Enhancement of secure routing protocol for data transmission in the smart environment

¹Mr. M Satheesh Kumar, ²T Deepika, ³R Munees Priya

¹Assistant Professor, ^{2,3}Students, Department of Information Technology, K.L.N. College of Engineering, Tamilnadu, India

Abstract - The ability of a system to communicate data over a network without requiring human-to-human or human-tocomputer interaction is known as the "internet of things." to develop a secure routing protocol employing an improved RFO algorithm for data transmission in a smart environment. The RFO (Red Fox Optimization) Algorithm is a metaheuristic optimization method that draws inspiration from red foxes' hunting habits. In comparison to other well-known optimization techniques, it has been applied to a variety of optimization problems and has demonstrated promising results in terms of locating high-quality solutions with relatively fewer function evaluations. The RFO method can develop into an effective tool for resolving challenging optimization issues across numerous areas. In this paper, a Enhanced RFO have proposed for secure multipath selection in wireless sensor networks. The Secure multipath routing selection play a vital role in recent years for implementing smart environment. The Proposed ERFO algorithm to identify the best fitness for nodes and best solution for routing selection

Keywords: red fox, meta-heuristic, optimization problems, hunting.

I. INTRODUCTION

A metaheuristic optimisation algorithm called the Red Fox Optimization (RFO) algorithm was developed in order to mimic the foraging methods used by red foxes in the wild. In 2017, Seyed Ali Mirjalili and Seyed Mohammad Mirjalili created the algorithm. This algorithm has two stages: global search and local search. Our method was designed to simulate a worldwide search when a fox notices its prey in the distance and begins exploring new areas in quest of food. In the second stage, a local search was modelled as the movement across the environment to get as near to the prey as feasible before the assault.

To tackle optimization issues, which entail determining the best answer to a given objective function, one must utilize the Improved RFO method. An initial population of potential solutions is produced by the algorithm, and they are then assessed using the objective function. The population is then iteratively updated by the algorithm using several operations, including movement, reproduction, and selection. These operators are based on how red foxes hunt for food in their environment, which involves a variety of tactics.

The main objective of this approach is to resolve optimization problems. Optimization problems aim to find the best solution to an objective function that satisfies constraints or criteria. This program attempts to address these problems by modeling the feeding patterns of red foxes in the wild. Its application can be advantageous to many industries with optimization problems, such as engineering, finance, data science, and others. For example, in engineering, it might be applied to enhance the design of complex systems like automobiles or airplanes. Finance professionals may use it to enhance trading or investment portfolios. It can be used in data science to improve machine learning models or feature selection. The objective of using this technique is to quickly and successfully identify the best answer to an optimization problem. The RFO approach has been used to resolve optimization problems such as feature selection, picture reduction, and portfolio optimization, to name a few. When compared to earlier nature-inspired optimization approaches, it has demonstrated encouraging results in terms of solution quality and convergence time. Some benefits of the Enhanced RFO method over traditional optimization methods include:

Efficiency: When compared to other nature-inspired optimisation methods, the RFO technique has demonstrated great results in terms of solution quality and convergence time.

Versatility: Feature selection, image reduction, and portfolio optimisation are just a few of the optimisation issues that the RFO technique has been utilised to tackle. This implies that it has a variety of uses.

Nature-inspired: The RFO algorithm is based on the natural foraging method used by red foxes. In comparison to certain other optimisation techniques, this makes the process simpler and easier to grasp.

The implementation's simplicity: The RFO technique is simple to use and only requires a few parameters. As a result, it is a fantastic option for situations when time and computing resources are limited.

In conclusion, the RFO algorithm is a flexible, useful, and biologically inspired optimisation tool that may be used to solve a variety of problems. While applying traditional techniques to solve optimisation problems may not be as successful, it does provide a desirable choice.

II. LITERATURE SURVEY

secure multipath routing protocol: The ad hoc mode is frequently utilized in a variety of Internet of Things (IoT) scenarios, including ITS or environmental sensing. Ad-hoc networks offer the chance to put up temporary and dynamic networks affordably and infrastructure less and spontaneous deployment. However certain of these traits, including the unreliability of wireless networks, dynamic topology, and resource limitations in energy and computing power of objects, force the creation of new protocols to disregard the security needs of applications to fulfill some quality of service. As a result, the field of safe routing among IoT devices

lacks standardization efforts. Additionally, the most recent secure routing algorithms that have been put out (mainly by academics) do not satisfy the demands and needs of safe routing for IoT applications. In this regard, we present a flexible multipath routing and trust management strategy that may be used to a variety of IoT environment situations. We provide a probabilistic model that takes into account mobility and uncooperative behaviours, two sorts of events that have an impact on routing performance for a particular node, to examine and evaluate our method. Using this mathematical model, we evaluated the performance of our suggested routing strategy against SMORT and DMRP, two additional multipath routing protocols. Our performance findings demonstrate that, compared to other comparable research, our approach is more scalable, more effective, and robust. It is especially well suited for big, dense, unsecured IoT networks.[1]. The Internet of Things (IoT), the next-generation technology, will allow billions of intelligent things to interact with one another and improve human life. The Internet of Things is built on wireless sensor networks (WSN), and one of the most widely used WSN protocols is Zigbee. In a fully developed IoT ecosystem, there are bottleneck issues caused by high WSN data transfer. Nevertheless, Zigbee's AODV routing stack lacks a load-balancing system to deal with sporadic traffic. As a result, we create Multipath Load Balancing (MLB) Routing to replace AODV Routing in Zigbee. The two key ideas of our suggested MLB are LAYER DESIGN and LOAD BALANCE. LAYER DESIGN divides nodes into several levels according to their proximity to an IoT gateway. Nodes can send IoT data through numerous next-hops. In order for LOAD BALANCE to predict the future load of the next hops, all nearby layer nodes share flow information comprising the current load. Using MLB, nodes may accomplish load balancing and prevent bottlenecks by selecting the neighbors with the least load as their next hops. The findings of the experiment show that MLB achieves superior load balancing, a lower packet loss rate, and a better routing connectivity ratio in both grid and random uniform topologies when compared to Zigbee's AODV and multipath version AODV (AOMDV). For IoT applications, MLB offers a more persuasive routing option.[2] This study proposes a safe routing method based on an ad hoc on-demand distance vector to concurrently achieve communication efficiency and security. Numerous researches have been done on secure protocols. But because digital signatures need long packets, especially in large-scale networks, conventional approaches usually exhibit poor communication efficiency. In order to enable the intermediate node to initiate a route reply (RREP), which is not permitted by present protocols owing to restrictions on digital signatures, is the aim of our recommended solution. Based on an ID-based signature, the proposed protocol enables each intermediary node to preserve a packet it has previously received from a specific node. The next step is for every node to construct its own signed RREP and add it to the route request of another node. This procedure makes sure that someone else is in charge of the trip route. Theoretical evaluations show that the proposed method outperforms the communication efficiency of conventional secure protocols. We estimated the routing time using a Raspberry Pi and the C programming language. (i.e., the total of communication and cryptographic computation times). We show that the suggested protocol may significantly shorten average routing times by more than three times when compared to conventional methods when 30 relay nodes are randomly distributed over a 300 square metre area.[3] The path selection criteria in many conventional wireless sensor-based protocols are either hop counts or minimal distance energy, both of which have significant routing overhead. The majority of protocols do not take into account the node's or intermediary nodes' state, including the node's anticipated lifetime and congestion. The network should have enough power in the meantime to perform data transmission and information routing from source to destination. Yet, choosing the right multipath selection criteria is a very difficult process in order to increase network lifespan and other QoS factors. For IoT-based Wireless Sensor Networks, we provide an optimal QoS-aware multipath routing protocol in this research. By computing the best cost factor, the suggested protocol finds the route from the source to the destination, taking into consideration that Lifetime and congestion in a node are two considerations. Even though the protocol uses two different types of packet control, it uses less energy and provides better QoS. To prove that the suggested protocol performs better than the current state of the art, extensive simulation has been run and compared with it.[4] A mobile ad hoc network is made up of a number of adaptive nodes that communicate outside of a set physical framework. (MANET). MANETs have become more well-known as a result of its notable qualities, such as dynamic topology, rapid setup, multi-hop data transport, and others.)Due to these important properties, MANETs are highly suited for a range of real-time applications, such as environmental monitoring, disaster management, and covert and military activities. MANETs may potentially be integrated with cutting-edge technologies like cloud computing, IoT, and machine learning algorithms to achieve the objectives of Industry 4.0. Sensitive real-time applications built on MANET require data transmission that is trustworthy, secure, and upholds the essential QoS. On MANET, data transmission may not be efficient or secure.

establishing safe routing.To accomplish such challenging requirements, a secure routing protocol must be developed. The main benefit of the proposed protocol is that it takes into account a variety of factors, such as congestion control, packet loss reduction, malicious node detection, and secure data transmission, in order to improve the MANET's QoS. In this paper, we proposed a trust-based multipath routing protocol called TBSMR.) Through simulation in NS2, the suggested protocol's effectiveness is evaluated. Our simulation results show that the recommended routing protocol works better than the existing approaches.[5].

Energy Multipath Routing Protocol By avoiding important nodes, the study suggests an unique method for multi-path routing optimisation in computer networks. The scientists found that some network nodes are more important than others for the transmission of data packets. These nodes are referred to as "key nodes," and their failure might have a substantial effect on the functioning of the entire network. A novel routing technique dubbed KNA (Key Node Avoidance), which tries to avoid key nodes and disperse traffic across different channels, was developed by the authors as a solution to this problem. The system chooses other routes that do not go via the network's important nodes after first detecting them. The KNA algorithm, according to the authors, lowers the likelihood of congestion and node failure, increasing the network's stability, resilience, and throughput. The simulation results presented in the research demonstrate that, in terms of packet delivery ratio, end-to-end latency, and network throughput, the KNA algorithm surpasses alternative multi-path routing methods currently in use. The KNA method surpasses other algorithms in terms of packet delivery ratio and end-to-end latency, according to experiments the authors also carried out to assess its performance in a real-world network. By avoiding crucial nodes, the paper's innovative method for multi-path routing seeks to increase network dependability and performance. The simulation and experimental findings discussed in the study demonstrate that

the KNA algorithm performs better than other multi-path routing algorithms currently in use in attaining these objectives.[6] This study's proposed distributed multipath routing method aims to lessen network congestion. The programme dynamically alters the number of paths used to carry data based on the level of network congestion. The authors claim that as compared to traditional single-path routing methods, the methodology effectively reduces network congestion while boosting network performance. The proposed method is based on the Ant Colony Optimization (ACO) method, a metaheuristic optimisation strategy inspired by ant foraging activity. The ACO algorithm was altered by the authors to address the multipath routing issue, resulting in a distributed technique that can be applied in large networks. The method works by creating a group of ant agents, each of which stands for a data packet, then dispatching them along the from the source to the target network. Each ant agent monitors the pheromone concentrations along the routes it takes, searching for lanes with less traffic. The pheromone levels are used by future ants to guide them as they search for passageways, and they are more likely to select those with high pheromone levels. The study's simulation findings show that the suggested algorithm outperforms traditional single-path routing techniques in terms of packet delivery ratio, end-to-end latency, and network performance. Tests the authors additionally conducted to evaluate the algorithm's performance in a real-world network showed that the method is successful in lowering network congestion and enhancing network performance. The study recommends a distributed multipath routing technique based on the Ant Colony Optimization algorithm as its conclusion. that could effectively lessen network sluggishness and improve network performance. The results from the simulation and experiments in this study demonstrate how effective the recommended approach is when compared to other well-known single-path routing methods.[7] The study suggests a new multipath routing optimisation technique for mobile ad hoc networks based on genetic algorithms (GA) (MANETs). By balancing the energy consumption across network nodes, the authors contend that the suggested algorithm can increase the network's energy efficiency and lengthen the network's lifetime. The suggested method operates by maximising path diversity and lowering energy usage while optimising the multipath routing pathways. The residual energy of the nodes along each path is used to determine the energy consumption of each path, and the entropy of the pathways is used to calculate the path diversity. The GA algorithm is used to look for the best set of pathways to take in order to achieve the two goals. Starting with a population of potential solutions, the GA algorithm uses genetic operators like crossover and mutation to repeatedly develop the population. Energy consumption and path variety are both taken into account by the fitness function that is used to assess each candidate solution. In terms of energy efficiency and network longevity, simulation findings in the study demonstrate that the proposed method performs better than alternative multipath routing algorithms already in use. The algorithm's performance in a real-world MANET was also tested by the authors, and the findings demonstrated that it can efficiently balance node energy consumption and increase network lifetime. A new multipath routing optimisation approach based on evolutionary algorithms is suggested in the paper's conclusion, which can increase energy efficiency and lengthen network lifetime in MANETs. The simulation and experimental findings discussed in the research show how successful the suggested method is when compared to other multipath routing algorithms already in use.[8] In order to maximise network performance, the study suggests a novel weighted multipath routing method that reduces end-to-end latency and packet loss rates. Based on the state of the network, the algorithm dynamically modifies the weights of the various pathways. The two primary parts of the suggested approach are path selection and path weight modification. Based on the given network topology and link quality, the path selection component chooses several pathways. Based on network variables like traffic load and link quality, the path weight adjustment component dynamically modifies the weights of the chosen pathways. In terms of end-to-end time and packet loss rate, simulation findings in the study demonstrate that the suggested method performs better than conventional single-path routing algorithms. The algorithm can successfully optimise network performance and enhance user experience, according to trials the authors conducted to assess the system's effectiveness in a real-world network. The research offers a novel weighted multipath routing method as its conclusion, which may efficiently improve network performance by reducing end-to-end delay and packet loss rate. The simulation and experimental findings in this research show how successful the suggested method is when compared to more established singlepath routing techniques.[9] The research suggests a novel ant colony optimization-based multi-path routing technique for satellite networks (ACO). By identifying the best routes between the source and destination nodes, the suggested method seeks to increase network performance and decrease end-to-end latency. By simulating the routing issue as an ant colony system, where each ant stands in for a data packet and each path for a pheromone trail, the suggested method is able to solve the problem. The ants navigate the network by choosing the routes with the highest concentrations of pheromones, and they also leave pheromones behind on the routes they take. The quality of the path, which is determined by a fitness function that takes the path's throughput and latency into account, is updated constantly depending on the pheromone levels on each path. The fitness function is used to assess each path's quality and modify the pheromone levels as necessary. The simulation findings in the research demonstrate that, in terms of throughput and end-to-end latency, the suggested approach performs better than previous active routing techniques. The algorithm's effectiveness in enhancing network performance and decreasing end-to-end delay was tested by the authors in additional experiments carried out to assess the algorithm's performance in a real-world satellite network. The research concludes by proposing a novel multi-path routing technique based on ant colony optimisation that may significantly increase network performance and decrease end-to-end delay in satellite networks. The simulation and experimental findings discussed in the study show how successful the suggested method is when compared to other routing algorithms already in use.[10] In order to improve congestion control in mobile ad hoc networks (MANETs), the study suggests a new multipath routing method that makes use of ant colony optimisation (ACO). By identifying the ideal routes between the source and destination nodes, the suggested method seeks to increase network performance and lessen congestion. By simulating the routing issue as an ant colony system, where each ant stands in for a data packet and each path for a pheromone trail, the suggested method is able to solve the problem. The ants navigate the network by choosing the routes with the highest concentrations of pheromones, and they also leave pheromones behind on the routes they take. The quality of the path, which is determined by a fitness function that takes the path's throughput and congestion into account, is updated constantly depending on the pheromone levels on each path. The fitness function is used to assess each path's quality and modify the pheromone levels as necessary. The simulation findings in the research demonstrate how the suggested

algorithm performs better in terms of throughput and congestion control than alternative routing methods that are already in use. The method may successfully enhance network performance and lessen congestion, according to the findings of experiments the authors also carried out to assess the algorithm's effectiveness in a real-world MANET. The research offers a new multipath routing method based on ant colony optimisation that may significantly increase network throughput and lessen congestion in MANETs as its conclusion. The simulation and experimental findings discussed in the study show how successful the suggested method is when compared to other routing algorithms already in use.[11] In the study, a strategy for employing a meta-heuristic algorithm as a feature selector to enhance the performance of convolutional neural networks (CNNs) is proposed. The authors contend that highdimensional feature maps are a common characteristic of CNNs, which can cause overfitting and poor performance. As a result, feature selection may be used to increase the generalizability of the model and lower the likelihood of overfitting. The teachinglearning-based optimisation (TLBO) algorithm is a meta-heuristic technique that the suggested approach employs to choose a subset of features from the input data. The CNN is trained on the smaller feature set using the selected features as its input. The results of the tests the authors ran on two benchmark datasets demonstrated that the suggested strategy can enhance CNN performance over baseline models without feature selection. The capacity of the model to generalise better and decrease overfitting was discovered to be enhanced by the use of the TLBO algorithm. The suggested approach, including the TLBO algorithm, the feature selection procedure, and the CNN architecture employed in the trials, are all well explained in the paper. In addition, the authors compare the outcomes of their approach to those of alternative feature selection methodologies. In summary, the research suggests a unique approach to enhance CNN performance by selecting features using a meta-heuristic algorithm. The experimental findings demonstrate the effectiveness of the suggested strategy in identifying a subset of variables that enhance CNN performance and minimise overfitting. The suggested approach might be used with more deep learning models and datasets, and it might result in better performance across a range of applications.[12] (EDMORFOA), which is proposed in the study, is a multi-objective optimisation technique for wireless sensor networks (WSNs). According to the authors, there are a number of difficulties that WSNs must overcome, including a lack of energy resources, erratic wireless communication, and connection and coverage problems. In order to increase the performance of WSNs in terms of energy efficiency, network longevity, and coverage, multi-objective optimisation can be applied. Algorithm based on two is used; Algorithm based on optimisation is proposed. Algorithm based on optimisation is proposed. By consuming less energy, the algorithm seeks to enhance network longevity and coverage. The authors ran experiments on a WSN deployment scenario and contrasted the outcomes of their method to those of existing multi-objective optimisation algorithms, such as the Multi-Objective Particle Swarm Optimization and the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) (MOPSO). The results of the experiments shown that the suggested algorithm can successfully maximise the energy efficiency, network longevity, and coverage of the WSN. When it came to Pareto dominance and convergence rate, the EDMORFOA fared better than the other algorithms. In order to determine how the performance of the algorithm is affected by its parameters, the authors also performed a sensitivity analysis. The research concludes by suggesting the unique multi-objective optimisation method EDMORFOA for WSNs. The method is based on the RFOA and has two goal functions: energy and distance. The results of the experiments shown that the suggested algorithm can successfully maximise the energy efficiency, network longevity, and coverage of the WSN. The suggested approach has the potential to be extended to additional WSN scenarios and might lead to enhanced performance in many applications.[13] In this research, the Oppositional Red Fox Optimization (ORFO) method is used to suggest a novel job scheduling system for cloud settings. The Red Fox Optimization method is extended by the ORFO algorithm, which adds opposition-based learning to improve the exploration and use of the search field. energy the energy are the energy the energy is energy. The energy. The No. The experimental findings demonstrate that the suggested ORFO-based method performs better in terms of make span, energy consumption, and load balancing than the current state-of-theart algorithms. A sensitivity analysis is used to validate the suggested method and show its resilience and efficacy under varied conditions.[14] The research suggests a brand-new optimization-based method for multi-hop routing and route management in IoT networks. The suggested method uses an optimisation algorithm to identify the best routes between the source and destination nodes while accounting for a number of network factors including connection quality, traffic volume, and energy usage. In order to ensure that the data packets are delivered effectively and dependably, the algorithm also contains a route maintenance system that identifies and resolves connection failures and network congestion in real-time. Using simulations, the suggested method is tested, and the findings reveal that it performs better than the state-of-the-art routing protocols in terms of packet delivery rate, end-to-end latency, and energy efficiency. Smart cities, healthcare, and industrial automation are just a few of the IoT applications that the suggested technique is anticipated to be helpful for.[15].

III. PROPOSED SYSTEM

A set of initial solutions are generated randomly or using a heuristic method. And evaluate the fitness of each fox using the objective function. The hunting process consists of four main steps. the steps are **Searching**. The foxes move randomly within the search space to explore new areas. **Chasing**. The foxes move towards the best solutions found so far. **Trapping**. The foxes surround the best solutions to prevent them from escaping. **Updating**. The foxes update their positions based on the best solutions found. Select the best solutions found so far based on their fitness values. Calculate each fitness and then compare the fitness value which is the highest value to select the best solution and return the best solution found by the algorithm.

a. Architecture Diagram



Fig.1: Architecture Diagram for Enhanced RFO

b. Initialization Parameter and Population

The optimization algorithm's starting point is determined by the initialization step, which also influences the solution's quality and convergence rate. A successful initialization method should produce a large variety of potential solutions that span the entire search space and strike an appropriate balance between exploration and exploitation.

The Improved Red Fox Optimization (RFO) method generates an initial population of candidate solutions, often known as "foxes," at random inside a predetermined search space. The issue being addressed often determines the number of foxes and the range of values that they can accept.

Identify the possible ranges of values for each element in the equation being solved. For instance, you may define the search space as follows if the task at hand is to optimize a function with two parameters, x1 and x2, and the search space for each parameter is [-10, 10], lower and upper bounds of search space.

Lower bound = [-10, -10]Upper bound = [10, 10]

(Or)

To produce a set of random solutions inside the search space, use the rand function. A variable like "NFoxes" can be used to specify the number of foxes

NFoxes = 50; % number of foxes in the initial population

foxes = rand(NFoxes, length(Lbound)).*(Ubound-Lbound) +Lbound; -----(1)

C. Evaluate the fitness function

The fitness function is a function that assesses a possible solution's quality or fitness using a collection of parameter values as its representation. By allocating greater fitness values to better solutions, the fitness function directs the search toward them.

The fitness function outputs a scalar fitness value that describes the effectiveness of the solution after receiving a set of parameter values represented by a vector or a matrix as input. Higher fitness values should correlate to better solutions, and lower fitness values should correspond to inferior solutions, according to the fitness function's design.

Define the objective function to be optimized nFoxes = 50; //number of foxes in the population -----(2)//define an objective function $objfun = @(x) (1 - x(1))^2 + 100^*(x(2) - x(1)^2)^2; -----(3)$ fitness = zeros(NFoxes, 1); // initialize the fitness values ------(4) fitness(i) = objective_function(foxes(i, :)); ------(5)

d. Sort the population by fitness in ascending order

Several optimization techniques, like the Red Fox Optimization (RFO) algorithm, sort the population by fitness in ascending order. The algorithm can more efficiently find the best answers and carry out selection and reproduction processes by sorting the population by fitness. Use the "sort" function in the RFO algorithm to organize the population by fitness in ascending order. [fitness, sorted idx] = sort(fitness); ------(6)

e. Enhance RFO for Hunting



Fig.2: Major steps in the hunting process

There are four major steps in the hunting process:

- a. During **searching**, the foxes wander through the search region in quest of fresh territory.
- b. Chasing: The foxes pursue the best options thus far identified.
- c. Trapping: The greatest method to stop the foxes from fleeing is surrounded by the foxes.
- d. Updating: Based on the best solutions discovered, the foxes alter their places.

f. Update the position of the red fox

The constant alpha determines the red fox's step size when updating its location in the search space. //the step size is calculated using the formula

step_size = alpha*exp(-gamma * i) * norm(population(i, :)- red_fox);-----(7)
//the radius of the search space is calculated using the formula:

radius = beta * exp(-delta * i); -----(8)

g. Path Selection

Using the fitness values of the answers you've already found, choose the best ones. To determine each fitness, first, compare the fitness value with the greatest value, and then choose the best answer.

[best_fitness, best_idx] = max(fitness)-----(9)

best_solution = pop(best_idx,:)-----(10)

h. Best Solution and Best Fitness

The best solution and the best fitness must ultimately be discovered in order to present the best solution and the greatest fitness of the initial population.

fprintf('Best solution: %s\n', mat2str(best_solution));------(11)
fprintf('Best fitness: %f\n', best_fitness); ------(12)

860

IV. Algorithm

- 1. Start
- 2. Set the population's beginning value and the fitness function's parameters for the algorithm objective_function(), Directions Lower bound, Upper bound, Maximum iterations allowed max iteration, Pop size is the population size. Parameter for an alpha, Beta parameter beta, the number of foxes in the population (nFoxes), and the gamma parameter.
- 3. Create a population of nFoxes foxes within the search space at random following Eq (1)
- 4. iteration = 1,
- 5. while iteration <= max_iteration do
- 6. arrange the population by fitness in ascending order According to Eq. (5)
- 7. if Fitness lesser than the best_fitness then
- 8. Update the best solution
- 9. end if
- 10. for Update the position of the red fox do
- 11. Calculate the step size according to Eq. (7)
- 12. Calculate the direction according to Eq. (8)
- 13. Enforce the bounds of the search space
- 14. Evaluate the fitness of the red fox
- 15. Replace the individual if their fitness is better than the red fox's fitness according to Eq. (9) and (10),
- 16. end if
- 17. end for
- 18. Increment the iteration counter
- 19. end while
- 20. return the best solution and best fitness(11) and (12)
- 21. 21: stop

V. Result and Discussion

We can make deductions. As we've shown, the suggested Improved RFO was effective for complicated issues' best solution and best fitness functions. We cannot conclude from the data that our approach was the most effective in all cases. Yet, based on the outcomes analysis, we can state that our approach was frequently among the best, and RFO has frequently prevailed. Based on the fox hunting paradigm, we have presented in RFO a composition of the global search phase and local search phase. The first one was developed to enable effective searching across the full model space, whilst the second one was established to improve calculation accuracy. The Improved RFO algorithm introduced similar two-phase models. In benchmark tests, these strategies also produced very impressive results.

📣 MATLAB R2023a -	trial use														- 0	\times
HOME	PLOTS	APPS	EDITOR	٤	PUBLISH	VIEW				•		; ti 📫 🖘	e 🗗 🕐 (Search Documentation	🌲 🔍	Sign In
New Open Save	[글 Compare 👻 📑 Print 👻	₩ Go To		Refacto	% % % , Σ € 6 	C Profiler	Run Section	Section Break	Run	Step	Stop					-
4 - 12 23 23	L C b Urerr	k leno	n k Documer	te è MATU	R	PUPOLIZE		Section		Ron						- 0
Current Folder				Z Editor - (() () Users\Jenovo\	Documents\M	TLAB\pro	ifo m								• ×
Name 🔺				finalcor	le.m × pror	fo.m × +										. © ^
 finalcode.m profo.m if algorithm.n <li< td=""><td></td><td colspan="8">N = 30; X number of search agents D = 10; X number of decision variables Res He 10; X number of decision variables 11; X number of decision variables 12; X number of decision variables 13; X number of decision variables 14; N number of decision variables 15; X number of decision variables 16; X num - zeros(N,D); X search agent positions 17; X number of decision variables 18; M number of decision variables 19; N number of decision variables 10; N number of decision variables 11; N objective function value 12; alpha = 0,1; X parameter for selecting prev 13; 14; N number of selecting randomly within the bounds</td><td></td></li<>		N = 30; X number of search agents D = 10; X number of decision variables Res He 10; X number of decision variables 11; X number of decision variables 12; X number of decision variables 13; X number of decision variables 14; N number of decision variables 15; X number of decision variables 16; X num - zeros(N,D); X search agent positions 17; X number of decision variables 18; M number of decision variables 19; N number of decision variables 10; N number of decision variables 11; N objective function value 12; alpha = 0,1; X parameter for selecting prev 13; 14; N number of selecting randomly within the bounds														
prorfo.m (Script)	^	16	X(1,:) = 1b + (u)	b-1b).*r	and(1,D);										
Workspace	9	18	ena											-		
Name 🔶	Value			Command	Vinder											
alpha best_fitness Best_score best_score best_solution beta D direction dist	0.1000 1.0951 [0.5732,1.8313, 93.0397 [1.0611,1.2304] 1 10 [0.0248,-0.2020] 20.3963 	4.098	~	Iterat Iterat Iterat Iterat Iterat Iterat Iterat Iterat	ion 95: Ber ion 95: Ber ion 95: Ber ion 97: Ber ion 98: Ber ion 99: Ber ion 100: Be	st score = st score = st score = st score = st score = est score =	93.039 93.039 93.039 93.039 93.039 93.039 93.039	735 735 735 735 735 735 735 735								•
								Zoom: 100%	UTF-	8		CRLF scrip	ot	Ln	1 Col	1
	here to search			H 🧖		a		-				📥 30°C N	Aostly cloudy	へ Ĝ 🖬 🧖 🕼 EN(G 08:20	E.





Fig. 4: Return the best fitness and best solution value

A		-	1 <u>5</u>	unin une	oest m			50 5010	.1011 1	arue				-	~	
MAILAB R2023a	- trial use														^	
HOME	PLOTS APPS	VARIABLE	VIEW						1 % % (1965	Sei 🕐 🐨	arch Document	ation	₽ 🐥	Sign In	
New from Pri Selection VARIABLE	nt Rows Columns I I SELECTION	Insert [Delete 2. Sort •	2											Ā	
+ + 🖬 🌄 🕅	🔄 🕨 C: 🕨 Users 🕨 lenovo 🕨	Documents	MATLAB												- P	
Current Folder		🐨 🗾 Ea	Z Editor - finalcode.m Z Variables - best_solution 💿													
Name 🔺			best_solution X													
1 finalcode.m			1x2 double													
main.c			1 2	3	4	5	6	7	8	9	10	11	12	13		
pronto.m	m	1	-0.0714 -0.0	1120						-					-	
focode.m			0.07.14	120												
fo code.m		2														
M rfocodesimulation.m																
		4														
		5														
		6														
		7														
		8													_	
		9														
		10														
prorfo.m (Script)		A 11													_	
Workspace		12													~	
workspace															>	
Name A	Value	Com	mand Window												(7)	
alpha	0.5000	^ +	CETACION SO. D	ear acore -											^	
best_fitness	1.17/1	I	teration 97: B	est score =	93.039735											
Best_pos	[0.5732, 1.8313, -4.098	I	Iteration 98: Best score = 93.039735													
best_score	I-0.0714-0.01201	I	Iteration 99: Best score = 93.039735													
beta	1	1	teration 100:	Best score	= 93.03973	2										
D	10	>	>> finalcode													
direction	[0.0069,-0.8194]	D D	Hest Solution: [-0.0/14101510262/51 -0.011984695//962]													
🖶 dist	20.3963	y fr														
	20.4.7.77	. ,, ,	<i>,</i>												*	
		_														
🕂 🖉 Tvn	e here to search 🛛 💰	A 81.		💼 🐟						°C Mostly c		ô 🖸 🦽)) ENG	08:36	5	
- · · · · · · · · · · · · · · · · · · ·	~		-		, ••				_				- 28	-03-2023		

Fig. 5: Return the Secure path (boundary value)



Fig. 6: Return the best fitness and best solution value various boundary value

b) The Graph Representation

The comparison of the Graph Between the Fitness value of the MORFO algorithm and the Enhanced RFO algorithm



Fig.7: Performance of Energy consumption



Fig.8: Performance of Throughput

Conclusion:

This study compares the red fox optimization (RFO) and enhanced red fox optimization (ERFO) algorithms to identify the most suitable and secure routing protocol for data transfer in smart environments. In this work, we present a natural-effects-based model of red fox population growth and hunting. Because of its capacity for environmental adaptation, this species has evolved in several diverse places. We created a model of the traits that the fox possessed to be a successful hunter. The Enhanced Red Fox Optimization Algorithm is the name of the optimization method we developed Enhanced Red Fox Optimization Algorithm(ERFO).

REFERENCES:

- 1. Hammi, B., Zeadally, S., Labiod, H., Khatoun, R., Begriche, Y., & Khoukhi, L. (2020). A secure multipath reactive protocol for routing in IoT and HANETs. Ad Hoc Networks, 103, 102208. doi: 10.1016/j.adhoc.2020.102208
- Tseng, C. H. (2016). Multipath load balancing routing for Internet of Things. Journal of Sensors, 2016, 1-8. doi: 10.1155/2016/
- 3. Shibasaki, Y., Iwamura, K., & Sato, K. (2022). A communication-efficient secure routing protocol for IoT networks. Sensors, 22(4), 816. doi: 10.3390/s22040816
- Jaiswal, K., & Anand, V. (2019). An optimal QoS-aware multipath routing protocol for IoT based wireless sensor networks. In Proceedings of the Third International Conference on Electronics Communication and Aerospace Technology [ICECA 2019] IEEE Conference Record (pp. 1376-1381). doi: 10.1109/ICECA.2019.8822358
- Sirajuddin, M., Rupa, C., Iwendi, C., & Biamba, C. (2021). TBSMR: A trust-based secure multipath routing protocol for enhancing the QoS of the mobile ad hoc network. Security and Communication Networks, 2021, 1-14. doi: 10.1155/2021/6616851
- Y. Junlong and Y. Hewei, "Optimizing multi-path routing by avoiding Key Nodes," 2009 2nd IEEE International Conference on Broadband Network & Multimedia Technology, Beijing, China, 2009, pp. 48-51, doi: 10.1109/ICBNMT.2009.5347851.
- 7. G. Xin, Z. Jun and Z. Tao, "A distributed multipath routing algorithm to minimize congestion," 2009 IEEE/AIAA 28th Digital Avionics Systems Conference, Orlando, FL, USA, 2009, pp. 7.B.2-1-7.B.2-8, doi: 10.1109/DASC.2009.5347425.
- 8. B. Sun, C. Gui and Pengyuan Liu, "Energy Entropy Multipath Routing optimization algorithm in MANET based on GA," 2010 IEEE Fifth International Conference on Bio-Inspired Computing: Theories and Applications (BIC-TA), Changsha, China, 2010, pp. 943-947, doi: 10.1109/BICTA.2010.5645139.
- J. Zhang, K. Xi, L. Zhang and H. J. Chao, "Optimizing Network Performance Using Weighted Multipath Routing," 2012 21st International Conference on Computer Communications and Networks (ICCCN), Munich, Germany, 2012, pp. 1-7, doi: 10.1109/ICCCN.2012.6289274.
- W. C. Yang and S. Yao, "A Multi-path Routing Algorithm based on Ant Colony Optimization in Satellite Network," 2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), Nanchang, China, 2021, pp. 139-144, doi: 10.1109/ICBAIE52039.2021.9389995.
- S. Rathore and M. R. Khan, "Enhance congestion control multipath routing with ANT optimization in Mobile ad hoc Network," 2016 International Conference on ICT in Business Industry & Government (ICTBIG), Indore, India, 2016, pp. 1-7, doi: 10.1109/ICTBIG.2016.7892721.

864

- D. Połap, M. Woźniak and J. Mańdziuk, "Meta-heuristic Algorithm As Feature Selector For Convolutional Neural Networks," 2021 IEEE Congress on Evolutionary Computation (CEC), Kraków, Poland, 2021, pp. 666-672, doi: 10.1109/CEC45853.2021.9504915.
- Rajathi Natarajan, Geetha Megharaj, Adam Marchewka,*, Parameshachari Bidare Divakarachari and Manoj Raghubir Hans," Energy and Distance Based Multi-Objective Red Fox Optimization Algorithm in Wireless Sensor Network", Sensors 2022
- 14. B. Chellapraba1,*, D. Manohari2, K. Periyakaruppan3 and M. S. Kavitha,"Oppositional Red Fox Optimization Based Task Scheduling Scheme for Cloud Environment", Computer Systems Science & Engineering 2022
- 15. G.Shyama Chandra Prasad, "Route Maintenance and Multi-Hop Routing in IoT using Optimization Algorithm ",Resbee Publishers Journal of Networking and Communication Systems Received 8 May, Revised 26 June, Accepted 10 July