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RESEARCH ARTICLE

Trust Aware Multi-Objective Metaheuristic Optimization Based Secure Route Planning Technique for Cluster Based IIoT Environment

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ABSTRACT Industrial Internet of Things (IIoT) finds use in several industrial applications like robots, medical devices, and software-defined manufacturing processes. Apart from the promising benefits of the IIoT networks, several challenging issues need to be resolved, such as network connectivity, security, privacy, heterogeneity, scheduling, and energy efficiency. Due to the large-scale deployment and heterogeneity of the nodes in IIoT networks, some energy-limited nodes have existed in the IIoT networks, resulting in reduced network lifetime. At the same time, security and privacy are also considered as the major issues that exist in the design of IIoT, which can be addressed using secure routing techniques. In this view, this study develops a trust-aware multiobjective metaheuristic optimization-based secure clustering with route planning (TAMOMO-SCRP) technique for cluster-based IIoT environment. The presented TAMOMO-SCRP technique mainly focuses on the design of bald eagle search (BES) algorithm for clustering and routing processes. The proposed TAMOMO-SCRP model derives a fitness function for accomplishing maximum energy efficiency and security. For an effective clustering process, the TAMOMO-SCRP model designs an objective function involving four parameters such as trust level (TL), communication cost (CC), residual energy (RE), and node degree (ND). Besides, the route selection process is based on the fitness function with two variables, namely, queue length and link quality. For assessing the enhanced performance of the TAMOMO-SCRP model, a wide range of experiments were carried out to get the outcomes of network life time(NLT) as 39451,half network die (HND) as 25950 and Stability period (SP) 8000 time calculated no. of alive nodes. The achieved outcomes make sure the better performance of the TAMOMO-SCRP technique against the other recent approaches.

INDEX TERMS Industrial Internet of Things, clustering, bald eagle search algorithm, trust aware protocols, security.

I. INTRODUCTION

The Industrial Internet of Things (IIoT) connects several physical devices to the Internet. A consistent structure is required for storing each data as effectively as possible [1]. IIoT can be benefitted from industrial and consumer applications. IIoT device frequently works in a noisy environment that should process and analyze the generated information. As a result, IIoT device is more susceptible to the proper delivery of control decisions and timely gathering of environmental information [2]. Therefore, it is necessary to ensure and provide the efficiency and flexibility of network

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management under IIoT. This device needs to be manually configured or updated and are independently managed that actually presents security problems. This situation is even worse in the IIoT environment since the main characteristic of IIoT is large equipment (for example, monitors and sensors) [3]. For this reason, several protocols, appliances, and security solutions have been deployed and developed to manage the continuously evolving security threat in IIoT [4]. As we know that this solution is inflexible, complex, hard to manage, and highly proprietary that sequentially makes the network more bloated and ossified. Thus, when a malicious attack occurs, it will be extremely difficult to eliminate, detect, and locate. In addition, the malicious attack controls the intermediate device to perform purposes like stealing critical data and forwarding messages to another destination rather than the actual destination [5].

Trust management offers behavior-based analysis of IIoT devices by utilizing the reputation and past behavior in the network. It is critical to prevent redundant activity performed by compromised devices [6]. Generally, trust can be either managed in a centralized way, where a single trust management entity manages the whole IIoT system, or in a distributed way, where all nodes evaluate the trust metrics of its neighbours [7]. However, a single centralized trust management entity is unable to constantly handle the trust in the plant IIoT system comprised of a massive amount of sensitive and heterogeneous devices. Indeed, distributed trust management system is extensively employed in the composition of services in IoT, however, they are not suitable for trust management in industrial environment [8].

The final solution alters the conventional structure of the plant IIoT system by grouping the IIoT devices into clusters for simplifying trust management. The secured routing is the main focus because the industrial environment is very susceptible and several potential threats (for example, selfish and DDoS attacks) are presented because of the Internet connection. To embrace the benefits of IIoT and prevent the threat from the Internet, a security-driven network architecture for routing is specially developed. Study on IIoT routing method based on wireless is a systematic engineering field and relatively complex. The smart factory is a standard application of IIoT that makes applicable routing protocols need to experience complicated scenarios [9]. Particularly, when wired and wireless connections are simultaneously applied and a massive number of mobile and fixed nodes exist, large industrial data often need to be transmitted via an intermediate nodes for multihop, and all hops result in unavoidable delays [10].

The main objective of this study is to develop a trust-aware multiobjective metaheuristic optimization-based secure clustering with route planning (TAMOMO-SCRP) technique for cluster-based IIoT environment. The presented TAMOMO-SCRP technique mainly focuses on the design of bald eagle search (BES) algorithm for clustering and routing processes. The proposed TAMOMO-SCRP model designs an objective function for clustering process involving four parameters such as trust level (TL), communication cost (CC), residual energy (RE), and node degree (ND). Moreover, the route selection process is based on the fitness function with two variables, namely, queue length and link quality. For providing better outcomes of the TAMOMO-SCRP model, a wide range of experiments were performed.

This paper presents a trust-aware multiobjective metaheuristic optimization-based secure clustering with route planning (TAMOMO-SCRP) technique for cluster-based IIoT environment. The remainder of the paper is organized as follows: Section 2 goes through similar efforts that use preexisting models. Section 3 describes the overall process and design of the proposed TAMOMO-SCRP model. Section 4 inspects the performance validation of the TAMOMO-SCRP model under distinct aspects. Finally, Section 5 concludes the key results of the proposed research.

II. RELATED WORKS

In [11], a three-level infrastructure of software defined network (SDN) or Network function visualization (NFV) was executed for all domains dependent upon that it is flexibly controlled and programs the basic forwarding device under this domain with the aim of computing an optimum routing policy. Conversely, the blockchain was implemented amongst distinct SDN controllers for creating trust and untamperable environments. Afterward, during this infrastructure, a secure routing process was presented as well for preventing the attack on the fundamentals of node identity authentication and node behavior authentication. In [12], a lightweight method was presented to an individual's node from IIoT which is not maintaining security. The LightTrust employs a centralized trust agent for generating and accomplishing trust certificates which permit nodes for communicating for a particular time with no execution trust computation. The trust agent has also maintained a trusted database for storing the present trust degree of the aggregation/propagation resolves.

Mehbodniya et al. [13] examined a Multilayer energy-aware Routing protocol (RPL) cluster for IoT to decrease network data traffic but improve the lifespan of networks. It can be divided as to 3 stages, all containing the formation of network ring, intra-ring division, and intercluster routing. Primarily, the virtual ring was generated from the network. Secondarily, all rings create a similar cluster and select the Cluster Head (CH) node. Eventually, it can be responsible for the performance and maintenance of Distance oriented directed acyclic graph (DODAG). Liu et al. [8] presented an efficient technique named Trust and Energy-aware based Holistic optimizing Algorithm for Spatial window query (TEHAS) that enhances the efficacy of query processing, decreases the energy utilization, and avoids the loss of important data. Besides the theoretical analysis, the experimental outcomes represent that the technique is carried out superior to one of the present techniques considering efficacy, communication security, and energy utilization. Pokhrel et al. [14]

established an AI based CRP structure to incorporate a small periphery of a set-shaped region to ameliorate such energy holes. The presented structure is not only energy-optimized along with perform as a robust method with large communication and informed data gathered.

Zhang et al. [15] presented a sealed first-price auction game model dependent upon a typical normal distribution, for ensuring that the auction node is attaining a superior return. According to an analysis of factor-affected reliable data broadcast from a large-scale IIoT method, a data forwarding auction game model was introduced. Eventually, for addressing this problem of selfish nodes, a dynamic revenue control process was presented for promoting co-operation amongst nodes. In [16], a new routing process dependent upon probability computation and segment routing was presented for solving the mobility and scalability problems in IIoT routing. Although, probability computation addresses the unbalanced load state affected by mobility by forwarding packets for distinct routings with particular probability. Conversely, segment routing allows the scalability and flexibility of packet forwarding, and it is also utilized for bypassing the overloaded link, so for achieving load balance.

Al-Zubaidie et al. [17] created a framework called Reliable and Efficient Integrity Scheme for Data Collection in HWSN (REISCH). Healthcare wireless sensor network (HWSN) provides a high throughput and optimized results for an integration of data. The benefits of this framework are high security and better results for data integration and access. K. Lakshmanna et al. [18] implements the Routing Scheme for IoT-Assisted with the help of optimized algorithm. The advantages of this work is to provide the better accuracy. The disadvantage of this work need to increase the quality of service parameters.

III. PROPOSED MODEL

In this study, a new TAMOMO-SCRP model has been developed for accomplishing energy efficiency and security in the IIoT environment. The proposed model follows the design of a newly developed metaheuristic algorithm called BES algorithm to select CHs and routes to destination. The proposed BES algorithm has concentrated on two processes, namely, clustering and routing. Fig. 1 showcases the block diagram of TAMOMO-SCRP technique.

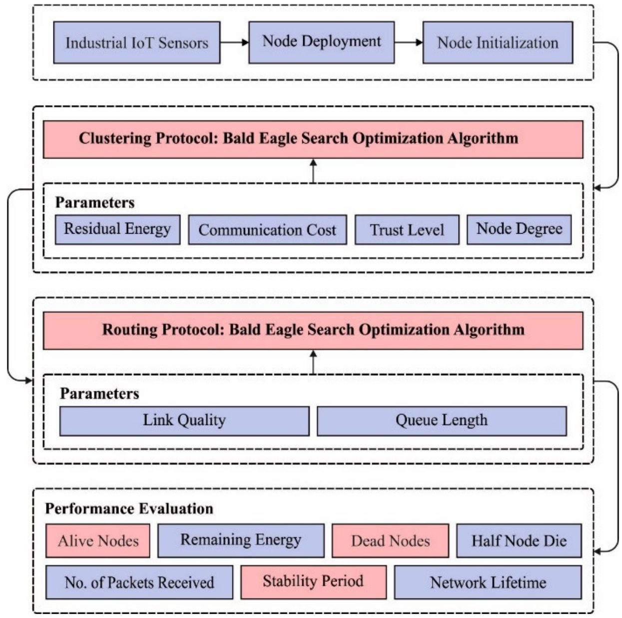

FIGURE 1. Block diagram of TAMOMO-SCRP technique.

A. DESIGN OF BES ALGORITHM

Bald eagles are occasional predators and are at the top of the food chain due to their size. They have the capacity to spot fish at long distances since finding fish from water is quite complex. Once it started to seek food on a water spot, this eagle set off in a certain direction and choose a specific region to start the search. Consequently, finding the searching space can be accomplished by tracking other birds and self-searching with the fish concentration (alive or dead) [19]. The presented method mimics the behavior of bald eagles at the time of hunting to validate the consequence of the hunting steps. This process was separated as to 3 parts, such as searching space, selective searching in the swooping, and selective searching space.

1) SELECTION STAGE

In this phase, bald, eagles find and choose the optimal region (interms of the amount of food) within the selected searching space. The mathematical expression can be given in the following (1).

$$P_{i,new} = P_{best} + \alpha * \left(P_{mean} - P_j\right) * r, \tag{1}$$

whereas α denotes the position change control variable that takes a value among 1.5 and 2 and r denotes an arbitrary value which takes a value within [0,1]; $P_{i,new}$ and P_i are upgraded and older location, correspondingly, at time i. Here, the bald eagles choose a region according to the data presented in the prior step. The eagles arbitrarily choose another searching region which differs from the preceding searching region, however, it is situated nearby. P_{best} represent the searching region viz. presently chosen by the bald eagles according to the optimal location recognized in the preceding search. The eagles arbitrarily search each point nearby the formerly selected searching space. In the meantime, P_{mean} designates that this eagle has utilized each data from the preceding point.

2) SEARCH STAGE

In this phase, bald eagles search for prey in the selected searching space and move in various directions in a spiral space to quicken the search. The optimal location for the swoop is arithmetically formulated in (2)

$$P_{i,new} = P_i + y\,(i) * (P_i - P_{i+1}) + x\,(i) * (P_i - P_{mean}) \tag{2}$$

where $x\,(i)$ is defined in (3)

$$x\,(i) = \frac{xr\,(i)}{\max\,(|xr|)}, \tag{3}$$

where $y\,(i)$ is defined in (4)

$$y\,(i) = \frac{yr\,(i)}{\max\,(|yr|)}, \tag{4}$$

where $xr\,(i)$ is defined in (5)

$$xr\,(i) = r\,(i) * \sin\,(\theta\,(i))\,, \tag{5}$$

where $yr\,(i)$ is defined in (6)

$$yr\,(i) = r\,(i) * \cos\,(\theta\,(i)), \tag{6}$$

Here $\theta\,(i)$ represents in (7)

Here $r\,(i)$ represents in (8)

$$\theta\,(i) = a * \pi * rand, \tag{7}$$

$$r\,(i) = \theta\,(i) + R * rand, \tag{8}$$

whereas a represents a variable that takes values within [5], [10] to define the corner point search from the central point and R take values within 0.5 and 2 to define the amount of searching cycles.

This approach employs the polar graph property to arithmetically denote this movement. Moreover, this property enables the BES approach for discovering novel space and increases the divergence by multiplying the variance among the present and following points with the polar point from the y-axis and addition the variance among the present point and the center point with the polar point from the x-axis. Then, utilize the average solution from the searching point since each searching point moves to the center point. Each point on the polar plot takes a value within $[-1, 1]$.

3) SWOOPING STAGE

In this phase, the bald eagle swings from the optimal location in the searching space to the targeted prey. Each point moves to the optimal point. The mathematical expression is given below (9)

$$P_{i,new} = rand * P_{best} + x1(i) * (P_j - c1 * P_{mean}) + y1(i) * (P_j - c2 * P_{best}) \tag{9}$$

where $x1\,(i)$ is defined in (10)

$$x1\,(i) = \frac{xr\,(i)}{\max\,(|xr|)}, \tag{10}$$

where $y1\,(i)$ is defined (11)

$$y1(i) = \frac{yr(i)}{\max(|yr|)}, \tag{11}$$

where $xr\,(i)$ is defined (12)

$$xr(i) = r(i) * sinh(\theta(i)) \tag{12}$$

where $yr\,(i)$ is defined (13)

$$yr(i) = r(i) * \cosh(\theta(i)) \tag{13}$$

Here $\theta(i)$ is represents in (14)

$$\theta(i) = a * \pi * rand \tag{14}$$

Here $r(i)$ is represents in (15)

$$r(i) = \theta(i) \tag{15}$$

In which $c1, c2 \in [1, 2]$.

B. DESIGN OF CLUSTERING TECHNIQUE

To create clusters, the TAMOMO-SCRP model established an objective function using four parameters, including TL, CC, RE, and ND. [20], [21]. The presented TAMOMO-SCRP model selects the secured optimum CH in the cluster to attain the secured data broadcast on the network [22], [23]. The aim is for choosing one of the optimum numbers of nodes like CHs. The objective is to complete a suitable fitness by formulating the TL, CC, RE, and ND. The parameters utilized in the clustering optimization are as follows:

The trust level is demonstrated by (16),

$$\mathrm{N}_{\mathrm{trust}} = r\,(N_i) \tag{16}$$

whereas $r(N)$ signifies the trust factor of nodes.

A primary objective is signified in (17).

$$Minimize\, f_1 = \frac{1}{N_T}\sum_{i=1}^{N} \mathrm{N}_{\mathrm{trust}}(N_j) \tag{17}$$

The cost important to transmit to the neighboring node is explained in (18).

$$C_{com} = \frac{d_{avg}^2}{d_0^2} \tag{18}$$

In which d_{avg}^2 has specified as distance amongst the neighbors and nodes; the node radius was determined as d_0^2.

The secondary objective has been defined in (19)

$$Minimize\, f_2 = \frac{1}{N_T}\sum_{i=1}^{N} \mathrm{N}_{prox}(N_i) \tag{19}$$

whereas N implies the count of nodes.

Residual Energy: The tertiary objective of RE is f_3 that is decreased and demonstrated in (20).

$$Minimize\, f_3 = \sum_{i=1}^{m} \frac{1}{E_{CHi}} \tag{20}$$

The ND is determined as the number of non-CH participants which goes to a specific mobile node. When the CH previously had decreased participants, it can endure for wide period, because of a preference for the minimal degree of nodes. Therefore, the last objective is f_3 that is reduced in (21).

$$Minimize\, f_4 = \sum_{i=1}^{m} I_i \tag{21}$$

The aforementioned objective is converting the multi-objective function to a single objective. Therefore, the normalized procedure $(F(x))$ was executed for all the objectives $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ in (22).

$$F\,(x) = \frac{f_i - f_{\min}}{f_{\max} - f_{\min}} \tag{22}$$

whereas the function value is represented as f_i, and $f_{\min}$ and $f_{\max}$ are stated as the minimal and maximal fitness values (FV) in (23).

$$Minimum\ fitness = \alpha_1 f_1 + \alpha_2 f_2 + \alpha_3 f_3 + \alpha_4 f_4 \quad (23)$$

where $\Sigma_{i=1}^{4} \alpha_i = 1$, and $\alpha_i \in (0, 1)$.

C. DESIGN OF ROUTE PLANNING TECHNIQUE

Once the clusters are generated in the IIoT network, the route selection process is based on the fitness function with two variables, namely, queue length and link quality. The parameters utilized by the TAMOMO-SCRP model in the route selection process such as queue length (QL) and link quality (LQ) are given as follows.

QL as demonstrated in (25) has assumed as the initial FV under the routing as it assumes the congestion level of all nodes in IIoT. The QL was utilized for improving the data delivery performance.

$$QL = \frac{RP_k}{Total\ buffer} \quad (24)$$

whereas the received packet at k^{th} node are signified as RP_k.

The LQ was utilized for defining the effective data delivery amongst the nodes k and l dependent upon the count of data packet transmission and retransmission that is written in (26).

$$Link\ quality = \frac{1}{f \times r} \quad (25)$$

In which f and r demonstrate the forwarded and reversed data broadcast amongst the nodes.

Next, every several objective fitness is conflicting with every other, thus it can be changed as to a single-objective FV as represented in (27)

$$Routing\ fitness = \delta_1 \times QL + \delta_2 \times Linkquality + \delta_3 \times CC + \delta_4 \times RE \quad (26)$$

whereas $\delta_1, \delta_2, \delta_3$, and δ_4 implies the weighted parameters that are equivalent to 0.3, 0.25, 0.25, and 0.2 correspondingly; CC and RE signify the communication cost and RE correspondingly.

IV. PERFORMANCE VALIDATION

This section inspects the performance validation of the TAMOMO-SCRP model with recent methods. The results are inspected under distinct rounds of execution.

Table 1 and Fig. 2 investigate the lifetime of the TAMOMO-SCRP model with recent methods, interms of network lifetime (NLT), half network die (HND), and stability period (SP). The experimental results indicated that the TAMOMO-SCRP model has outperformed the other methods with maximum values of NLT, HND, and SP. For instance, with respect to NLT, the TAMOMO-SCRP model has offered a higher NLT of 39451 rounds, whereas the CIRP, MEEC, ZCA, OCHR, and IDHR models have obtained lower NLT of 38147, 35687, 34058, 34001, and 30001 rounds respectively.

TABLE 1. Lifetime analysis of TAMOMO-SCRP model with recent algorithms.

Methods	Network Lifetime (NLT)	Half Network Die (HND)	Stability Period (SP)
TAMOMO-SCRP	39451	25950	8000
CIRP	38147	20000	7970
MEEC	35687	22050	4000
ZCA	34058	22000	4000
OCHR	34001	22000	3200
IDHR	30001	19000	3000

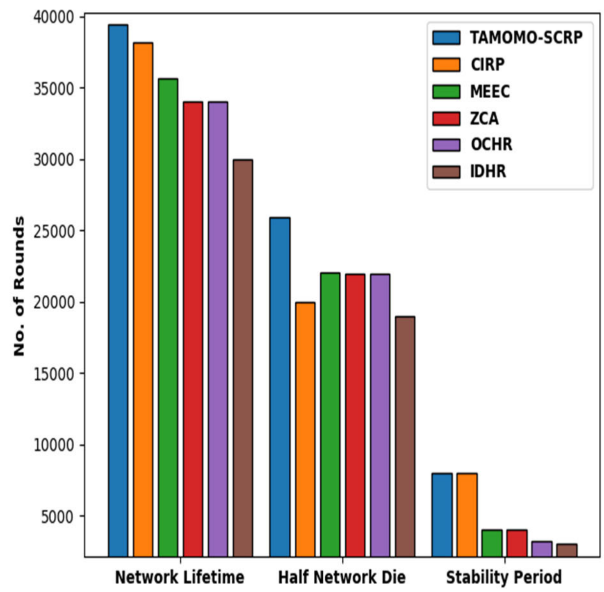

FIGURE 2. Lifetime analysis of TAMOMO-SCRP model.

At the same time, with respect to HND, the TAMOMO-SCRP model has obtainable increased HND of 25950 rounds, whereas the CIRP, MEEC, ZCA, OCHR, and IDHR models have obtained lower HND of 20000, 22050, 22000, 22000, and 19000 rounds correspondingly. In line with, in terms of SP, the TAMOMO-SCRP model has accessible higher SP of 8000 rounds, whereas the CIRP, MEEC, ZCA, OCHR, and IDHR models have gained lesser SP of 7970, 4000, 4000, 3200, and 3000 rounds correspondingly.

A detailed comparative examination of the TAMOMO-SCRP method with the recent approach interms of NALN under distinct rounds is provided in Table 2 and Fig. 3. The results indicate that the TAMOMO-SCRP approach has accomplished higher NALN over the other methods [23], [24], [25]. For instance, with 8000 rounds, the TAMOMO-SCRP model has resulted in an increased NALN of 99, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR models have obtained reduced NALN of 97, 95, 93, 94, and 90 respectively.

TABLE 2. NALN analysis of TAMOMO-SCRP technique with recent algorithms under distinct rounds.

No. of Alive IoT Nodes (NALN)						
No. of Rounds	TAMOMO-SCRP	CIRP	MEEC	ZCA	OHCR	IDHR
0	100	100	100	100	100	100
2000	100	100	100	100	100	100
4000	100	100	99	99	98	98
6000	100	100	98	97	98	95
8000	99	97	95	93	94	90
10000	98	93	93	90	93	87
12000	95	91	92	90	90	86
14000	93	80	88	85	85	80
16000	87	69	82	78	79	73
18000	81	59	71	70	70	60
20000	75	50	63	59	61	40
22000	66	47	53	50	50	31
24000	59	45	43	30	30	12
26000	49	44	29	27	24	8
28000	43	42	26	25	20	5
30000	37	41	25	25	5	1
32000	31	31	14	7	4	0
34000	24	28	11	5	1	0
36000	22	17	8	0	0	0
38000	19	13	5	0	0	0
40000	0	0	0	0	0	0

Simultaneously, with 12000 rounds, the TAMOMO-SCRP method has resulted in a maximal NALN of 95, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR techniques have obtained reduced NALN of 91, 92, 90, 90, and 86 correspondingly. Concurrently, with 20000 rounds, the TAMOMO-SCRP model has resulted in an enhanced NALN of 75, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR systems have obtained reduced NALN of 50, 63, 59, 61, and 40 respectively. At last, with 30000 rounds, the TAMOMO-SCRP algorithm has resulted in a superior NALN of 37, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR systems have obtained lower NALN of 41, 25, 25, 5, and 1 correspondingly.

Table 3 and Fig. 4 portray a comprehensive NDDN examination of the TAMOMO-SCRP model with existing models. The experimental values reported that the TAMOMO-SCRP model has the ability to attain minimal NDDN over the other methods under all rounds. For instance, with 8000 rounds, the TAMOMO-SCRP model offered NDDN of 1, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR models have reached increased NDDN of 3, 5, 7, 6, and 10 respectively. Simultaneously, with 16000 rounds, the TAMOMO-SCRP method obtainable minimum NDDN of 13, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR models have reached increased NDDN of 31, 18, 22, 21, and 27 correspondingly. Concurrently, with 30000 rounds, the TAMOMO-SCRP method offered NDDN of 63, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR approaches have reached higher NDDN of 59, 75, 75, 95, and 99 correspondingly.

A brief comparative examination of the TAMOMO-SCRP algorithm with recent approaches in terms of NRE under distinct rounds is provided in Table 4 and Fig. 5.

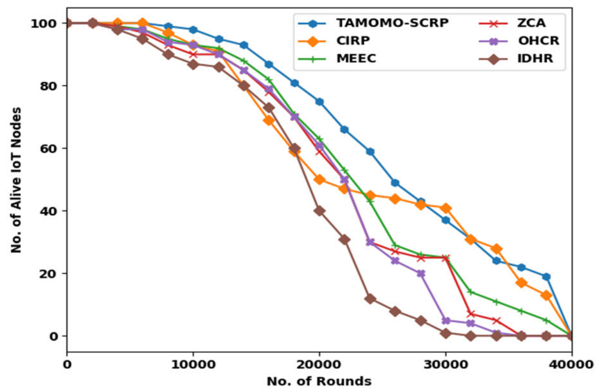

FIGURE 3. NALN analysis of TAMOMO-SCRP technique under distinct rounds.

TABLE 3. NDDN analysis of TAMOMO-SCRP technique with recent algorithms under distinct rounds.

No. of Dead IoT Nodes (NDDN)						
No. of Rounds	TAMOMO-SCRP	CIRP	MEEC	ZCA	OHCR	IDHR
0	0	0	0	0	0	0
2000	0	0	0	0	0	0
4000	0	0	1	1	2	2
6000	0	0	2	3	2	5
8000	1	3	5	7	6	10
10000	2	7	7	10	7	13
12000	5	9	8	10	10	14
14000	7	20	12	15	15	20
16000	13	31	18	22	21	27
18000	19	41	29	30	30	40
20000	25	50	37	41	39	60
22000	34	53	47	50	50	69
24000	41	55	57	70	70	88
26000	51	56	71	73	76	92
28000	57	58	74	75	80	95
30000	63	59	75	75	95	99
32000	69	69	86	93	96	100
34000	76	72	89	95	99	100
36000	78	83	92	100	100	100
38000	81	87	95	100	100	100
40000	84	91	100	100	100	100

The results expose that the TAMOMO-SCRP technique has accomplished higher NRE over the other methods [26], [27]. For instance, with 4000 rounds, the TAMOMO-SCRP technique has resulted in increased NRE of 127J, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR models have obtained reduced NRE of 121J, 115J, 111J, 104J, and 101J

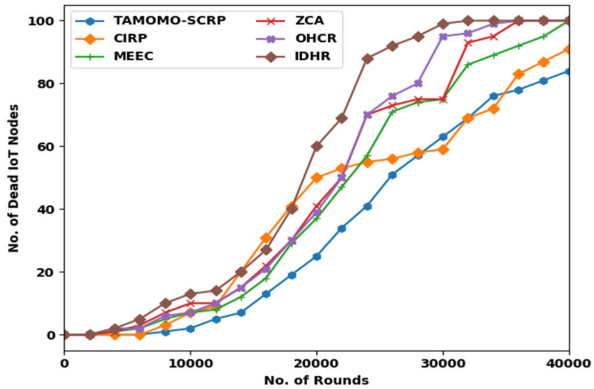

FIGURE 4. NDDN analysis of TAMOMO-SCRP technique under distinct rounds.

TABLE 4. NRE analysis of TAMOMO-SCRP technique with recent algorithms under distinct rounds.

Network Remaining Energy(NRE) in Joule						
No. of Rounds	TAMOMO-SCRP	CIRP	MEEC	ZCA	OHCR	IDHR
0	140	140	140	140	140	140
4000	127	121	115	111	104	101
8000	113	107	101	92	78	72
12000	99	91	84	72	54	44
16000	87	80	71	58	41	26
20000	75	68	58	35	25	15
24000	56	42	33	19	6	2
28000	41	27	16	6	0	0
32000	30	18	9	2	0	0
36000	18	11	5	0	0	0
40000	15	6	1	0	0	0

respectively. Likewise, with 12000 rounds, the TAMOMO-SCRP approach has resulted in increased NRE of 99J, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR models have obtained reduced NRE of 91J, 84J, 72J, 54J, and 44J respectively. Moreover, with 28000 rounds, the TAMOMO-SCRP model has resulted in increased NRE of 41J, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR algorithms have obtained reduced NRE of 27J, 16J, 6J, 0J, and 0J correspondingly. Finally, with 32000 rounds, the TAMOMO-SCRP approach has resulted in increased NRE of 30J, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR methodologies have obtained reduced NRE of 18J, 9J, 2J, 0J, and 0J corresponding.

Table 5 and Fig. 6 demonstrate a comprehensive NPSBS examination of the TAMOMO-SCRP system with existing models. The experimental values demonstrated that the

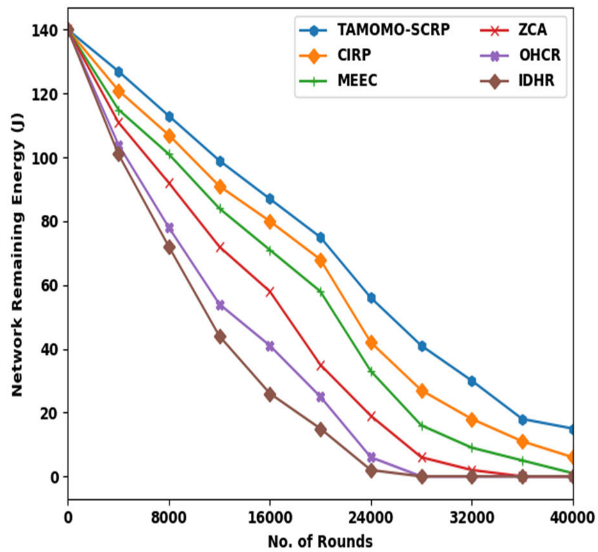

FIGURE 5. NRE analysis of TAMOMO-SCRP technique under distinct rounds.

TABLE 5. NPSBS analysis of TAMOMO-SCRP technique with recent algorithms under distinct rounds.

No. of Packets Sent to Base Station (NPSBS)						
No. of Rounds	TAMOMO-SCRP	CIRP	MEEC	ZCA	OHCR	IDHR
0	0	0	0	0	0	0
4000	16604	19874	6558	8193	14034	4689
8000	31322	28985	12866	10763	25481	7025
12000	44171	39498	24547	18940	36461	7025
16000	54917	49544	35293	29219	43937	7259
20000	63795	58422	43704	39966	54684	6791
24000	71738	68935	53749	48142	64029	6261
28000	78747	79447	64262	50946	73841	5874
32000	86222	82485	70103	45175	78513	0
36000	86690	82952	65001	0	0	0
40000	0	0	0	0	0	0

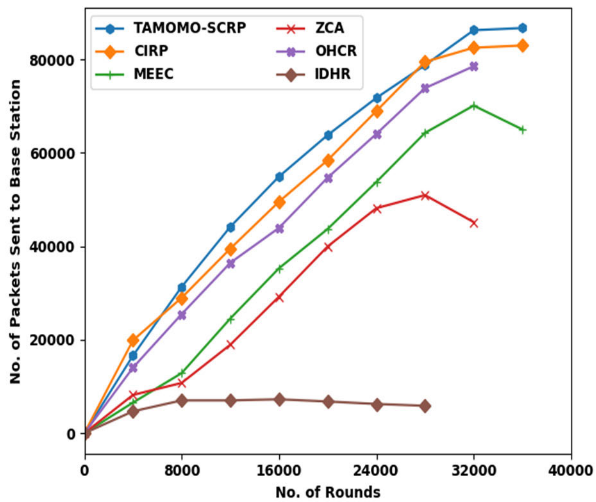

FIGURE 6. NPSBS analysis of TAMOMO-SCRP technique under distinct rounds.

TAMOMO-SCRP methodology has the ability to attain lower NPSBS over the other methods under all rounds.

For sample with 8000 rounds, the TAMOMO-SCRP model offered NPSBS of 31322, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR models have reached enhanced NPSBS of 28985, 12866, 10763, 25481, and 7025 respectively. Concurrently, with 16000 rounds, the TAMOMO-SCRP approach offered NPSBS of 54917, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR techniques have attained improved NPSBS of 49544, 35293, 29219, 43937, and 7259 correspondingly. Concurrently, on 28000 rounds, the TAMOMO-SCRP approach offered NPSBS of 78747, whereas the CIRP, MEEC, ZCA, OHCR, and IDHR models have reached increased NPSBS of 79447, 64262, 50946, 73841, and 5874 correspondingly.

After observing the aforementioned results and discussion, it could be confirmed that the TAMOMO-SCRP model has shown promising performance over the other methods in accomplishing energy efficacy and security in the IIoT environment.

V. CONCLUSION

In this study, a new TAMOMO-SCRP model was developed to accomplish energy efficiency and security in the IIoT environment. The proposed BES algorithm has concentrated on two processes, namely, clustering and routing. At the clustering stage, the TAMOMO-SCRP model has designed an objective function involving four parameters such as TL, CC, RE, and ND. Secondly, the route selection process is based on the fitness function with two variables, namely, queue length and link quality. For ensuring better outcomes of the TAMOMO-SCRP approach, a wide range of experiments were performed. The obtained outcomes ensured the better performance of the TAMOMO-SCRP technique against the other recent approaches. The TAMOMO-SCRP model has designed an objective function involving four parameters such as TL, CC, RE, and ND to construct clusters. If add more parameters in the proposed work to increase the performance. The limitations of the paper is route selection process depends on queue length and link quality parameters.. In future works, data encryption and blockchain technology will be used to further enhance the security level in the IIoT environment.

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