optimization spaces, WOA is effective in global task optimization and coordination of far-away nodes' communication. Nonetheless, the Firefly Algorithm is employed for local sensor node data collection task management in the fog computing system. Since it can simulate the firefly swarming nature, the algorithm is optimally suited for local task optimization and coordination of data-collection operations at the sensor level. Through the integration of the two meta-heuristic methods as a hybrid method, the proposed method aims to leverage the strengths of both algorithms while addressing the unique requirements of fog computing task management. WOA module is employed for global communication optimization and coordination to facilitate efficient data exchange and task allocation among far-away nodes. Meanwhile, the Firefly Algorithm module is employed for local data collection optimization processes, increasing sensor node efficiency and enabling smooth integration with cloud storage systems. the hybrid algorithm is a prospective method of task management in fog computing, which provides an optimal solution balancing global and local tasks and reducing the effect of communication network latency. By synergistically combining WOA and Firefly Algorithm, the proposed method is likely to enhance the overall performance and efficiency of fog computing systems and ultimately increase their data processing and storage capacity in distributed systems. Figure 1 depict the system architecture of fog computing for processing data as local devices.

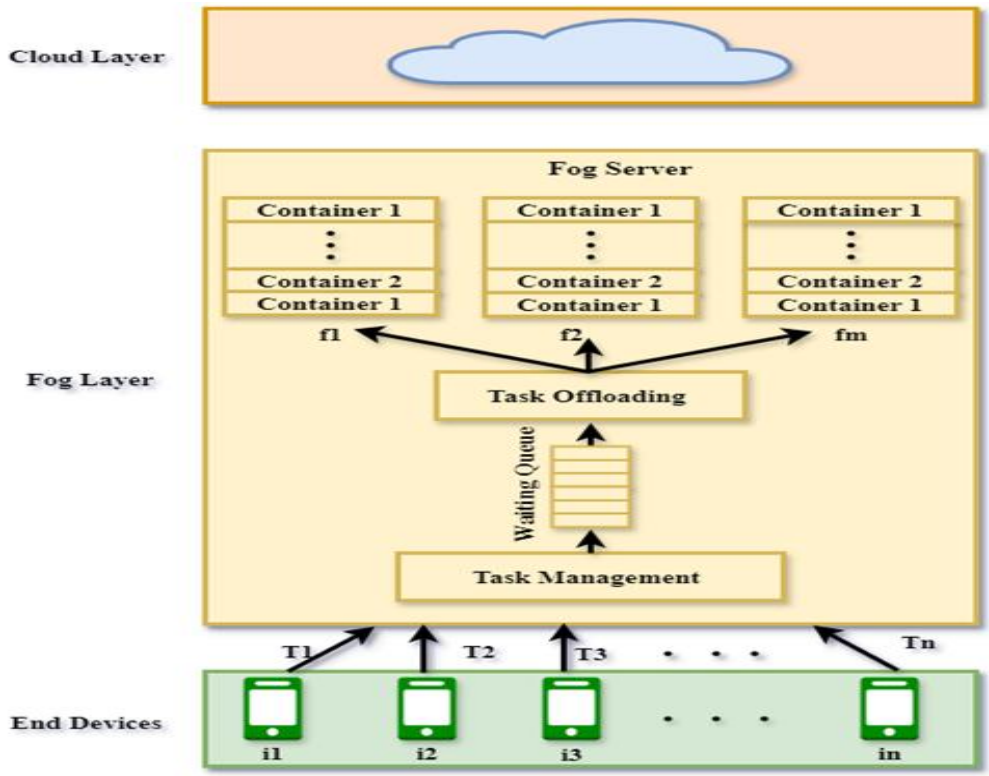


Fig. 1. Processing of data in fog computing and interconnection of cloud computing

The proposed methodology explores in two sections, in 1st section describes whale optimization algorithm (WOA), in 2nd section explores firefly optimization algorithm (FA)

The proposed methodology explores in three sections, in 1st section describes whale optimization algorithm (WOA), in 2nd section explores firefly optimization algorithm (FA) and finally describes proposed methodology in section 3.

1st section Whale Optimization Algorithm

A bio-inspiration-based optimization algorithm, the Whale Optimization Algorithm (WOA), is inspired by the social aspect and hunting style of humpback whales. The steps for the Whale Optimization Algorithm [31] are below:

Initialization:

Generate a population of candidate solutions, which are potential solutions to the optimization problem.

Assign initial positions randomly to all of the whales in the search space.

Objective Function Assessment:

Compute the objective function for every whale in the population to quantify its fitness or quality.

Adjust the Best Solution:

Identify the best solution to date in the population based on objective function evaluations.

Encircling Prey

For each individual in the population, calculate the distance to the best global solution found thus far.

Substitute the position of each whale by the following formula:

New Position = Global Best Position − (A × Distance to Global Best)

New Position=Global Best Position− (A× Distance to Global Best)

Where A – A is a coefficient that controls the spiral-type motion of the whales.

Randomly move the position of some whales to explore areas outside the neighborhood of the global optimum.

Exploitation:

Shift the whales' locations around the global best to converge towards the optimal solution.

Apply the given formula to modify the position of every whale:

New Position = Global Best Position − (C × Random Value)

New Position=Global Best Position− (C× Random Value)

where C - C is a coefficient, and Random Value - Random Value is a random value between 0 and 1.

Update Velocity and Position:

Update the position and velocity of every whale based on the above steps and confine them within the boundaries of the search space.

Objective Function Analysis:

Evaluate the objective function of each new candidate solution to measure its fitness.

Termination Criteria:

Repeat steps 4 to 8 until a terminating condition is met (e.g, iteration count, convergence tests).

Answer:

Print the best solution found as the solution to the optimization problem.

2nd section Firefly Optimization Algorithm (FA)

The Firefly Algorithm is a meta-heuristic optimization method developed based on the flash behavior of fireflies in nature. Firefly Algorithm solves NP-hard problems and deals with the dynamic nature of data effectively. Firefly Algorithm is a randomized algorithm, i.e., it performs a random search to get a collection of solutions. Generally, the Firefly Algorithm (FA) generates solutions in a search space and selects the optimal possible solution. A random search avoids being trapped in local optima. Exploration in met heuristic algorithms is discovering diverse solutions in the search space, while exploitation is the process of enhancing the best neighboring solutions. The firefly algorithm has three basic features are (1) The firefly becomes brighter and more attractive as it moves randomly, and all the fireflies are of the same sex. (2) The firefly attractiveness is directly proportional to the intensity of the light and the distance from it. The light absorption coefficient γ controls the reduction in light intensity.

The value of the objective function also determines the luminance of the firefly. (3) the distance between the fireflies is calculated from equation (1) such that Xi,k is the kth component of the spatial coordination and ith firefly[32].

$$r_{i,j=}\sqrt{(xi-xj)^2+(yi-yj)^2} \quad (1)$$

The movement of firefly and attracted fireflies measured as

$$X_i = X_i + B0^{erij2}(Xj - Xi) + a\left(rand - \frac{1}{2}\right) \quad (2)$$

A is a randomizer variable, rand is a random integer between [0, 1], and B is the light source's attractiveness. The parameter is established by variations in attraction.

The process of optimizing the stock price

The firefly algorithm (FA) used in stock data as initial population and assigned the value of parameters as α,γ,βand t=0 and Fes=0; the factors of brightness of data is Ii at Xi is measured by f(Xi). Define light absorption coefficient γ;
While (not meet the stop conditions)
For i=1:N; all N fireflies
For j=1: N for every N fireflies
If Ij > Ii Then
Translate firefly i to firefly j across all dimensions by Equation (2);
End If
Attractiveness depends on distance
Assess the new solution and modify its brightness; Fes=Fes+1;
End For
End For
Rank the fireflies and find the current best;
t=t+1;
End While
Optimized stock price data
End

IV. EXPERIMENTAL PARAMETERS AND EVALUATION BASIS

The parameter values below are transcribed from the supplied parameter table. Their exact units and operational definitions are not specified in the source for every symbol; the original notation is therefore retained.

Parameter	Value
Sensor nodes	250–2500
Fog Nodes	10–25
X_p	250–1024 KB
λ_i	5–50
λf	10–50
λc	25–75
μf	50–300
μc	100–400
Nants	40
Maxiter	125
P	0.1
A	0.5
ϒ	5.0
Bf	50 MB/s
Bc	100 MB/s

V. RESULTS AND DISCUSSION

The supplied latency plot compares six methods as the number of IoT sensors increases from 500 to 2500. All plotted methods show an increasing latency trend as the sensor population grows, indicating that the scheduling problem becomes more demanding at larger scale. The RR curve rises most sharply and reaches approximately 128 at 2500 sensors. The proposed curve remains near the lower end of the comparison throughout the plotted range.

The following values are approximate readings from the provided chart, not raw measurements. They are included to make the visual comparison explicit; small differences may arise from reading the plotted markers.

IoT sensors	Throttle	SACO	RR	Proposed	MPSO	BLA
500	68	65	70	62	70	68
1000	77	74	83	71	82	76
1500	89	84	97	82	88	86
2000	96	91	107	88	95	94
2500	106	98	128	96	105	102

Table 1. Approximate latency values read from the supplied comparison plot (chart units are not specified).

5.1 Comparison at 2500 sensors

At 2500 sensors, the proposed method is approximately 96, compared with 98 for SACO, 102 for BLA, 105 for MPSO, 106 for Throttle, and 128 for RR. Relative to RR, the proposed curve is about 25% lower using the plotted

values: (128 − 96) / 128 × 100. The difference is smaller against SACO and the other bio-inspired baselines. This suggests that the strongest observed benefit in the supplied figure is against RR; the chart alone does not establish statistical significance or explain energy consumption, deadline misses, or fairness.

5.2 Interpretation and limitations

The trend is consistent with the motivation for hybrid optimization: global search can help identify promising assignments, while local refinement can improve nearby decisions. However, the supplied document does not include raw logs, the precise latency unit, hardware/software configuration, task-size distribution, number of independent runs, standard deviations, or significance tests. Accordingly, the results are descriptive and figure-based. A complete empirical study should report these details and evaluate response time, throughput, energy use, load balance, deadline-miss ratio, and algorithm runtime under the same workloads.

VI. Conclusion and Future Scope

This paper presents a hybrid WOA–FA approach for latency-aware task scheduling in healthcare fog computing. The framework assigns WOA to global search and coordination and FA to local refinement of sensor-side task placement. The supplied comparison plot shows latency increasing with sensor population for all methods, while the proposed method remains among the lowest-latency curves and is substantially below RR at the largest plotted scale. These observations support further investigation of hybrid meta-heuristic scheduling, but they should be validated using raw experimental data and a fully documented test setup.

Future work should: (i) formalize the objective function and all resource/deadline constraints; (ii) implement the method in a repeatable fog/IoT simulator or test bed; (iii) compare algorithms over multiple random seeds and report mean, variance, and statistical tests; (iv) extend optimization to energy, reliability, fairness, and deadline satisfaction; (v) incorporate dynamic task arrivals, node failures, and changing network conditions; and (vi) integrate privacy-aware scheduling and secure task offloading for sensitive healthcare data.

REFERENCES

[1]. El-Rashidy, Nora, Shaker El-Sappagh, SM Riazul Islam, Hazem M. El-Bakry, and Samir Abdelrazek. "Mobile health in remote patient monitoring for chronic diseases: Principles, trends, and challenges." Diagnostics 11, no. 4 (2021): 607.

[2]. Kishor, Amit, Chinmay Chakraborty, and Wilson Jeberson. "A novel fog computing approach for minimization of latency in healthcare using machine learning." (2021).

[3]. Qiu, Yu, Haijun Zhang, and Keping Long. "Computation offloading and wireless resource management for healthcare monitoring in fog-computing-based internet of medical things." IEEE Internet of Things Journal 8, no. 21 (2021): 15875-15883.

[4]. Shakir, Hayder Makki, and Jaber Karimpour. "Survey on load balancing in fog computing in smart healthcare system." In 2021 International Conference on Advanced Computer Applications (ACA), pp. 128-131. IEEE, 2021.

[5]. Patwary, Abdullah Al-Noman, Ranesh Kumar Naha, Saurabh Garg, Sudheer Kumar Battula, Md Anwarul Kaium Patwary, Erfan Aghasian, Muhammad Bilal Amin, Aniket Mahanti, and Mingwei Gong. "Towards secure fog computing: A survey on trust management, privacy, authentication, threats and access control." Electronics 10, no. 10 (2021): 1171.

[6]. Sreekala, keshetti, and b. Indira. "Organizing iot health care based on fog computing: corona tasks scheduling based on the priority." (2021).

[7]. Subbotin, Alexey N. "Applying Machine Learning in Fog Computing Environments for Panoramic Teeth Imaging." In 2021 XXIV International Conference on Soft Computing and Measurements (SCM), pp. 237-239. IEEE, 2021.

[8]. Wang, Li. "Intelligent decision support system of emergency language based on fog computing." Mathematical Problems in Engineering 2021 (2021): 1-11.

[9]. Jain, Rachna, Meenu Gupta, Anand Nayyar, and Nitika Sharma. "Adoption of fog computing in healthcare 4.0." Fog Computing for Healthcare 4.0 Environments: Technical, Societal, and Future Implications (2021): 3-36.

[10]. Muneeb, Muhammad, Kwang-Man Ko, and Young-Hoon Park. "A fog computing architecture with multi-layer for computing-intensive IoT applications." Applied Sciences 11, no. 24 (2021): 11585.

[11]. Shakir, Hayder Makki, and Jaber Karimpour. "Systematic study of load balancing in fog computing in iot healthcare system." In 2021 International Conference on Advanced Computer Applications (ACA), pp. 132-137. IEEE, 2021.

[12]. Kaur, Mandeep, and Rajni Aron. "Focalb: Fog computing architecture of load balancing for scientific workflow applications." Journal of Grid Computing 19, no. 4 (2021): 40.

[13]. Shukla, Saurabh, Subhasis Thakur, Shahid Hussain, John G. Breslin, and Syed Muslim Jameel. "Identification and authentication in healthcare internet-of-things using integrated fog computing based blockchain model." Internet of Things 15 (2021): 100422.

[14]. Maragathavalli, P., S. Atchaya, N. Kaliyaperumal, and S. Saranya. "Cloud data security model using modified decoy technique in fog computing for E-healthcare." In IOP Conference Series: Materials Science and Engineering, vol. 1065, no. 1, p. 012044. IOP Publishing, 2021.

[15]. Meena, V., Meghana Gorripatti, and T. Suriya Praba. "Trust enforced computational offloading for health care applications in fog computing." Wireless Personal Communications 119 (2021): 1369-1386.

[16]. Mutlag, Ammar Awad, Mohd Khanapi Abd Ghani, Mazin Abed Mohammed, Abdullah Lakhan, Othman Mohd, Karrar Hameed Abdulkareem, and Begonya Garcia-Zapirain. "Multi-agent systems in fog–cloud computing for critical healthcare task management model (CHTM) used for ECG monitoring." Sensors 21, no. 20 (2021): 6923.

[17]. Saeed, Waqar, Zulfiqar Ahmad, Ali Imran Jehangiri, Nader Mohamed, Arif Iqbal Umar, and Jamil Ahmad. "A fault tolerant data management scheme for healthcare Internet of Things in fog computing." KSII Transactions on Internet and Information Systems (TIIS) 15, no. 1 (2021): 35-57.

[18]. Shynu, P. G., Varun G. Menon, R. Lakshmana Kumar, Seifedine Kadry, and Yunyoung Nam. "Blockchain-based secure healthcare application for diabetic-cardio disease prediction in fog computing." IEEE Access 9 (2021): 45706-45720.

[19]. Fetjah, Laila, Kebira Azbeg, Ouail Ouchetto, and Said Jai Andaloussi. "Towards a smart healthcare system: an architecture based on IoT, blockchain, and fog computing." International Journal of Healthcare Information Systems and Informatics (IJHISI) 16, no. 4 (2021): 1-18.
[20]. Nandankar, Praful, Rukhsana Thaker, Shafqat Nabi Mughal, Malgireddy Saidireddy, Anusha Linda, J. E. Kostka, and M. A. Nag. "An iot based healthcare data analytics using fog and cloud computing." Turk. J. Physiother. Rehabil 3 (2021): 32.
[21]. Karakaya, Aykut, and Sedat Akleylek. "A novel IoT-based health and tactical analysis model with fog computing." PeerJ Computer Science 7 (2021): e342.
[22]. Bharti, Rajendra Kumar. "An IoT and fog computing enabled intelligent health care monitoring system to optimize the cloud storage." Turkish Journal of Computer and Mathematics Education (TURCOMAT) 12, no. 10 (2021): 2085-2091.
[23]. Rajab, Hadeel T., and Manal F. Younis. "Dynamic fault tolerance aware scheduling for healthcare system on fog computing." Iraqi Journal of Science (2021): 308-318.
[24]. Kumar, Dinesh, Ashish Kumar Maurya, and Gaurav Baranwal. "IoT services in healthcare industry with fog/edge and cloud computing." In IoT-based data analytics for the healthcare industry, pp. 81-103. Academic Press, 2021.
[25]. Xue, Dong, Shah Nazir, Zhiqiang Peng, and Hizbullah Khattak. "Selection and Ranking of Fog Computing-Based IoT for Monitoring of Health Using the Analytic Network Approach." Complexity 2021 (2021): 1-11.
[26]. Dave, Rushit, Naeem Seliya, and Nyle Siddiqui. "The benefits of edge computing in healthcare, smart cities, and IoT." arXiv preprint arXiv:2112.01250 (2021).
[27]. Al Mudawi, Naif. "Integration of IoT and fog computing in healthcare based the smart intensive units." IEEE Access 10 (2022): 59906-59918.
[28]. Verma, Parag, Rajeev Tiwari, Wei-Chiang Hong, Shuchi Upadhyay, and Yi-Hsuan Yeh. "FETCH: a deep learning-based fog computing and IoT integrated environment for healthcare monitoring and diagnosis." IEEE Access 10 (2022): 12548-12563.
[29]. Quy, Vu Khanh, Nguyen Van Hau, Dang Van Anh, and Le Anh Ngoc. "Smart healthcare IoT applications based on fog computing: architecture, applications and challenges." Complex & Intelligent Systems 8, no. 5 (2022): 3805-3815.
[30]. Elhadad, Ahmed, Fulayjan Alanazi, Ahmed I. Taloba, and Amr Abozeid. "Fog computing service in the healthcare monitoring system for managing the real-time notification." Journal of Healthcare Engineering 2022 (2022).
[31]. Sing, Ranumayee, Sourav Kumar Bhoi, Niranjan Panigrahi, Kshira Sagar Sahoo, Nz Jhanjhi, and Mohammed A. AlZain. "A whale optimization algorithm based resource allocation scheme for cloud-fog based iot applications." Electronics 11, no. 19 (2022): 3207.
[32]. Abed, Marwa M., and Manal F. Younis. "Developing load balancing for IoT-cloud computing based on advanced firefly and weighted round robin algorithms." Baghdad Science Journal 16, no. 1 (2019): 130-139.
[33]. Movahedi, Zahra, Bruno Defude, and Amir Mohammad Hosseininia. "An efficient population-based multi-objective task scheduling approach in fog computing systems." Journal of Cloud Computing 10, no. 1 (2021): 53.