

Research Article

Analysis of Smart Grid Using Multimedia Sensor Networks with Effective Resource Allocation

Yuvaraja Teekaraman ¹, **Irina Kirpichnikova**,¹ **Hariprasath Manoharan** ²,
Ramya Kuppusamy,³ and **Arun Radhakrishnan** ⁴

¹Faculty of Energy and Power Engineering, South Ural State University, Chelyabinsk 454 080, Russia

²Department of Electronics and Communication Engineering, Panimalar Institute of Technology, Chennai 600 123, India

³Department of Electrical and Electronics Engineering, Sri Sairam College of Engineering, Bangalore 562 106, India

⁴Faculty of Electrical & Computer Engineering, Jimma Institute of Technology, Jimma University, Jimma, Ethiopia

Correspondence should be addressed to Yuvaraja Teekaraman; teekaramani@susu.ru and Arun Radhakrishnan; arun.radhakrishnan@ju.edu.et

Received 11 February 2022; Revised 2 March 2022; Accepted 31 March 2022; Published 18 May 2022

Academic Editor: Saeid Jafarzadeh Ghouschi

Copyright © 2022 Yuvaraja Teekaraman et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In recent days, for smart grid network updates, video sensors are used where each node needs to be compressed before transmission. This is very much useful for developing countries as in future the smart grid communication process will play a major role in entire society. Therefore, in this article, minimization of power, energy consumption, and delay for wireless video sensor networks have been computed by providing better quality of service at a similar period. Also, the problem of optimizing transmission and delivery rate has been studied. For solving the aforementioned problems, the intuitive migrant algorithm has been implemented for providing better energy consumption. Additionally, modified larvae optimization tool has been integrated for providing better convergence rate, where all the nodes will be compressed at a better rate with necessary quality of service. The simulation results show that by applying algorithms in two folds, and each video sensor node is compressed by satisfying necessary constraints with fast convergence rate.

1. Introduction

It is well known that there are a lot of interconnecting devices that have been integrated with personal computers through Internet with secured connection. However, it is not possible to say that these connections will be secured all time because the competency of various objects is surrounding each individual. Therefore, wireless sensor networks (WSN) can be used for both detection and data communication in wireless medium. The WSN in this medium can be regarded as smart object due to its nature, and it can be used by a lot of people all over the world in an apparent way [1]. A lot of emerging technologies have been established following the perception indicated in [1], and they are denoted as Internet of Things (IoT) [2]. Recently, with advancements in image sensors, it is highly possible to create images, where the resolution of

image will be higher with less cost. In line with the above concern, it is much possible on creating smart objects for capturing image and video with high-quality pixels [3].

Correspondingly, multimedia content is becoming more popular on Internet, and therefore, it is vital that difficulties on wireless video sensor networks (WVSN) have to be solved by utilizing the energy effectively with common supply. Likewise, the interest on various green energies that transforms the output to expand wireless networks has been emerging with long-term sustainability. This curiosity has made several researchers [4–7] to exploit the green energy by providing sufficient sustainability on entire network. Further, it is discussed [8] that for designing effective WSN to transform energy, resource allocation plays an important role. Correspondingly, WSN supports a wide range of applications by providing diverse quality of service as per

requirements, and it is not possible that each user can access it directly through air transmission [9].

For establishing commercial WSN, each user laptop needs to be connected with hotspot for providing services at different levels by using a particular network with good quality of service such as availability of service, improved bandwidth, and reduction in data loss [10]. Generally, the performance of every network will be measured in terms of bandwidth and latency. For measuring the aforementioned metrics, data bits will be transmitted in a particular time, where each user can predict delivery of data from their end. Identically, an algorithm that is used for allocating the channel defines interference range with corresponding node number for minimizing intrusions [11, 12]. The correlation considering interference using improved game-based channel allocation algorithm has been propounded [13] by placing the target node more closely to interference source.

However, the disadvantage in this model [13] is that it does not follow any actual rule for minimizing interference. Additionally, the same model has been used with Nash equilibrium with a physical model and also considering breadth first channel search algorithm [14, 15]. Both models in [14, 15] form a loss function by providing linkage for achieving maximum throughput. In correlation with the models in [14, 15], a channel allocation strategy for instantaneous data flow in entire network has been proposed [16–18]. Similarly, a wireless channel network for accepting other nodes by utilizing energy efficiently using multiple channels has been established with necessities in negotiating high synchronization time with huge overhead cost [19].

The problem on resource allocation has been handled by providing feedback in OFDM-based mesh networks [20], where designing quantization codebook with equal probability distribution, amount of power distributed, etc. will be considered as parameters for allocating subcarriers by utilizing Lagrange multipliers with restrictions on feedback. Conversely, for supporting traffic in different modules (flexible and inflexible modes), an algorithm on resource allocation is deliberated [21] by providing calculations on first-order Lagrangian techniques in addition to utilities for nonconvex problems, which is finally converted to convex one. This type [21] of problem can be solved using decomposition method by applying it in two folds. At the final stage, integration of the projected resource allocation framework has been accomplished adaptively for both modes. However, the difficulty [21] is that the method does not provide any global solution under different networking conditions.

As an alternative of [21], a bio-inspired method using multihop desynchronization algorithm with time division multiple access has been projected [22], which is entirely based on resource allocation in distributed networks. This type of algorithm is able to calculate data transmission rate that attempts to act as reference source for allocating resources in addition to collision detection. By implementing [22], the problem on hidden nodes in multihop networks is resolved effectively by sharing resources with nodes that are located adjacently. Identical to [21, 22], for providing good performance, a resource-aware task scheduling method is implemented [23] for exploiting weight exponentially with

exploitation to track all relevant applications on WSNs. The algorithm integrated in [23] will also track the quality and consumption of energy by using some learning techniques.

Comparatively, the resources have been allocated based on priority for sharing primary resources [24] between multiple networks in wireless medium. Also, the algorithm that has been integrated is premeditated by arranging the mechanisms that adhere to IEEE 802.15.6 standards. By doing this, the entire traffic will be under control with specified parameters. Thus, the transfer rate on each network will be derived based on priority. Furthermore, for monitoring multiple stages in production lines, industrial WSNs are used [25] with cascaded topology by considering necessary characteristics and prerequisites. In this kind of process, minimizing the resource allocation problem has been studied by formulating proper channel allocation problem within each field network.

For proving better quality on robotic images, the author in [26] has applied a sonographic system for ultrasound scan. The primary thought in this type of implementation [26] is that there is no need for any physicians to go for onsite monitoring. Moreover, for accessing and compressing the quality of medical images, a new technique for storing the required information has been anticipated [27–29]. Incorporating the sensor nodes by optimizing the lifetime of ad-hoc networks with energy efficient topology has been discussed [30]. Using the same method [30], effective resources have been allocated to multimedia sensor networks for increasing the throughput with maximized energy [31, 32]. In addition, multipath routing protocols for supporting multimedia data for improving quality of service have been deliberated [33]. Recently, analysis has been carried out in operating characteristics of receiver for designing required prototype, and this type can be extensively used for assessing the performance with adequate support on providing conditions in diagnosis. Ultimately, for significant dynamic range metrics has been assessed in perceptual quality by compressing intensity with individual counting for proportions that are paired. In current generation, a new cognitive model has been designed as an alternative of sensor networks as handheld remote operations can be assured [34]. In the abovementioned model, a Zigbee technology is integrated with high control mechanisms using distinct algorithms where high quality of service is attained. However, the use of cognitive networks in smart grid environment is highly cost effective, and several constraints have to be measured before infrastructure installation process. Therefore, as an alternate to cognitive models, the researchers [35] have suggested introduction of 5G networks as high operation of network speed with edge computing technologies are enabled. By enabling high-speed infrastructure security of smart grid is also transformed as high-end technologies.

1.1. Research Gap and Motivation. Even though high effective measures and resources are allocated for converting the grid to be smart, only few researchers have addressed the problem in a precise way [1–33]. In recent networking structure [34, 35], research gap on smart grid networks with

high cost of installation is observed, and in other developed models, a crucial task on minimization of power with better quality of service with constraints such as distortion and transmission delivery rates has not been solved in an accurate manner. However, all the procedures enumerated [1–33] grieves from any one drawback. Therefore, the entire system thus needs an effective methodology for assimilating the channel model thus satisfying the consistency desires. Therefore, to decipher many challenging errands, the gap has been solved using the integrated system model with IMO algorithm.

As an outcome of providing effectual and high-quality videos by observing the entire network performance, an IMO algorithm that improves the consumption of power through clustering technique has been projected. In the proposed model, a unified assessment will be performed by integrating the algorithms in twofolds for the purpose of increasing power consumption in entire network. Subsequently, the MLO technique has been smeared to compute for fast convergence with less number of parameters.

1.2. Objectives. To the best of author's knowledge, there has been no prior exertion on adjoining the manifold objectives such as minimization of (i) power, (ii) energy consumption of nodes, and (iii) delay and maximization of throughput. Therefore, the prime objective of the proposed exertion is to select best nodes thus satisfying the above-mentioned objectives by integrating the algorithms in twofolds and then applying MLO tool for virtuous decision-making (check for better convergence). In addition, the projected model prominently expands the performance of video in a less computational time even for large networks.

2. Problem Formulation

The proposed method focuses on minimization on consumption of power for video sensors by optimizing both transmitted and encoded power at each node. The channel model with probability outage [3] for such networks can be given from:

$$\text{Power}_{n,m}^{\text{outage}} = 1 - e^{(-\delta G_0 w_{nm}/T_n^k)}, \quad (1)$$

where $\text{Power}_{n,m}^{\text{outage}}$ represents the probability of outage transmitted from node n to m , δ indicates the signal-to-noise ratio threshold and it is defined according to application of sensors G_0 designates Gaussian variation in noise, w_{nm} signifies the distance between the nodes n and m , and T_n^k shows the power transmitted from node n .

For characterizing both success and failure on reception of messages, the outages should be lesser than certain threshold values. For each video node, the messages will be delivered at a rate P_n^e/L_t , which is given in seconds. For video sensors, the distortion will be taken into account with two components (source and channel) where the process will consist of compression and encoding. Thus, distortion of video sensors [2] can be computed from:

$$\text{Distortion}_n^p = \alpha^2 e^{(-\eta P_n^e \text{Power}_{n,m}^{2/3})}, \quad (2)$$

where η represents the efficiency of encoding process and α^2 signifies average variance on input side.

2.1. Minimization of Power. Another important element that should be resolved for video sensors is the problem of channel distortion where in this case the video frames will be transmitted in a parallel way that causes several errors, while transmission of signals and this type of distortion depend on packet loss rate. In the projected model, first, the information will be passed to sink node. This is done for two path networks in order to make the loss rate almost equal to corresponding outage probabilities. Thus, for i th node, the channel distortion [3] will be calculated from:

$$\text{Channel Distortion}_i = \mu_i \alpha_i \frac{\sigma_i}{1 - \sigma_i}, \quad (3)$$

where μ_i represents the corresponding model parameter that entirely depends on encoding parameters and α_i is the average time difference between two frames.

(3) can be modified for calculating entire video distortion as follows:

$$TD_i = \mu_i \alpha_i \left(e^{\varphi d_o} \left(\frac{D_i^{\varphi}}{P_i} \right) - 1 \right). \quad (4)$$

Here, the total distortion represents the sum of distortion caused by both channel and source [12]. Thus,

$$TD_i = \text{Distortion}_i^{\text{source}} + \text{Distortion}_i^{\text{channel}}. \quad (5)$$

The primary objective on minimizing the total power that is consumed by each node can be calculated by optimizing the transmitted and encoded power in addition to source rate at each node. Also, high quality of video can only be achieved if the power consumption is increased at all corresponding nodes, which is not discussed and calculated in [34]. The objective of power minimization is given in:

$$\min p_{i,j} = \left(\sum_{i=1}^N P_i^{\text{source}} + P_i^{\text{channel}} \right) + \sum_{j=1}^N P_j^{\text{channel}}. \quad (6)$$

In case if node priority is considered, then the nodes will be ranked based on weighted sum as given in Equation (6) and is subject to the following constraints.

2.1.1. Total Distortion. For minimizing the power that is consumed by each node, the distortion at transmitter, channel, and receiver end should always be low. In the proposed method, the threshold distortion value for real set of data will be given as input, and if any deviation (error) occurs, then there is a need to increase the power of sensor nodes. (7) indicates that the total distortion must be always less than or equal to threshold distortion [3].

$$\text{Distortion}_i^{\text{source}} + \text{Distortion}_i^{\text{channel}} \leq \text{Distortion}_i^f, \quad (7)$$

where distortion_i^f represents the threshold at i th node.

2.1.2. Transmission Rate

$$TR_i^{\text{source}} \leq z_i TR_i^{\text{max}}, \quad (8)$$

where TR^{max} represents the maximum transmission rate and (8) indicates that the source transmission rate should be less than or equal to maximum transmission rate.

2.1.3. Constraint Based on Sensor Node. (9) specifies that for each sensor node set of constraints will be implemented. The sensor node set is indicated by Z_{i_s} and it should not be greater than 1. If any interference occurs in sensor nodes, then that node will not be allowed for transmitting the information in same channel.

$$\sum_{i=1}^N Z_i \leq 1, \quad (9)$$

where Z_i represents the set of nodes and the nodes that are interfering cannot be transmitted in same channel.

2.1.4. Decision Variables. In the proposed method, the decision variables are used for defining the major objective, which is called power factor of sensors. In decision variables, maximum power will be predefined as input and it should not go beyond specified threshold value. It can be seen from (10) that the power transmitted at source and channel should not go beyond least value (zero).

$$P_i^{\text{source}}, P_i^{\text{channel}}, P_j^{\text{channel}}, TR_i \geq 0. \quad (10)$$

2.2. Quality of Service

2.2.1. Delivery Rate. Combinations of both variable and invariable traffic will be generated while transmission and compression of video where the sensor inclines to behave badly if it is heterogeneous in nature. Due to this, the data rate will be affected that does not make the constraints (equations (8)–(10)) satisfied. In case of variable traffic of the data rate is lesser than the required rate, then all invariable traffic will reach zero, and this will not satisfy the constraint as given in (10). Therefore, the quality of service is an important factor while testing the efficiency of multiple services.

$$DQ_i([p_i^t - P_i^t, p_i^t]) = \frac{RA_i([p_i^t - P_i^t, p_i^t])}{RV_i([p_i^t - P_i^t, p_i^t])}, \quad (11)$$

where DQ_i represents the delivery rate during certain time period, RA_i indicates the packets that is sent to node, and RV_i designates the number of valid packets.

2.2.2. Energy. There are lots of probabilities of producing error while compressing the video using required sensors. In such cases, the energy should be as high as possible; therefore, the efficiency of entire network can be automatically improved and is given in (12). In the proposed method, if video has been compressed at transmitter end,

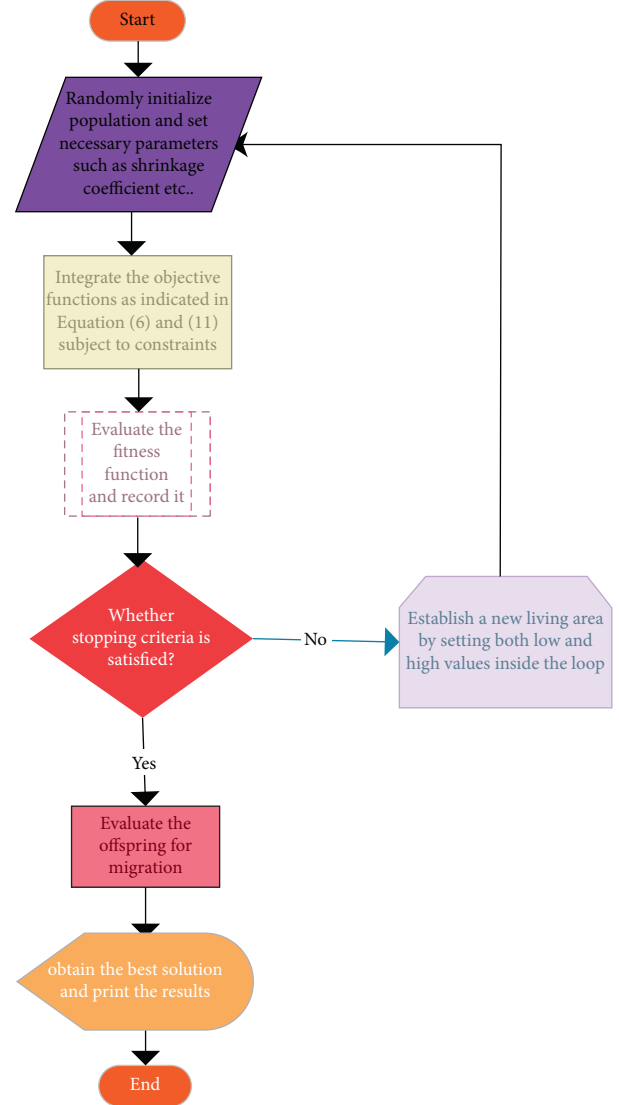


FIGURE 1: Implementation of IMA for smart surveillance.

then energy transmitted through channel should always be higher. If the node energy is higher, the quality of service at the receiver end will be much higher. Therefore, for this process, energy will be sensed, and it will be informed at the transmitter where the sensed energy at the transmitter will be sent to the receiver as shown in:

$$\text{Total Energy}_i = \begin{cases} \text{Energy}_{\text{sense}} + \text{Energy}_{\text{transmitted}} & \text{if energy is sensed from node } i, \\ \text{Energy}_{\text{transmitted}} + \text{Energy}_{\text{received}} & \text{if } z \in Z_i, \\ 0, & \text{Otherwise.} \end{cases} \quad (12)$$

3. Optimization Algorithms

The foremost advantage of the proposed model is that it minimizes the power by maintaining good quality of service that is not focused on existing literature. Therefore, for

analyzing the performance of projected model, the algorithms are integrated in two folds. In first phase, an intuitive migrant algorithm (IMA) is applied for improving consumption of energy through clustering techniques. In second stage, modified larvae optimization (MLO) algorithm is integrated for allocating resources to multiple users [36].

3.1. IMA for Smart Surveillance. IMA is one of the famous algorithms that is considered for optimization problems. This type of nature-inspired algorithm will search for optimum solutions within less computational time. Here, the main role of IMA is that during migration it should mimic the behavior of animals for searching best food and shelter. In general, there are two important steps in IMA, and they are as follows:

- (i) Migration by replacing the existing location with newer ones
- (ii) Updating the population

In step 1, if the animal changes from one position to other, then it must obey three rules they are (i) collision prevention, (ii) moving in same direction, and (iii) endure closer. During migration, there is a chance of adding new animals if existing ones gets unrestrained. Finally, if the topology is created, then a random neighbor will be selected and each individual position will be updated by following equation (13), and the implementation flow chart is shown in Figure 1.

$$NP(i+1) = NP(i) + \eta(CP_i^{\text{neighbourhood}} - CP_i), \quad (13)$$

where $NP(i+1)$ and $NP(i)$ represents old and new positions of i th individual and CP_i indicates the current position of i th individual.

As shown in Figure 1, the process of relocation and population updating is necessary for finding an optimal solution. After integrating the objective functions, each individual with best fitness value is established and then they are migrated from one location to other. At the first stage, if there are i number of animals that are doing their random process, then the best position is calculated. However, as the process continues, the amount of work that the animals are doing gradually reduces; therefore, the animals should be migrated to other areas, which are having high amount of natural components. The global optimal solution thus obtained nearby is always treated as best solution (current solution). After executing each iteration, the area will be reduced further and as a result acceleration process will be started for determining convergence and to test precise nature of the algorithm. The boundary values can be calculated using:

$$\begin{aligned} \text{low}_i &= CS_{\text{best}} - LAR, \\ \text{up}_i &= CS_{\text{best}} + LAR, \end{aligned} \quad (14)$$

where CS_{best} represents the best current solution and LAR signifies the amount of radius.

Since both upper and lower boundaries are provided ((14)), the intuitive migrant algorithm has the ability to

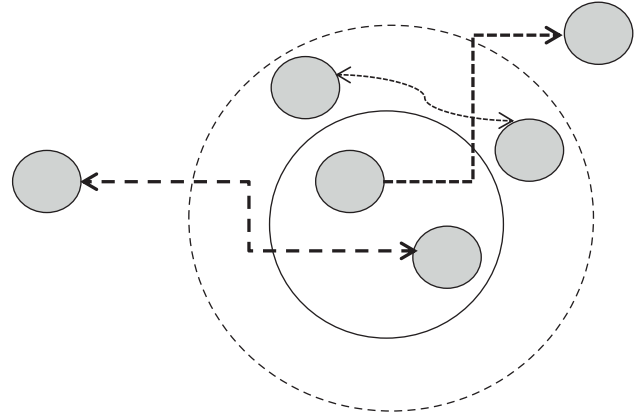


FIGURE 2: Expansion and migration of larvae.

converge earlier. In other algorithms for each sensor nodes, there will be no boundary conditions, and the loop will execute constantly where the convergence time will be much higher. However, due to best fitness value in the search space and boundary conditions of sensor nodes, the algorithm will converge earlier. The best individual in each case is obtained by calculating the fitness function as given in:

$$\text{fitness}_i^{\text{best}} = \sum_{i=1}^N \min \|x_i - d_i\|^2, \quad (15)$$

where d_i represents the distance between two individuals.

3.2. Modified Larvae Optimization. The primary advantage on integrating MLO is that it has only less parameters and it is able to achieve convergence at the earliest. This type of algorithm is mainly observed for all routing, sensor problems, etc. and in line with the above concern the MLO has been integrated as second fold in this article. At the starting stage, each larvae will start exchanging the necessary information by updating its position during each iteration. This is done by sending a short beam to all its neighbors that are positioned within the search space. At the same time, each larvae will start moving from one position to another to choose the best one.

In MLO, each individual attraction is proportional to intensity and also it is inversely proportional to distance between them, which is given in:

$$Z_i^l = (1 - \delta)Z_i(l-1) + \mu J(y_i^l), \quad (16)$$

where y_i represents the position of y th individual separated by a distance l at regular time intervals μ that indicates the corresponding updating coefficient.

Following (16), the position of each individual is updated as

$$Z_{i+1}^l = Z_j^l + r \left(\frac{Z_i - Z_j}{\|Z_i - Z_j\|} \right). \quad (17)$$

If the number of individuals is high, then the local solution will be affected since concentration of each individual

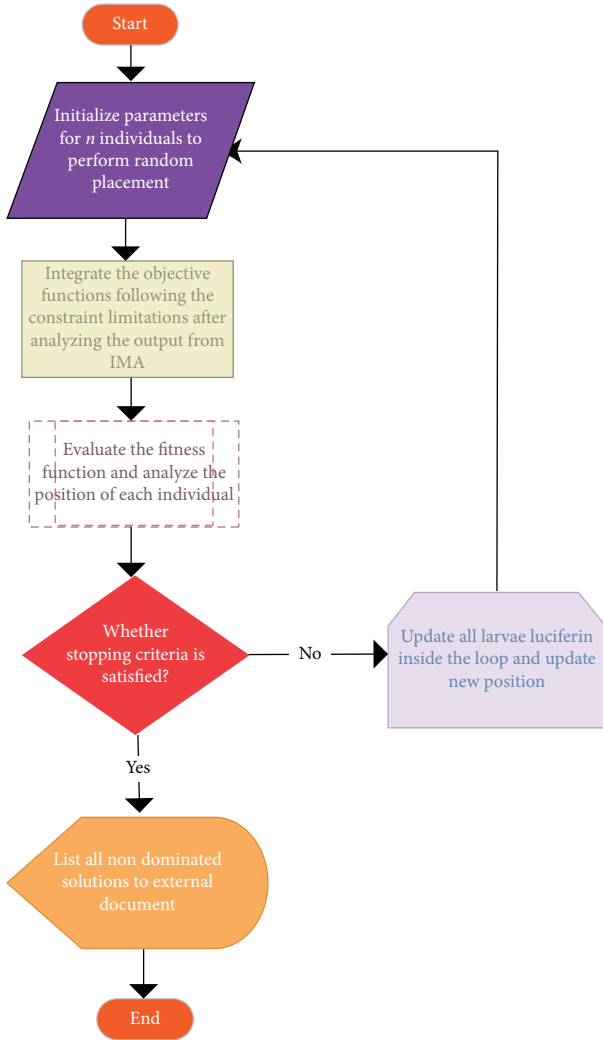


FIGURE 3: Integration of MLO for better convergence.

tends to lower its neighboring radius. So if the density is high, then it directly reflects the radius range that will be reduced at the final stage as shown in Figure 2. Moreover, in MLO, the larvae will be ranked in a particular order for calculating the fitness value as shown in Figure 3, which includes both coding and decoding schemes with varying step values. Both schemes are preferred for reducing the difficulties where the constraints will not be considered at this stage. The reason behind such considerations is to improve the efficiency of the proposed model. At initial stage, both upper and lower bounds are assigned by following the description on finding the first node for calculating the fitness value.

4. Results and Discussion

The outcome of the proposed MLO algorithm is examined using different test conditions. The transmission range of sensor nodes is 100 m and sensing range is 30 m. The initial energy of sensor nodes is 1.4 to 4.9 Mbps, the initial power consumption of transmitting circuit is 0.51 W, and the receiving circuit is 0.25 W, as indicated in Table 1. The

TABLE 1: Simulation parameters.

Parameters	Values
Number of nodes	10 to 100
Data rate	516 to 994 bits per second
Network area	$103 \times 103 \text{ m}^2$
Energy of sensor nodes	1.4 to 4.9 mbps
Initial power consumption of transmitting circuit	0.51 W
Initial power consumption of receiving circuit	0.25 W

performance of the proposed method is compared with the existing [31, 32] methods by considering four parametric scenarios.

4.1. Scenario 1. In this scenario, the power supplied to the sensor nodes has been calculated from (1). Figure 4 shows the calculation of power where the number of sensor nodes has been varied from 10 to 100. It can be seen from Figure 4 that power supplied to the sensor nodes in the proposed method is much lesser than the existing method [31]. For example, if the number of sensor node is 40, then power supplied will be 0.25 W, whereas for existing method [31], the power will be much higher that is equal to 0.56 W. Also, the power supplied in the proposed method will become constant during less sensor nodes implementation (equal to 40), but for the existing method [31], power will become constant at high sensor node implementation that is equal to 70. This proves that the proposed method with MLO proves to be more efficient in terms of power.

4.2. Scenario 2. In this scenario, energy saving of each sensor node that is one of the important parameter in wireless networks is calculated from equation (12) and is simulated. For a virtuous sensor, energy consumed by each node should be as low as possible. Figure 5 specifies the energy consumption where for each sensor node separate energy values are calculated. It can be seen from Figure 5 that proposed method conserves very less energy when compared to the existing method [31]. For example, if the number of sensor node is 60, then the energy consumed by the proposed method will be 3.1 megabits per second, whereas for the existing method [31], it is 4.2 megabits per second. This proves that energy consumed from transmitter to receiver is much lesser in the proposed method than the existing method [31].

4.3. Scenario 3. Once the energy consumed by sensor nodes is low, then it is also necessary that the delay of each node should be lesser. Delay can be defined as the amount of time required for each aggregated data to reach the receiver. Figure 6 represents the delay caused by channel that is represented in milliseconds. For a good data network, the delay should be lesser that is obtained by the proposed method. It can be seen from Figure 6 that the delay caused by the proposed method for transmitting the data during each

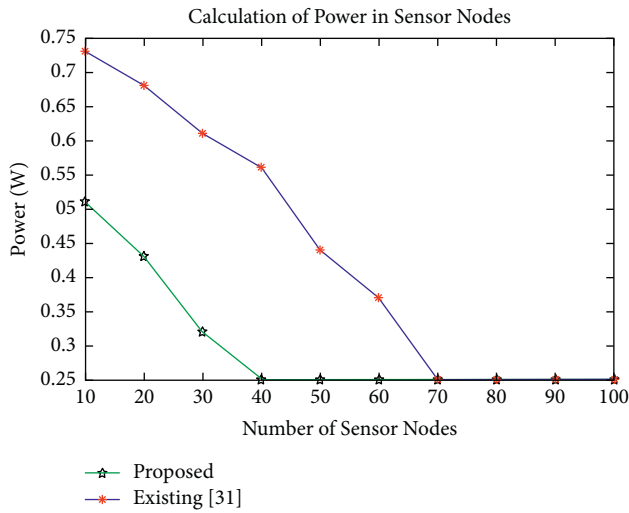


FIGURE 4: Calculation of power in sensor nodes.

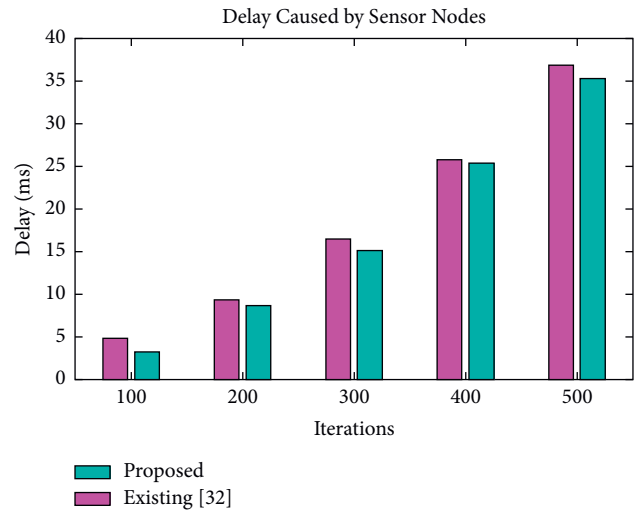


FIGURE 6: Calculation of delay.

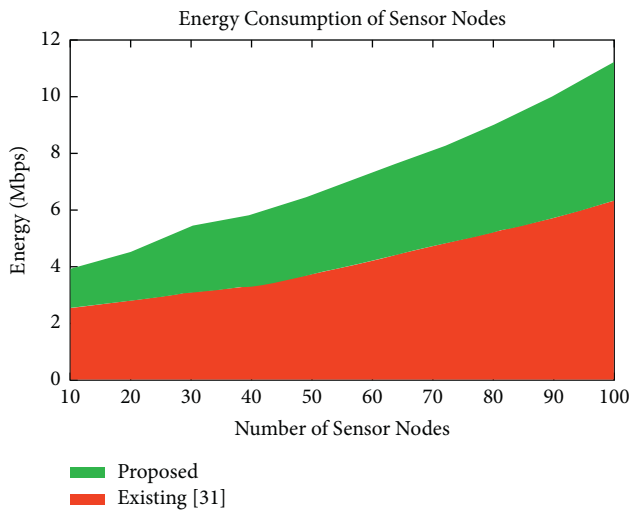


FIGURE 5: Energy consumption of sensor nodes.

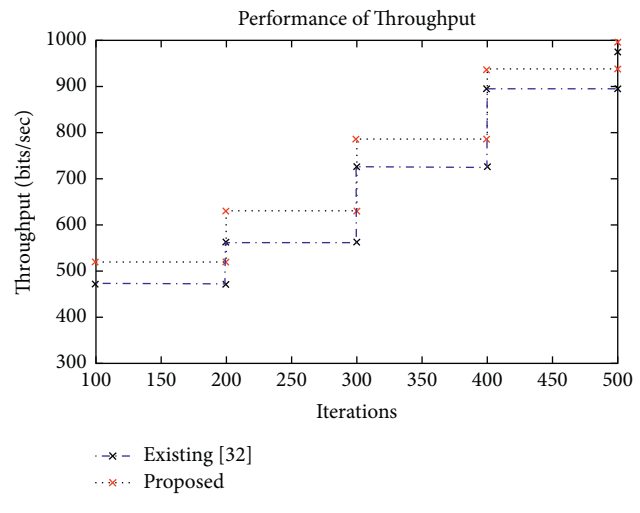


FIGURE 7: Performance of throughput.

iteration is much lesser when compared to the existing method [32]. For example, if iteration is equal to 300, then data sent from transmitter to receiver will suffer by a delay of 15 ms, whereas for existing method, the data delay will be higher that is equal to 16.5 ms. This proves that projected method proves to be more efficient in terms of delay.

4.4. Scenario 4. After minimizing all necessary parameters such as energy consumption, delay, and power, the throughput of entire network will be automatically maximized. Figure 7 shows the performance of throughput, which is represented in bits per second. The step values obtained during each iteration proves that throughput from transmitter to receiver and vice versa is much higher in the proposed method than the existing method [32]. It can be seen from Figure 7 that each iteration is increased to a much higher extent. For example, if iteration is equal to 300, then throughput for proposed method will be 783 bits per second,

whereas for existing method it is lesser that is equal to 724 bits per second. This scenario proves that throughput of multimedia data networks is maximized at higher extent.

5. Conclusions

In this article, an investigation has been carried out for compressing video sensor nodes by minimizing the power in smart grid communication networks thus retaining necessary quality of service constraints. This novel technique has been carried out to meet the demand of future updating smart grid networks. If the nodes are properly compressed, then the need of virtual reality applications will be satisfied. An efficient algorithm that provides better energy consumption and fast convergence rate has been applied in twofold. The simulation results have been compared with other existing techniques where very low throughput with high power and energy consumption of nodes has been achieved [31, 32]. However, the projected method achieves

better quality of service (Throughput) with less power and energy consumption.

Furthermore, the proposed model will be able to support more number of users (nodes) without any reduction in efficiency. In future, the proposed work can be extended by using wireless nodes to monitor smart cities without any attack from external sources, and the delivery of data will be maximized from the transmitter end.

5.1. Policy Implications. The proposed multimedia video sensors can be applied in industry 4.0 for monitoring the following.

- (i) Presence and absence of surrounding objects
- (ii) Record measurements in production units, and
- (iii) Checking the quality of products

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] H. Arjmandi and F. Lahouti, "Resource optimized distributed source coding for complexity constrained data gathering wireless sensor networks," *IEEE Sensors Journal*, vol. 11, no. 9, pp. 2094–2101, 2011.
- [2] P. Del Fiorentino, C. Vitiello, V. Lottici et al., "Resource allocation in short packets BIC-UFMC transmission for Internet of Things," *Proceedings of the IEEE Globecom Work GC Wkshps 2016*, Washington, DC, USA, December 2016.
- [3] Z. He and W. Dapeng, "Resource allocation and performance analysis of wireless video sensors," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 16, no. 5, pp. 590–599, 2006.
- [4] J. Zou, H. Xiong, C. Li, R. Zhang, and Z. He, "Lifetime and distortion optimization with joint source/channel rate adaptation and network coding-based error control in wireless video sensor networks," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 3, pp. 1182–1194, 2011.
- [5] C. Li, J. Zou, H. Xiong, and C. W. Chen, "Joint coding/routing optimization for distributed video sources in wireless visual sensor networks," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 21, no. 2, pp. 141–155, 2011.
- [6] M. Imran, K. Khurshed, N. Lawal, M. O'Nils, and N. Ahmad, "Implementation of wireless vision sensor node for characterization of particles in fluids," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 22, no. 11, pp. 1634–1643, 2012.
- [7] M. Imran, N. Ahmad, K. Khurshed, M. A. Waheed, N. Lawal, and M. O'Nils, "Implementation of wireless vision sensor node with a lightweight bi-level video coding," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 3, no. 2, pp. 198–209, 2013.
- [8] X. Lu, P. Wang, D. Niyato, and Z. Han, "Resource allocation in wireless networks with RF energy harvesting and transfer," *IEEE Network*, vol. 29, no. 6, pp. 68–75, 2015.
- [9] P. D. Diamantoulakis, *Resource Allocation in Wireless Networks with Energy Constraints*, pp. 68–75, 2018.
- [10] I. Loumiotis, T. Stamatidi, E. Adamopoulou, K. Demestichas, and E. Sykas, "Dynamic backhaul resource allocation in wireless networks using artificial neural networks," *Electronics Letters*, vol. 49, no. 8, pp. 539–541, 2013.
- [11] M. Peltomaki, J. M. Koljonen, O. Tirkkonen, and M. Alava, "Algorithms for self-organized resource allocation in wireless networks," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 1, pp. 346–359, 2012.
- [12] R. J. J. Green, H. Joshi, M. D. D. Higgins, and M. S. S. Leeson, "Recent developments in indoor optical wireless [Optical wireless communications]," *IET Communications*, vol. 2, pp. 3–10, 2008.
- [13] N. Dowler and C. J. Hall, "Safety issues in telesurgery - summary," *IEE Colloquium on 'Towards Telesurgery'*, London, UK, June 1995.
- [14] Y. B. Choi, J. S. Krause, H. Seo, K. Capitan, and C. Kyusuk, "Telemedicine in the USA: standardization through information management and technical applications," *IEEE Communications Magazine*, vol. 44, no. 4, pp. 41–48, 2006.
- [15] R. S. H. Istepanian, E. Jovanov, and Y. T. Zhang, "Guest editorial introduction to the special section on M-health: beyond seamless mobility and global wireless health-care connectivity," *IEEE Transactions on Information Technology in Biomedicine*, vol. 8, no. 4, pp. 405–414, 2004.
- [16] N. Golmie, D. Cypher, and O. Rejala, "Performance analysis of low rate wireless technologies for medical applications," *Computer Communications*, vol. 28, no. 10, pp. 1266–1275, 2005.
- [17] S. Sneha and U. Varshney, "Enabling ubiquitous patient monitoring: model, decision protocols, opportunities and challenges," *Decision Support Systems*, vol. 46, no. 3, pp. 606–619, 2009.
- [18] D. J. Vergados, D. D. Vergados, and I. Maglogiannis, "NGL03-6: applying wireless DiffServ for QoS pmet," *IEEE Globecom 2006*, pp. 4–8, 2006.
- [19] D. Cypher, N. Chevrollier, N. Montavont, and N. Golmie, "Prevailing over wires in healthcare environments: benefits and challenges," *IEEE Communications Magazine*, vol. 44, no. 4, pp. 56–63, 2006.
- [20] J. Esch, "A Survey on ambient intelligence in healthcare," *Proceedings of the IEEE*, vol. 101, no. 12, pp. 2467–2469, 2013.
- [21] L. Xu, Y. Yang, and Y. Li, "Resource allocation of limited feedback in clustered wireless mesh networks," *Wireless Personal Communications*, vol. 75, no. 2, pp. 901–913, 2014.
- [22] B. Q. Han, G. F. Feng, and Y. F. Chen, "Heterogeneous resource allocation algorithm for ad hoc networks with utility fairness," *International Journal of Distributed Sensor Networks*, vol. 11, no. 1, Article ID 686189, 2015.
- [23] Y. J. Kim, H. H. Choi, and J. R. Lee, "A bioinspired fair resource-allocation algorithm for TDMA-based distributed sensor networks for IoT," *International Journal of Distributed Sensor Networks*, vol. 12, no. 4, Article ID 7296359, 2016.
- [24] M. I. Khan, "Resource-aware task scheduling by an adversarial bandit solver method in wireless sensor networks," *EURASIP Journal on Wireless Communications and Networking*, vol. 2016, no. 1, p. 10, 2016.
- [25] S. Kim and B. K. Song, "A prioritized resource allocation algorithm for multiple wireless body area networks," *Wireless Networks*, vol. 23, no. 3, pp. 727–735, 2017.
- [26] F. Lin, C. Chen, T. He, K. Ma, and X. Guan, "A separation principle for resource allocation in industrial wireless sensor

- networks,” *Wireless Networks*, vol. 23, no. 3, pp. 805–818, 2017.
- [27] R. S. H. Istepanian, N. Philip, M. G. Martini, N. Amso, and P. Shorvon, “Subjective and objective quality assessment in wireless teleultrasonography imaging,” in *Proceedings of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 5346–5349, Vancouver, BC, Canada, August 2008.
- [28] K. Vidhya and S. Shenbagadevi, “Performance analysis of medical image compression,” in *Proceedings of the International Conference Signal Process Syst ICSPS*, Kathmundu, Nepal, November 2009.
- [29] A. Arar, A. Mohamed, A. A. El-Sherif, and V. C. M. Leung, “Optimal resource allocation for green and clustered video sensor networks,” *IEEE Systems Journal*, vol. 12, no. 3, pp. 2117–2128, 2018.
- [30] P. Yan, S. Choudhury, F. Al-Turjman, and I. Al-Oqily, “An energy-efficient topology control algorithm for optimizing the lifetime of wireless ad-hoc IoT networks in 5G and B5G,” *Computer Communications*, vol. 159, pp. 83–96, 2020.
- [31] F. Al-Turjman, B. D. Deebak, and L. Mostarda, “Energy aware resource allocation in multi-hop multimedia routing via the smart edge device,” *IEEE Access*, vol. 7, Article ID 151203, 2019.
- [32] F. Al-Turjman, M. Z. Hasan, and H. Al-Rizzo, “Task scheduling in cloud-based survivability applications using swarm optimization in IoT,” *Transactions on Emerging Telecommunications Technologies*, vol. 30, no. 8, pp. 1–20, 2019.
- [33] M. Z. Hasan, H. Al-Rizzo, and F. Al-Turjman, “A survey on multipath routing protocols for QoS assurances in real-time wireless multimedia sensor networks,” *IEEE Commun Surv Tutorials*, vol. 19, no. 3, pp. 1424–1456, 2017.
- [34] E. Ogbodo, D. Dorrell, and A. Abu-Mahfouz, “Energy-efficient distributed heterogeneous clustered spectrum-aware cognitive radio sensor network for guaranteed quality of service in smart grid,” *International Journal of Distributed Sensor Networks*, vol. 17, no. 7, Article ID 155014772110283, 2021.
- [35] R. Borgaonkar, I. Anne Tøndel, M. Zenebe Degefa, and M. Gilje Jaatun, “Improving smart grid security through 5G enabled IoT and edge computing,” *Concurrency and Computation: Practice and Experience*, vol. 33, no. 18, pp. 1–16, 2021.
- [36] X. Li, J. Zhang, and M. Yin, “Animal migration optimization: an optimization algorithm inspired by animal migration behavior,” *Neural Computing & Applications*, vol. 24, no. 7-8, pp. 1867–1877, 2014.