International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Enhancing Healthcare 4.0: A Fog Computing-Enabled, Secure, and Energy-Efficient Framework

Mohit Lalit[1], Gaurav Bathla[2*] and Surender Singh[3]

Submitted: 03/11/2023 **Revised**: 26/12/2023 **Accepted**: 04/01/2024

Abstract: The realm of healthcare monitoring is broadening to include cutting-edge topics like athlete's health, gym exercise, daily living, and disease-specific. The real-time data transmission in such applications is the difficulties posed by the growing need for healthcare monitoring. To accomplish these goals, an innovative approach is used called "Fog computing-enabled healthcare frameworks," which addresses the gaps left by cloud computing. Every framework requires essential quality of service (QoS) metrics such as interoperability, convergence, and reliability for effective communication, although energy consumption is a crucial feature in a constrained device context. These parameters are not yet attained in various developed frameworks, and the aim of this paper is to optimise these QoS parameters for sustainable communication in healthcare. With the use of the Firefly (FFLY) and Grey Wolf Optimisation (GWO) algorithms, this study provided an optimal framework to meet the emerging demands of the healthcare sector by improving interoperability, convergence, reliability, and energy consumption. Security is another issue that has been shown to be lacking in present healthcare frameworks, and the integration of ECC and RSA is being evaluated for data security during simulation. The suggested optimised healthcare system outperforms the core findings and yields notable outcomes in terms of QoS parameters and security. The optimized results for interoperability, convergence, reliability, and energy consumption, respectively, are 9.76%, 16.36%, 23.09%, and 12.62% better than the base values, which were 0.761, 0.438, 0.251, and 0.6046 for interoperability, convergence, reliability, and energy consumption. While in the simulation employing the security properties of ECC and RSA, ECC outperforms RSA in terms of encryption time, decryption time, and key size.

Keywords: *Healthcare 4.0, optimization, interoperability, convergence, reliability, energy efficiency*

1. Introduction

By enabling healthcare objects to communicate data automatically for healthcare monitoring reasons, the idea of "Healthcare 4.0" is intended to apply concepts from "Industry 4.0.". In today's busy world, healthcare monitoring is one of every person's essential needs, and fog computing (FC) is the paradigm that has revolutionized it. FC complies with the low latency and low bandwidth requirements for indoor and outdoor real-time application demands [1]. The fog nodes installed nearer to edge of sensors for instant services as compared to centralized database system in cloud computing. It brings the host services provided by cloud nearer to the edge of the network through internet. FC excels due to the rapid communication and calculation of large amounts of data, beside sending on a centralized cloud server, however the permanent storage of voluminous data still requires the use of cloud computing. For many applications in the recent past, including smart homes, smart buildings, and industrial IoT applications, different architectures and frameworks were proposed. These applications are static in nature, whereas smart transportation and smart health care applications are highly dynamic in nature [2] due to the high mobility of smart devices, as shown in Fig. 1. To mobilize such dynamic natured applications demands optimized architectures and frameworks for efficient operations in healthcare 4.0. It is increasingly essential to optimise FC enabled frameworks because of the limited resources. There are several optimisation techniques that may be used to FC-equipped healthcare systems [3], [4]. Numerous optimisation methods have been developed for the optimisation challenges that have been posed by researchers all around the world. Oyinlola et al. conducted the most recent study on optimisation methods for FC in 2021. With the aid of a linear objective function, the combined usage of enhanced FFLY algorithm and improved particle swarm optimisation is carried out for the selection of the best fog nodes [5]. Another development in the FFLY optimization algorithm proposed for speeding the convergence and the use of them is described in various engineering applications [6]. The naive Bayes method-based healthcare framework is optimised through the usage of FFLY to produce a better selection of features for increased accuracy [7]. Security for trustworthy and secure communication is another element that a framework should preserve. Although many proposed frameworks use the traditional Rivest-Shamir-Adleman (RSA) algorithm [8], the constrained devices ask for a more lightweight security system. In this regard, a well-known lightweight method called elliptic curve cryptography (ECC) [9] is being used

*1*Research Scholar, Department of Computer Science and Engineering, Chandigarh University, Mohali, Punjab, mohit19862007@gmail.com*
[2]Professor Department of Computer Science and Engineering Chandigarh University, Mohali, Punjab, gauravbathla86@gmail.com
[3]Head Career Program, Code Quotient Pvt. Ltd. Mohali, Punjab, surendahiya@gmail.com
**Corresponding author(s). E-mail(s): mohit19862007@gmail.com;*

and tested in a variety of contexts as a low-latent and low-energy security mechanism. A smaller key size of 256 bits that offers a similar degree of security to RSA's 3072-bit key size is one benefit ECC has over RSA. As seen in Equations 1 and 2, ECC also requires less computational resources, such as memory and computing power. Compared to RSA-generated cypher texts, ECC-generated cypher texts are shorter, and ECC is a fresh mathematical notion capable to handle current cyber-attacks [10] .

$$Key\ Size\ (in\ bits) :\ log\ 2\ (P) \ldots\ldots\ldots\ldots\ldots (1)$$

where P is the prime number

Public and private keys are two different sorts of keys that are created in ECC; the former is available to everyone, while the latter is computed as follows :

$$Q = d * G \ldots\ldots\ldots\ldots (2)$$

Where G is the base point to elliptic curve and Q is the resulting public key and d is the randomly generated scalar value used for key generation. Here, ECC provide more secure and less complex communication in comparison to RSA algorithm and the basic working diagram of e-healthcare monitoring system using security mechanism is depicted in Fig. 1.

Motivation

FC is an extension to cloud computing and thus inherits some classic challenges, however the commendable features of FC have proven to be helpful. Along with numerous advantages, it also has some drawbacks which shows least presence of QoS parameters [11][12], which demands for optimization to enable various IoT health sensors to access fog services. These shortcomings drive the development of an improved framework that offers IoT-enabled healthcare monitoring services for patients suffering from natural disasters or with a variety of chronic diseases.

The main contributions of the paper are given as:

The recently proposed and established healthcare monitoring frameworks have been used to identify a few concerns.

By introducing the FFLY and GWO algorithms, the suggested framework's QoS is improved.

To verify the framework in terms of QoS criteria, a qualitative comparison of FFLY and GWO is conducted.

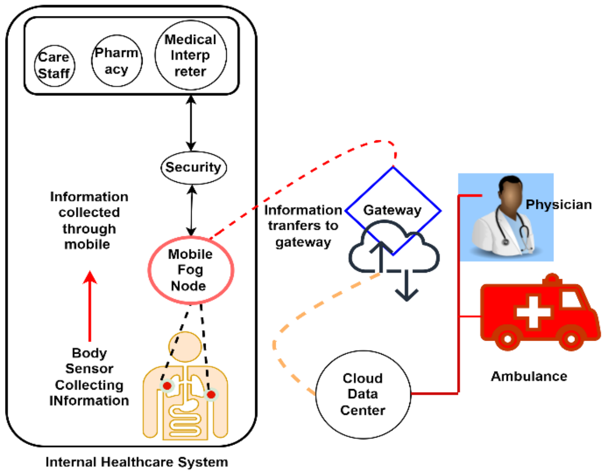

Fig. 1 Working diagram of E-Healthcare Monitoring System

The simulation of RSA and ECC is evaluated to achieve minimal time consumption for encryption/decryption with the least key size in comparison to RSA in order to produce a long-lasting and secure connection

The paper is divided into six sections: an introduction to healthcare 4.0, fog computing, cloud computing, and optimization methods; a description of related work in the fields of IoT enabled healthcare, fog computing, and cloud computing; and a proposal for an optimized FC enabled healthcare monitoring framework that draws on current trends in several applications. The implementation of the proposed framework has been covered in section 4 of the article. Several performance settings that improved are reviewed in section 5 and conclusion and future directions are covered in Section 6.

2. Related Work

This section provides a few works connected to the issue that we took into consideration while developing the proposed system. One of the intelligent frameworks for ongoing monitoring of Parkinson's disease was proposed by Raza et al. in 2021[13] with the implantation of various sensors for monitoring of Parkinson disease patients. This framework gathers information from implanted sensors and facilitates communication from diverse sensors. Another paradigm called FogChain, developed by Mayer et al. [14] in 2021, combines blockchain technology and fog computing. By facilitating quick decision-making, blockchain reduces the latency of PHR operations for the seamless running of IoHT activities. A system for tracking one's health using wearable body sensors and information from social media was proposed by Ali et al [15]. The prime source of data collection includes sensors, social networking sites, and medical records. In continuation to health monitoring, the multiple tasks execution in a gym requires a continuous monitoring, so does a framework is required for the same Hussain et al. [16] presented a framework to continuously track the working of gym environment by implanting various body sensors.

The framework presented in 2021 by Sood et al [17], which combines mobile technology, fog computing, and cloud computing in order to identify and contain dengue virus outbreaks. The information gathered at the fog layer will be uploaded to the cloud and used to pinpoint the person's location using a global positioning system [18]. In order to keep users informed in case of an emergency, Hu et al. proposed a system designed to store and monitor physiological measures and pertinent information. Further, the framework for early diabetes identification using wearable sensors was provided by Ramesh et al. [19]. Health indicators such blood oxygen levels, diastolic blood pressure, heart rate, systolic blood pressure, glucose levels, medication checks, step counts, activity types, and overall activity counts are tracked. Yildirim et al[20] presented a framework for diabetes patients enabled through fog, cloud and IoT terminologies and the communication in framework consists of inter WBANs and intra WBANs. Another, three-tier architecture is presented based on FC for monitoring of critical health metrics such as heart rate, temperature, pulse rate [21]. The aim of the presented framework is to manage the load balancing while the base stations deployed nearer to fog nodes for maintaining communication produces some delay because of overload [22]. The healthcare framework proposed by Elhadad et al for remote monitoring enabled through Internet of Things (IoT) is aimed to provide for prognosis and diagnosis of patients. The QoS parameters are necessity of any frameworks for a sustainable and reliable communication. Either the developed frameworks used artificial intelligence, machine learning, big data fundamentals to develop some components of framework, however none of them focused the QoS parameters and requirement of s secure communication. One of the authors [12] developed monitoring framework are lacking the performance of QoS and security as well. The optimization of QoS parameters is necessarily required for effective monitoring of patients. The applications like healthcare generates continuous data for various chronic diseases, that required huge storage such as cloud computing, however for frequent delivery of data required advanced technological fundamentals like FC for local monitoring and frequent decision making [23].

3. Proposed Framework

The functioning model of any programmes created with full intent is the framework or architecture. One of the frameworks provided by Sodhro et al. is one of several prospective frameworks that have been developed and presented in recent years [12] in 2021 incorporates a similarity matrix created using fuzzy logic with the idea of an eigenvalue and eigenvector to bring the healthcare monitoring framework into action. However, the QoS parameter values are insufficient for a secure and continual communication, as latent data transmission may result in the loss of life. A new framework is required that optimises the QoS Parameters and embeds security elements for a reliable connection can address the flaws in the framework described by Sodhro et al. The framework shown in Fig. 2 provides the optimum collection of performance improvisations.

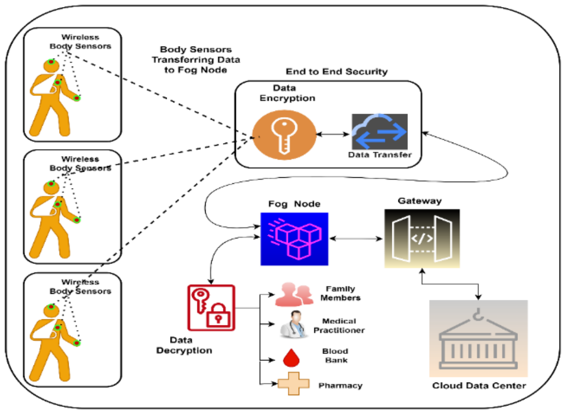

Fig. 2 Fog-Cloud Computing Centric Healthcare Framework

According to the design outlined in Fig 2., people with a history of chronic conditions would wear body sensors that broadcast encrypted data through Bluetooth, WiFi, ZigBee, mobile data, etc. to the closest fog node. Additionally, this encrypted data will be distributed to the appropriate parties in the event of an emergency, such as relatives, medical professionals, blood banks, and pharmacies. The fog node, which can perform storage, computation, analysis, acceleration, and control functions, manages adjacent healthcare application activities, and receives sensor data [24]. The article [25] presented a system for monitoring of various body health parameters such as blood pressure, temperature, humidity, room temperature etc. and relevant data is shared with medical practitioners. In continuation, the next section will be going to discuss materials and methods for execution of proposed optimized healthcare framework.

4. Method and Materials

A nature-inspired optimisation technique called the FFLY technique (FA) was initially presented in 2007 by Xin-She Yang[26] based on flashing behaviour of fireflies. The QoS parameters race towards the optimal levels and generate optimised outcomes, much as each firefly is drawn to the brighter firefly. Brighter fireflies or higher QoS values signify superior solutions, while values below the base parameters will be rejected. The method begins with a minimal population of fireflies and incrementally improves the solution by replicating firefly flashing characteristics. The QoS parameter readings vary as a result of simulation runs, and more optimised values are sought for.

The light absorption factor β can be calculated as (Eq. 3) :

$$\beta = \beta_0 \times e^{-\gamma \times r^2{}_{ij}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where β indicates light absorption, gamma indicates absorption coefficient and r indicates the distance between two QoS parameters (fireflies). The Euclidean Distance (ED) among QoS parameters (fireflies) calculates as (Eq. 4):

$$r = \sqrt{((x1 - y1)^2 + (x2 - y2)^2 + \cdots + (xn - yn)^2)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

the distance between two points, presents by $x = (x1, x2, \ldots\ldots, xn)$ and $y = (y1, y2, \ldots., yn)$ in a space of n dimensional.

4.1 Execution steps of FFLY algorithm

1.Initialize a population of fireflies with random positions by generating the population w.r.t IN, CON, REL and EC parameters as mentioned below

2. Determine the brightness of each FFLY (QoS parameters) such as IN, CON, REL and EC

3. For each QoS parameter, move towards the brightest QoS parameter in its vicinity by the

following equation:

$$X\_i(t+1) = X\_i(t) + Beta * exp\,(Gamma * r\wedge 2) * (x\_j(t) - x\_i(t)) + Alpha * (rand\,() - 0.5)$$

4. Calculate the fitness of new population of QoS parameter using objective function given in Eq 5

5. Update the brightness of each QoS parameter based on their brightness

6. Repeat the steps (1 to 5) until completion of all iterations

7.Select the QoS parameter with the highest fitness value as solution

8. Return best solution as QoS values

4.2 Objective function

This optimization work in this healthcare framework is based on the objective function (fitness function) mentioned in Eq.5.

objective function = $-\left(\frac{1}{(1+IN)} + \frac{1}{1+CON} + \frac{1}{1+REL} - \frac{1}{1+EC}\right)$ **…………………. (5)**

Whereas,

Interoperability (IN) = 0.761,

Convergence (CON)= 0.438

Reliability (REL)= 0.251

Energy Consumption (EC) =0.6046

taken as the basic values driven by Sodhro et. al [12] in 2021.

4.3 Algorithm 1: Firefly Optimization (FFLY)

1. n = 4 // Decision variables
2. Lower Bound = 0
3. Upper Bound = 0
4. Max Iterations = [250 to 2500]
   // number of iterations
5. No of Fireflies = 50 and 100
   // no of fireflies
6. gamma = 0.8 // Absorption Coefficient
7. alpha = 0.2 // scaling factor

4.4 FFLY Algorithm

1. set the objective function f(x) where $x = (x_1, x_2, x_3, \ldots, x_n)$
2. generate and initial population n of fireflies with respect to IN, CON, REL and EC
   $xi = (1, 2, 3\ldots\ldots\ldots.n)$
3. identify I for intensity and γ for absorption coefficient
4. **for t = 1 to max generations**
5. **for i= 1 to n**
6. **for j = 1 to n**
7. **if (f(xi) > f(xj) then**
8. then move the corresponding value of IN, CONV, REL and EC towards the optimal value
9. **end if**
10. **end for**
11. **end for**
12. now calculate new solution using fitness function and update values of IN, CONV, REL and EC
13. **end for**

Another optimization algorithm proposed by Mirjalili et al. in 2014 for solving the multi objective problems [27]. The algorithm is based on how wolves hunt in packs and every wolf in the pack is considered as a QoS parameter solution. Each wolf is given a fitness rating based on how they approached the prey. The pack employs the fitness value to place the wolves in order to find the optimal outcome in terms of QoS parameters. The wolves were divided into groups like alpha, beta, delta, and omega to simulate the internal leadership system. The first, second, and third-best wolves are regarded as the best, while the remaining wolves are regarded as omega.

4.5 Execution of GWO

Initialization

n= 4

lower bound = 0

upper bound = 1

population = 50 and 100

max Iterations = [250:250:2500]

alpha = zeros (1, n)

// initializing positions of alpha wolves

beta = zeros (1, n)

// initializing positions of beta wolves

delta = zeros (1, n)

// initializing positions of delta wolves

omega = zeros (1, n)

// initializing positions of omega wolves

Algorithm 2: Grey Wolf Optimization (GWO)

1. Initialize a population of wolves with random positions by generating the population w.r.t IN, CON, REL and EC parameters as per objective function is defined in Eq.3.
2. now, calculate values of alpha, beta, delta, and omega wolves with respect to the first best, second best, third best and rest of the values for INT, CONV, REL and EC (QoS parameters)
3. ***for i = 1 to max iterations***
4. ***a = 2 - iteration * (2 / max iterations)***

   //Update the position of the wolves
5. ***calculate Alpha, Beta, Delta as***
6. ***Alpha = population (1, n), Beta = population***
7. ***(1, n), Delta = population (1, n)***
8. $\boldsymbol{X1 = alpha - A.* alpha}$

   // calculates the first best value of QoS parameters
9. $\boldsymbol{X2 = beta - A.* beta}$

   // calculates the second-best value of QoS parameters
10. $\boldsymbol{X3 = delta - A.* delta}$

    // calculates the third best value of QoS parameters EC
11. $\boldsymbol{Population = (X1 + X2 + X3 + omega) / 4}$
12. ***End of for loop***
13. Update the position of QoS parameters based upon objective function.

The two algorithms discussed above that are utilised to optimise the QoS parameters. In the next part, results and analysis are discussed, which is evaluated based on objective function defined in Eq.5.

5. Results and Analysis

The fundamental QoS parameters that were previously identified are used as the input in this section, and based on those parameters, an objective function is framed for the optimization of various performance parameters that are essential for healthcare data communication between sensors and the receiving devices with various configurations. Interoperability, which enables communication between disparate devices, is the first parameter. The second parameter, convergence, is a second prioritized measure that allows for seamless media-based communication between numerous devices. Reliability, the third factor, ensures that data packets are delivered with the lowest possible failure rate. The fourth parameter is energy consumption, which is closely related to the first three. These factors are intimately linked and interdependent. A paradigm for optimal healthcare monitoring is suggested in Fig. 2 based on these criteria. The impactful optimization is captured in simulation using optimization methods like FFLY, GWO and MATLAB is the experiment simulator of choice.

The declared initial populations are 50 and 100, and there are between 250 and 2500 iterations. In both trials, the performance parameters are optimized, and the results are displayed in the figures below. The first outcome is based on interoperability, which is our first performance criterion for the framework. The objective function specified in Eq. 3 is used to optimize using the FFLY and GWO technique, as shown in Fig 3. There are more possibilities to choose the ideal solution for each performance statistic due to the diversity in population size. The results of the FFLY method and the GWO algorithm are documented respectively.

The GWO and FFLY algorithms were used to optimize interoperability with the 50-population size, and the resulting improvements over the baseline value were 3.74% and 7.89%, respectively. Additionally, the FFLY and GWO algorithms show 5.60% and 7.24% improvement, respectively, with a population size of 100 as depicted in Fig. 3. The number of iterations used to construct the trials with random values varies, and the average of those values is used to compare the findings. Because the population is dispersed randomly and there are extremely few chances of optimal value selection in the first iterations, the value of GWO was smaller than FFLY in iterations of 250 and 500.

Convergence, the second prioritised criterion, is crucial in the current situation since it allows users to access numerous services using a single communication infrastructure. With a population size of 50, FFLY and GWO have shown improvements of 3.57% and 6.89%, respectively. In contrast, FFLY and GWO saw improvements of 4.54% and 7.87% with a population size of 100, which is nearly equivalent to results with a population size of 50. In Fig. 4, the outcomes of both algorithms are depicted.

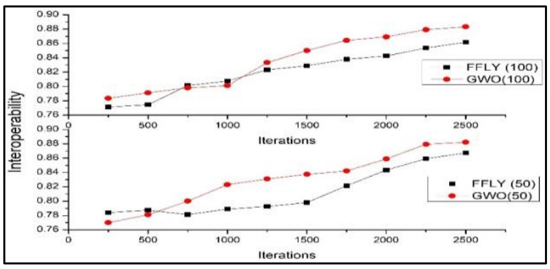

Fig 3. Interoperability Curves on 50 and 100 Dimensions

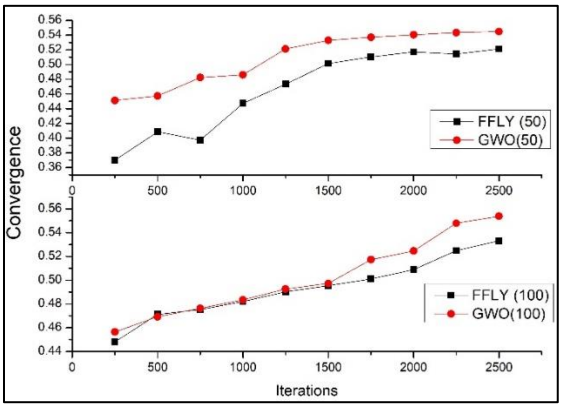

Fig 4. Convergence Curves on 50 and 100 Dimensions

Reliability is the third factor, which is essential for flawless communication. The number of data packets that are successfully transmitted depends on how dependable the communication is. With FFLY and GWO algorithms, the 50 population size leads to improvements of 6.94% and 7.15% above the basic value, respectively. Contrarily, the results of the FFLY and GWO algorithms for a population size of 100 are 6.88% and 8.41%, respectively, as shown in Fig. 5.

The fourth parameter is energy consumption, which is crucial for IoT devices because of their limited energy resources. The energy consumption performance indicator can be applied to Internet of Medical Things (IoMT), where an emergency like an earthquake interrupts a continuous supply of electricity. The unit use in base values to measure the energy consumption is Jules/sec. With the FFLY and GWO algorithms, a population size of 50 provided results that were 3.82% and 4.79% better than the base value, and a population size of 100 produced results that were 4.71% and 6.07% better than the base value as displayed in Fig. 6. Compared to the previously developed framework, this enhancement will use less energy during data transmission.

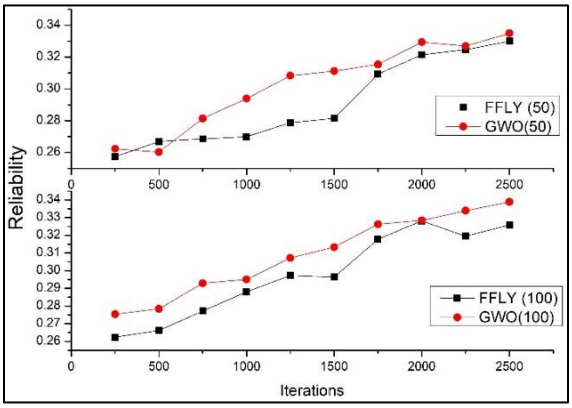

Fig 5. Reliability Curves on 50 and 100 Dimensions

Most of the data transmission in advanced frameworks was found to be unsecure, which is another gap that has been examined in the literature. During the simulation procedure, the effects of RSA and ECC are examined based on message size and key size. The key length is a crucial factor that determines how long limited nature sensors can operate. As a result, the key length sizes for ECC and RSA are compared, and Fig. 7 shows that ECC outperforms the RSA technique. Another issue is the size of the message, which affects how long it takes to encrypt and decrypt data. The encryption and decryption time of ECC and RSA have both been compared, and the findings demonstrate that ECC is significantly faster than the RSA method, as predicted in Figs. 8(a) and 8(b).

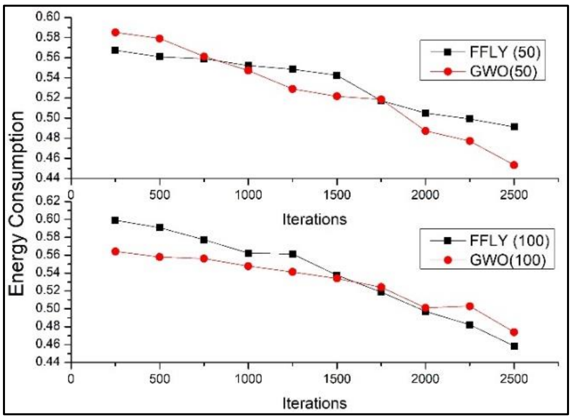

Fig 6. Energy Consumption Curves on 50 and 100 Dimensions

The suggested framework has been optimised and produced significant outcomes for all four parameters. In order to foster healthy communication between patients and the other parties involved and to take immediate action, these conditions must be addressed. Any piece of information that is inaccurate or missing can affect a patient's diagnosis, and the current optimised framework can detect and close this gap.

6. Conclusion and Future Directions

This study introduces a healthcare framework that uses FFLY and GWO to track patients' health. The FFLY and GWO algorithm’s fundamental function is to facilitate communication across heterogeneous devices, which must be highly interoperable for effective communication. The framework has been refined to the point that it can offer an interoperable, reliable, convergent, and energy-efficient environment for monitoring patient health.

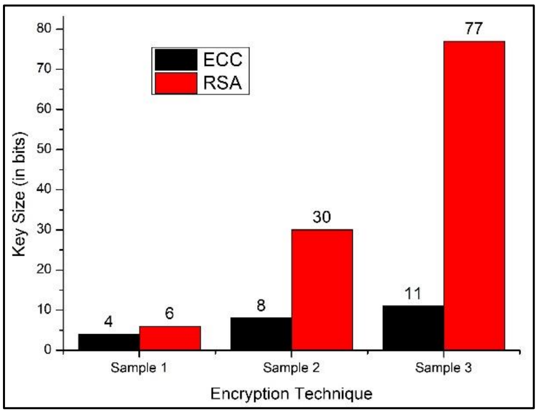

Fig 7. Key size comparison of ECC and RSA

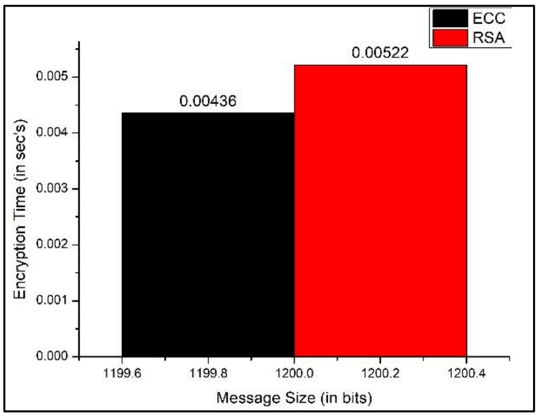

Fig 8 (a). Encryption Time Comparison of ECC vs RSA

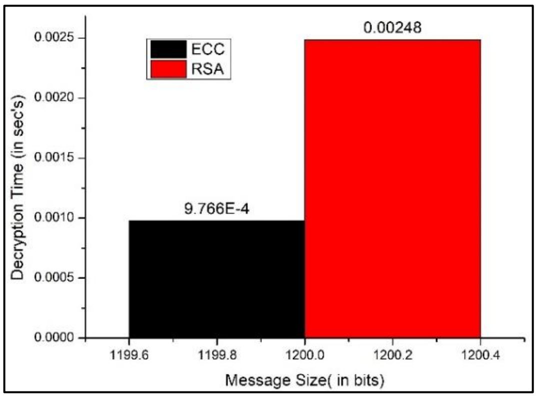

Fig 8 (b). Decryption Time Comparison of ECC vs RSA

With the aid of multi-objective optimisation algorithms like FFLY and GWO, the best value for each performance indicator is selected from the population of randomly generated data. The new framework outperforms the basic findings in terms of interoperability, convergence, dependability, and energy usage. The outcomes analysis, where FFLY and GWO both adjust the performance parameters, is shown in Section 5. The generation of the random population is done to choose the best values of the performance parameters. The optimized results are better than the base values and are 9.76%, 16.36%, 23.09%, and 12.62% for interoperability, convergence, dependability, and energy consumption, respectively. Whereas in terms of security, ECC surpasses RSA in terms of encryption time, decryption time, and key size in the simulation using the security features of ECC and RSA. The primary need for a framework with fog computing capabilities is that all ECC security measures use less energy when compared to RSA. Machine learning principles can be applied to the selection of suitable data security methods for future usage.

Author contributions

Mohit Lalit: Conceptualization, Methodology, Software, Field study, Writing-Original draft preparation Gaurav Bathla: Data curation, Field study Surender Singh: Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] S. Singh, R. Kumar, A. Sharma, J. Abawajy, R. K.-C. Computing, and undefined 2022, “Energy efficient load balancing hybrid priority assigned laxity algorithm in fog computing,” Springer.

[2] S. Ogundoyin, I. K.-A. S. Computing, and undefined 2023, “An integrated Fuzzy-BWM, Fuzzy-LBWA and V-Fuzzy-CoCoSo-LD model for gateway selection in fog-bolstered Internet of Things,” Elsevier, Accessed: Jun. 07, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1568494623004118

[3] M. Bansal, S. M.-S. C. I. and Systems, and undefined 2020, “A multi-faceted optimization scheduling framework based on the particle swarm optimization algorithm in cloud computing,” Elsevier, Accessed: May 02, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2210537920301566

[4] G. Shyam, I. C.-C. computing for optimization: Foundations, and undefined 2018, “Resource allocation in cloud computing using optimization techniques,” Springer, Accessed: May 02, 2023. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-319-73676-1_2

[5] S. O. Ogundoyin and I. A. Kamil, “Optimal fog node selection based on hybrid particle swarm optimization and firefly algorithm in dynamic fog computing services,” Eng Appl Artif Intell, vol. 121, p. 105998, May 2023, doi: 10.1016/J.ENGAPPAI.2023.105998.

[6] C. Wang, X. C.-I. Access, and undefined 2019, “An improved firefly algorithm with specific probability and its engineering application,” ieeexplore.ieee.org, Accessed: May 02, 2023. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8704720/

[7] “Hassan: EoT-driven hybrid ambient assisted living... - Google Scholar.” https://scholar.google.com/scholar_lookup?title=EoT-driven%20hybrid%20ambient%20assisted%20living%20framework%20with%20na%C3%AFve%20bayes%E2%80%93firefly%20algorithm&author=M.%20K.%20Hassan&author=A.%20I.%20E.%20Desouky&author=M.%20M.%20Badawy&author=A.%20M.%20Sarhan&author=M.%20Elhoseny&author=M.%20Gunasekaran&publication_year=2018 (accessed May 02, 2023).

[8] Kumari, V. Kumar, and M. Y. Abbasi, “EAAF: ECC-based anonymous authentication framework for cloud-medical system,” International Journal of Computers and Applications, vol. 44, no. 5, pp. 491–500, 2022, doi: 10.1080/1206212X.2020.1815334.

[9] S. Singh and V. K. Chaurasiya, "Mutual authentication framework using fog computing in healthcare," Multimed Tools Appl, vol. 81, no. 22, pp. 31977–32003, Sep. 2022, doi: 10.1007/S11042-022-12131-8.

[10] V. Sri Vigna Hema and R. Kesavan, "ECC Based Secure Sharing of Healthcare Data in the Health Cloud Environment," Wireless Personal Communications 2019 108:2, vol. 108, no. 2, pp. 1021–1035, May 2019, doi: 10.1007/S11277-019-06450-7.

[11] S. Ogundoyin, I. K.-S. and E. Computation, and undefined 2021, "Optimization techniques and applications in fog computing: An exhaustive survey," Elsevier, Accessed: Jun. 07, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2210650221000985

[12] H. Sodhro and N. Zahid, "Ai-enabled framework for fog computing driven E-healthcare applications," Sensors, vol. 21, no. 23, 2021, doi: 10.3390/s21238039.

[13] M. Raza, M. Awais, N. Singh, … M. I.-I. J. on, and undefined 2020, "Intelligent IoT framework for indoor healthcare monitoring of Parkinson's disease patient," ieeexplore.ieee.org, Accessed: Feb. 18, 2023. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9186157/?casa_token=DZzyjwV1Hw8AAAAA:VMf41TDvGJD_BKY-19dJLP-zjzbrhEInTk6Ewje0xvbph1um6--9Wa-k5A2vDBrrFTVBcg7nDKM_AFo

[14] H. Mayer, V. F. Rodrigues, C. A. Da Costa, R. Da Rosa Righi, A. Roehrs, and R. S. Antunes, "FogChain: A Fog Computing Architecture Integrating Blockchain and Internet of Things for Personal Health Records," IEEE Access, vol. 9, pp. 122723–122737, 2021, doi: 10.1109/ACCESS.2021.3109822.

[15] F. Ali et al., "An intelligent healthcare monitoring framework using wearable sensors and social networking data," Elsevier, vol. 114, pp. 23–43, 2021, doi: 10.1016/j.future.2020.07.047.

[16] Hussain, K. Zafar, and A. R. Baig, "Fog-Centric IoT Based Framework for Healthcare Monitoring, Management and Early Warning System," IEEE Access, vol. 9, pp. 74168–74179, 2021, doi: 10.1109/ACCESS.2021.3080237.

[17] S. K. Sood, V. Sood, I. Mahajan, and Sahil, "An intelligent healthcare system for predicting and preventing dengue virus infection," Computing, 2021, doi: 10.1007/s00607-020-00877-8.

[18] J. Hu, W. Liang, O. Hosam, M. Y. Hsieh, and X. Su, "5GSS: a framework for 5G-secure-smart healthcare monitoring," Conn Sci, vol. 34, no. 1, pp. 139–161, 2022, doi: 10.1080/09540091.2021.1977243.

[19] J. Ramesh, R. Aburukba, and A. Sagahyroon, "A remote healthcare monitoring framework for diabetes prediction using machine learning," Healthc Technol Lett, vol. 8, no. 3, pp. 45–57, 2021, doi: 10.1049/htl2.12010.

[20] E. Yıldırım, M. Cicioğlu, and A. Çalhan, "Fog-cloud architecture-driven Internet of Medical Things framework for healthcare monitoring," Med Biol Eng Comput, 2023, doi: 10.1007/S11517-023-02776-4.

[21] Asghar, A. Abbas, H. A. Khattak, and S. U. Khan, "Fog Based Architecture and Load Balancing Methodology for Health Monitoring Systems," IEEE Access, vol. 9, pp. 96189–96200, 2021, doi: 10.1109/ACCESS.2021.3094033.

[22] Elhadad, F. Alanazi, A. I. Taloba, and A. Abozeid, "Fog Computing Service in the Healthcare Monitoring System for Managing the Real-Time Notification," J Healthc Eng, vol. 2022, 2022, doi: 10.1155/2022/5337733.

[23] H. Ben Hassen, W. Dghais, B. H.-H. information science and, and undefined 2019, "An E-health system for monitoring elderly health based on Internet of Things and Fog computing," Springer, Accessed: Apr. 26, 2023. [Online]. Available: https://link.springer.com/article/10.1007/s13755-019-0087-z

[24] G. K.-G. Scholar and undefined 2015, "Fog computing and mobile edge cloud gain momentum open fog consortium, etsi mec and cloudlets," yucianga.info, 2015, Accessed: May 11, 2023. [Online]. Available: http://yucianga.info/wp-content/uploads/2015/11/15-11-22-Fog-computing-and-mobile-edge-cloud-gain-momentum-%E2%80%93-Open-Fog-Consortium-ETSI-MEC-Cloudlets-v1.pdf

[25] D. Upadhyay, P. Garg, S. Aldossary, J. Shafi, S. K.-Electronics, and undefined 2023, "A Linear Quadratic Regression-Based Synchronised Health Monitoring System (SHMS) for IoT Applications," mdpi.com, 2023, doi: 10.3390/electronics12020309.

[26] X. S. Yang, "Firefly algorithms for multimodal optimization," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 5792 LNCS, pp. 169–178, 2009, doi: 10.1007/978-3-642-04944-6_14.

[27] S. Mirjalili, I. Aljarah, M. Mafarja, A. A. Heidari, and H. Faris, "Grey wolf optimizer: Theory, literature review, and application in computational fluid dynamics problems," Studies in Computational Intelligence, vol. 811, pp. 87–105, 2020, doi: 10.1007/978-3-030-12127-3_6.

[28] X. Chen, M. Ma, and A. Liu, "Dynamic power management and adaptive packet size selection for IoT in e-Healthcare," Computers & Electrical Engineering, vol. 65, pp. 357–375, Jan. 2018, doi: 10.1016/J.COMPELECENG.2017.06.010.