Bivalence Fuzzified Decision Stump Bootstrap Aggregation for Energy and Cost-Efficient 6G Communication

Robbi Rahim
   Sekolah Tinggi Ilmu Manajemen Sukma

Parameshwaran Ramalingam
   National Institute of Technology Tiruchirappalli

Manikandan Ramachandran
   SASTRA University School of Computing: Shanmugha Arts Science Technology and Research Academy School of Computing

Vidhyacharan Bhaskar (✉ meetvidhyacharan@yahoo.com)
   San Francisco State University   https://orcid.org/0000-0003-3820-2081

Ambeshwar Kumar
   SASTRA University School of Computing: Shanmugha Arts Science Technology and Research Academy School of Computing

---

Research Article

BIVALENCE FUZZIFIED DECISION STUMP BOOTSTRAP AGGREGATION FOR ENERGY AND COST-EFFICIENT 6G COMMUNICATION

Robbi Rahim
Department of Management Informatics, Sekolah Tinggi Ilmu Manajemen Sukma
Medan, Indonesia
E-mail: usurobbi85@zoho.com

Parameshwaran Ramalingam
Department of Electronics and Communication Engineering, National Institute of Technology-Tiruchirappalli, India
E-mail: paramu32@gmail.com

Manikandan Ramachandran
School of Computing, SASTRA Deemed University, Thanjavur, India
E-mail: srmanimt75@gmail.com

Vidhyacharan Bhaskar
Dept. of Electrical and Computer Engineering,
San Francisco State University,
San Francisco, CA 94132, USA.
Email:vcharan@gmail.com

Ambeshwar Kumar
School of Computing, SASTRA Deemed University, Thanjavur, India
E-mail: ambeshwar.kumar@gmail.com

Abstract

Future Sixth generation (6G) wireless networks are anticipatedto offer entirecoverage, improved spectral, energyandcost-efficient communication.The 6G will enable a network collectivelyand offer seamless wireless connectionsbetween the devices. While the deployment of 5G is ongoing, mobile communication networks are still suffering many basic challenges such as high-energy consumption and operating costs. To address these issues, it is very important to consider and develop new technologies in next-generation mobile communication, namely 6G. Novel machine learning can potentially assist the 6G to obtain better communication. Bivalence Fuzzified Decision Stump Bootstrap Aggregating (BFDSBA) model is introduced for energy and

cost efficient communication. The BFDSBA model considers the nodes i.e. devices in the forecasting process before the data communication in the 6G network. The Bootstrap Aggregative technique utilizes set of weak learners as Bivalence Fuzzified Decision Stump. For each device in the network, energy, signal strength, and bandwidth is measured. Based on the estimated resources, efficient devices are selected for the 6G network architectural design. This in turn helps to improvedata communication with lesser cost in6G networks. The result exposesimprovement of BFDSBA model than the conventional methods.

1. Introduction

With the development and forthcoming sixth-generation (6G), the expectationand development of the networkhave attracted a large deal of consideration.The upcoming 6G network is alargely connected complex network that able to provide users' required services with better resource utilization such as energy and cost. To attain these requirements, 6G networks design requires a noveltechnology that offers reliable andlow latency communication for many applications.

For energy and cost-efficient communication, A Multivariate Regressive Deep Stochastic Artificial Structure Learning (MRDSASL) method was presentedin [1]. But designed technique failed to analyze the bandwidth to achieve higher delivery rate and minimizes the cost. A hybrid NOMA system was developed in [2] to lessen energy consumption of data transmission. Reliable delivery was not improved with minimum cost.

A vision for 6G mobile networks was discussed in [3] to solve some challenges including physical-layer transmission and network designs. Multiple Machine Access Learning was introduced in [4] formaking effective communication. The designed learning scheme reduces the latency but it failed to increase the Quality of Experience (QoE) of the 6G user's application demands. Feasible applications and technologies were emerged in [5] for future 6G communication and its network structural design. But it failed to apply any machine learning techniques to optimize the resource utilization. An AI/ML-driven air interface design and

optimization technology were developed in [6] for the achievement of improved performance of latency as well as reliability of the 6G system.

Cellular joint communication and sensing (JCAS) system was developed in [7] to facilitate low latency communication services. But the designed system failed to perform energy-aware communication. A novel method was designed in [8] for combining energy, computation, and communication (ECC). An AI-enabled 6G communication technology was developed in [9] for a broad range of future applications. A transmit diversity method was introduced in [10] to transmits messages over several paths to improve the signal-to-noise ratio.

 UAV-to-Everything (U2X) networking architecture was introduced in [11] to improve the communication modes along with the requirements of their sensing applications. In [12], A Distributed AI as Service (DAIaaS) model was designed for Internet of Everything (IoE) and 6G. Different technology was studied in [13] for the energy-efficient wireless networks and federated learning systems to meet the 6G requirements.

A Quantum Machine Learning algorithm was introduced in [14] for 6G communication. But a detailed discussion on energy and cost-aware communication was not performed. Various machine learning techniques and their working process were developed in [15] for the 6G communication system. But the latency and resource management were not considered for 6G communication. A few potential technologies were developed in [16] for supporting the ultra-reliable and low-latency services.

In [17], a complete and forward-looking vision for 6G was described for delay and minimizing the energy consumption. To enhance 6G communication, A Reconfigurable Intelligent Surface-Based Index Modulation was explained in [18]. AI-enabled intelligent structural design was designed in [19] for 6G networks to identify knowledge detection and lesser resource consumption for intelligent service provisioning. A survey on various machine learning methods wasexplained in [20] for 6G vehicular communication.

Contribution of BFDSBA model are summarized as given below,

☐ To enhance 6G communication, BFDSBA model is introduced based on the Bootstrap Aggregative technique

☐ The Bootstrap Aggregative technique uses the Fuzzified Decision Stump for analyzing the different characteristics such as energy, signal strength, and bandwidth. The ensemble technique finds the energy-efficient nodes for data transmission in a 6G network. This assists to enhance delivery ratio and reduces cost.

☐ Finally, an extensive simulation is conducted with various parameters to highlight improvement of BFDSBA over conventional techniques.

Work is systematized into different sections. Section 2, discusses the BFDSBA model. In section 3, Simulation settings are provided. Performance evaluation and results of the proposal and conventional methods are carried out and are discussed in Section 4. Section 5 concludes the article.
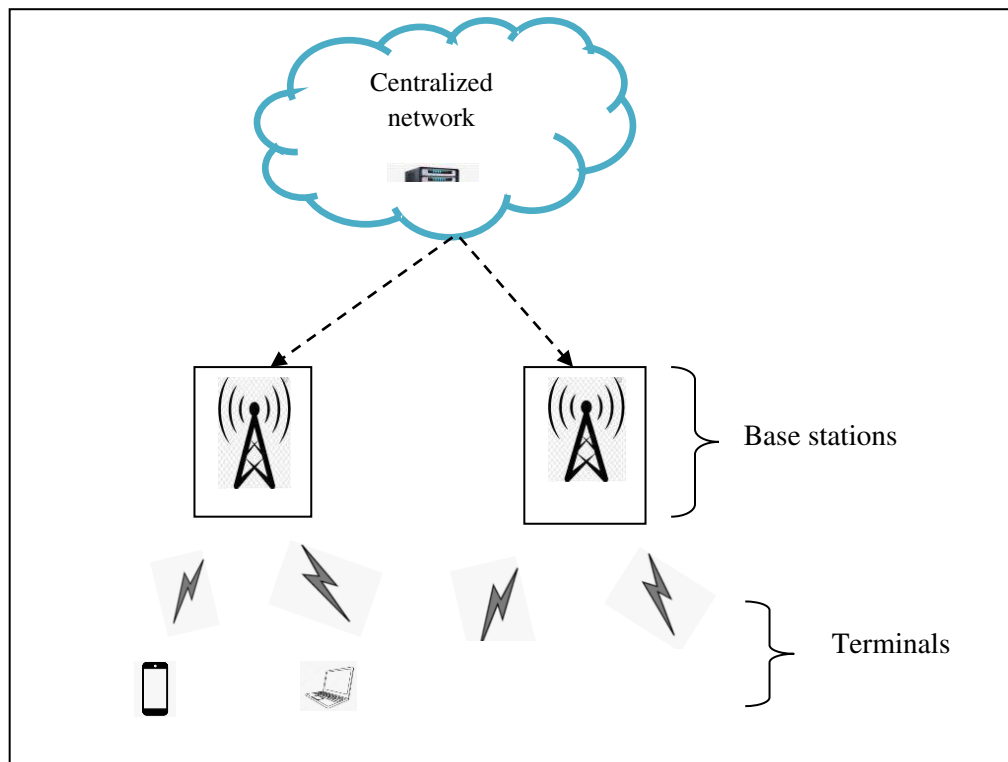
2. Methodology

With the continuous development of technology, wireless networks helped the users to send sensitive information without any human interaction. These technologies help to improve the communication speed of the data from one device to another. In general, many wireless technologies are available in the marketplace such as 1G, 2G, 3G, 4G, 5G, and so on. These technologies diverged from one to another based on the feature values such as availability, range, performance and coverage, bandwidth, speed of data transfer, latency, and so on. The 1G (1st generation) data rate is 2.4kbps and it suffers lot of difficulties like poor network speed and it has no security. The 2G generation was introduced in 1990s with a network speed upto 64kbps. The 3G generation was established with a transmission rate of upto 2Mbps. This network combines high-speed mobile access to services with Internet Protocol (IP). Next, 4G technology was introduced with a speed of upto 20 Mbps. With the development in the user's demand, 4G technology gets replaced with 5G technology which addresses the different challenges, namely higher data rate >1Gbps, lesser latency, high device connectivity, minimal cost, and reliable quality of service provisioning.

5G wireless networks offer majoradvantages beyond LTE (i.e. 4G technology), but may not capable to meet the reliable data connectivity demands of the futuredigital world. Therefore, a novel model of wireless communication, 6G system, will developnew attractive features namelygreater system capacity, greater data rate, less latency, and enhanced quality of service (QoS) than 5G wireless networks.
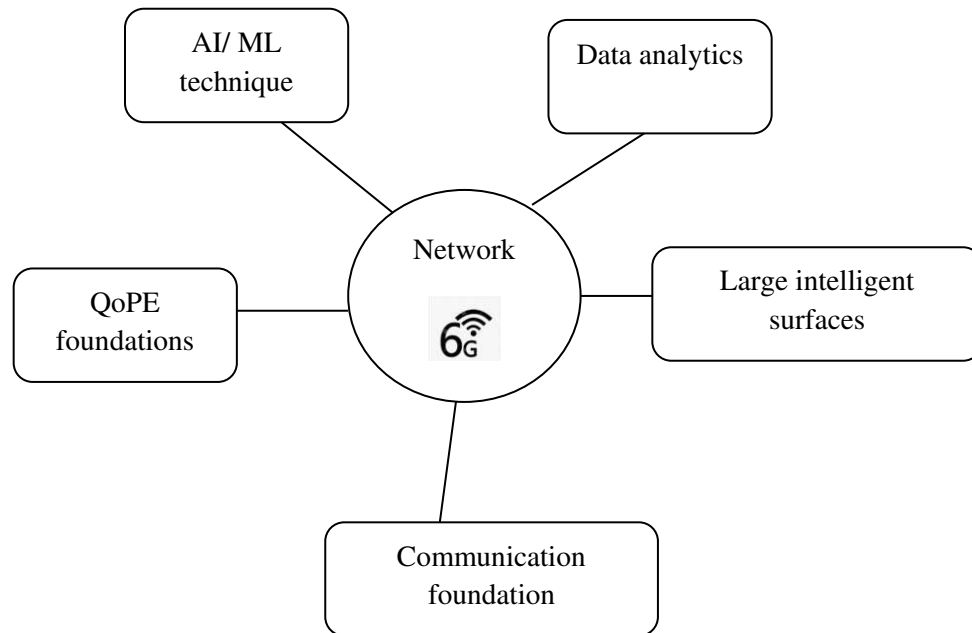
6G technology is considered to be inexpensive and fast network speed data ranges up-to 11 Gbps. The most significant advantages for 6G wireless networks are the abilityto managehuge data and offers high-data-rate connectivity.

The future sixth-generation networks have the ability to support novel and various services with completely different features and requirements than the 5G network. To build an intelligent 6G network, every node must possess adequate communication, computing, and caching resources to handle intelligent operations for proving various services. The service aware architecture is shown in figure 1.

Figure 1 service aware architecture of 6G network

Figure 1 shows the service-aware architecture of the 6G network. The 6G will offer a virtual connection between the terminal, base stations, and centralized network. The base stations route the data service requests to centralized network.Centralized network offers the requested services to terminal namely self-driving cars, mobile devices, laptops, and so on through wireless connection with higher data rate and low latency.

Figure 2 analytical foundations for 6G

Figure 2 illustrates the different analytical foundations for the 6G network. The Large intelligent surfaces (LIS) are a promisingtechnology in6G networkto enhance signal-to-noise ratio and spectral efficiency but also minimize the energy consumption during the transmission.
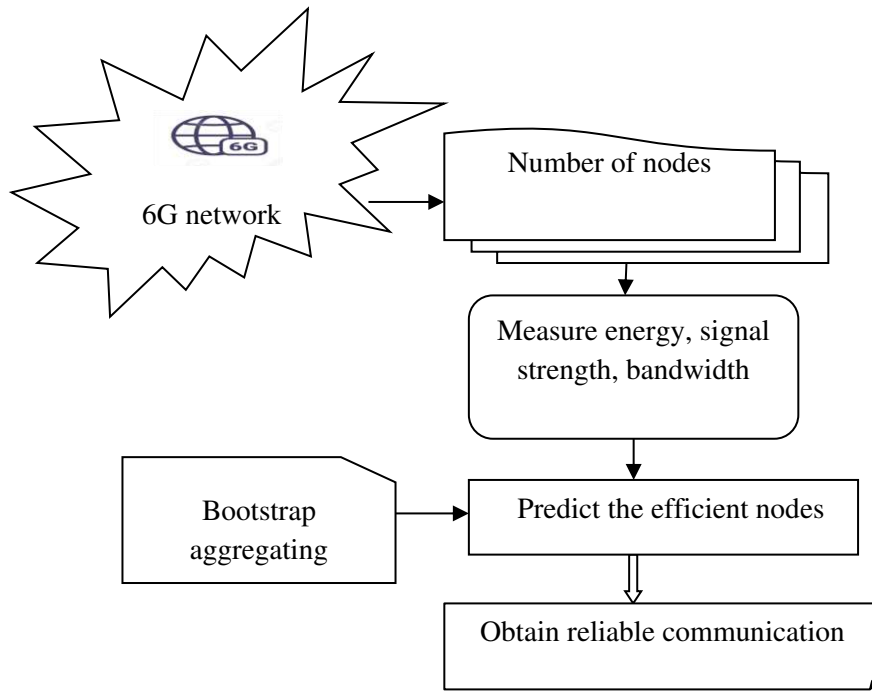
The combined design of AI and Machine Learning (ML) is a significant area of research for 6G networks. These techniques are used to deliver applications with low-latency, high-reliability, and scalability.

Data analytics is a method of observing, refinement,and modeling the data with the aim of finding useful information. There are various kinds of data analytics such as classification, diagnostic, and predictive.

Quality of Physical Experience (QoPE) foundations combines the human factors from the user with conventional QoSand QoE. QoS handles data traffic to minimize packet loss, latency, and jitter on a network and it controls the network resources. QoEis developed from Quality of

Service (QoS), which efforts to objectively evaluatethe service factors namely loss rates and average throughput.

The 6G network will support the Reliable Low Latency Communication. It will also support security and long-distance networking, multimedia video and high-speed Internet connectivity telecommunication, navigation, and so on. A few concerns of 6G network communication is carried out to provide energy and cost-efficient communication. Since high-energy consumption increases the operating costs. To forecast energy and cost-aware communication, a novel machine learning concept called BFDSBAmodel is introduced in the 6G network architecture to scrutinize devices (i.e. node) status for enhancingreliable communication.
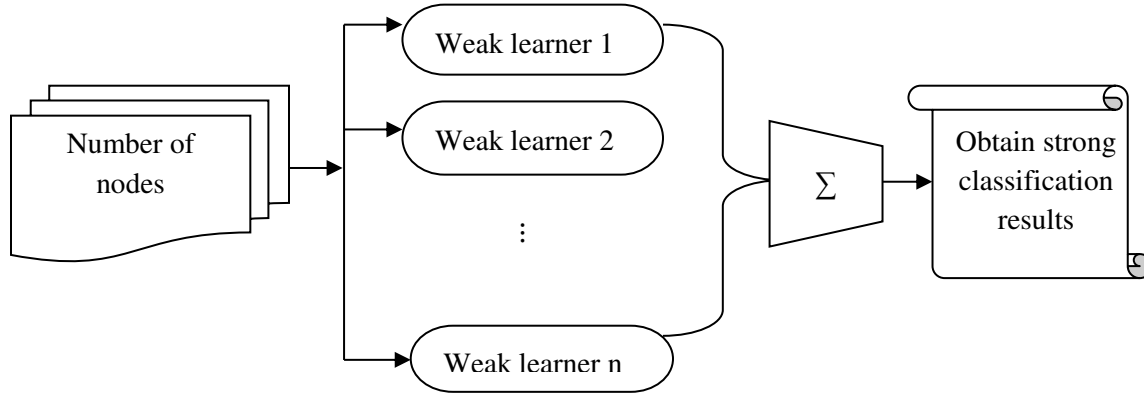

Figure 3 architecture of the BFDSBA model

Figure 3 portrays the architecture of BFDSBAmodel. Initially, the nodes $N_1, N_2, N_3 \ldots, N_n$ are considered as input to analyze the features to improve reliable data communication in 6G network. For each node, features namely energy, signal strength, and bandwidth are measured and apply the Bootstrap aggregating technique. The ensemble technique finds the efficient nodes and designs 6G withnodes which are employedto attain reliable communication.

The Bootstrap aggregating is an ensemble meta-algorithm that provides improved classification performance than any of the weak learners alone. A weak learner is a machine

learning algorithm that provides the classification outcomes with the probability of some error. In contrast, a Bootstrap aggregating is a strong learner that correctly provides an improved Bootstrap aggregating performance with lesser error.

Figure 4 block diagram of Bootstrap aggregating

Figure 4 shows the block diagram of the Bootstrap aggregating classification techniqueto obtain an accurate prediction of energy and cost-aware communication. The Bootstrap aggregating technique considers the training set $\{N_i, Z_i\}$ where$N_i = N_1, N_2, ..., N_n$' denotes the number of nodes and $Z_i$indicates the classification outcomes of the ensemble technique. As shown in figure 4, the Bootstrap aggregating technique constructs 'm' weak learners$R_1, R_2, R_3, ... R_b$and the results are combined to obtain strong classification results. The Bootstrap aggregating techniqueuses the weak learner as a Bivalence Fuzzified Decision Stump to identify the efficient node to perform the reliable communication. A Bivalence Fuzzified Decision Stump comprises one root nodewhichis linked toleaf node. Here, Bivalence represents the decision tree has exactly one truth valuewith the help of the fuzzy rule.

For each node in the network, three features are evaluated such as energy, signal strength, and bandwidth. The energy level of the node is measured as the product of power together with time. Therefore, the energy is measured as given below,

$$E = pr * t \qquad (1)$$

Where E denotes the energy of the nodes in the 6G network, E indicates power and t represents the time. The energy is measured in the unit of a joule. Next, the signal strength of the node is measured as given below,

$$SS_r = SS_t * \left[\frac{W_t W_r * \text{h}_t^2 \, \text{h}_r^2}{D^4}\right] \qquad (2)$$

Where, SS_r denotes a received signal strength, SS_t denotes a transmitted signal power, W_t, W_r are transmitter and receiver antenna gain, h_t^2, h_r^2 indicates transmitter and receiver antenna height, D is distance among transmitter and receiver antenna. Received signal power is measured in decibel milliwatts (dBm).
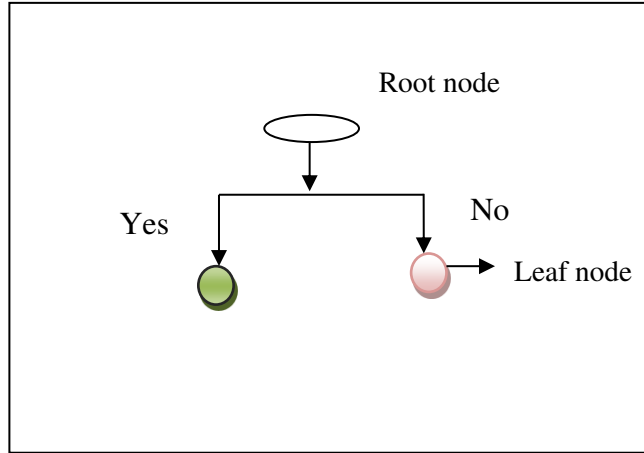
Bandwidth is calculated as maximum rate at which data is transferred in network. It is defined as the data that sent in a given time over a particular connection.

$$B = \frac{\text{data sent (bits)}}{\text{time (s)}} \qquad (3)$$

Where, B denotes a bandwidth and measured in bits per second (bps). By applying the Bivalence Fuzzified Decision Stump, the root node verifies that the estimated value of the node is higher than the threshold value using the fuzzy rule. The fuzzy rule is used to link the inputs (i.e. estimated values) with the outputs. These rules are formulated using IF (condition) and $then$ (conclusion).

$$H = \begin{cases} (E > T_E) \, and \, (SS_r > T_{SS_r}) \, and \, (B > T_B) & ; select \, the \, node \\ otherwise & ; not \, selected \end{cases} \qquad (4)$$

Where, H denotes an ouput of weak learner, δ_e is threshold for energy, ϑ is threshold for signal strength, T_E denotes threshold for energy, T_{SS_r} denotes threshold for signal strength, T_B indicates threshold for bandwidth. Decision stump-based classification is performed as shown in figure 5.

Figure 5 Bivalence Fuzzified Decision Stump based classification

The weak learner has some training errors during the classification process. In order to improve the classification accuracy, all weak learner results are combined to attain the strong classification as follows,

$$Z = \sum_{i=1}^{m} H_i \quad (5)$$

Where, Z indicates an output of ensemble classification, H_i indicates the weak learner. After combing the weak learner, the voting method is applied to the weak learner results for accurately finding the efficient nodes. The majority votes of the weak learner are given below,

$$Z = arg\max_{m} \ \beta \ (H_i) \qquad (6)$$

Where β indicates a majority votes whose decision is identified in the mth classifier, '$arg\max_{m}$' indicates an argument of the maximum function that helps to find the majority votes of results. The results which have higher votes are selected as final ensemble classification results. In this way, the nodes with greater energy, signal strength, and bandwidth areenhancing reliable data transmission in6G network.

\\ Algorithm 1 Bivalence Fuzzified Decision Stump bootstrap aggregating model
Input: Number of nodes $N_i = N_1, N_2, \ldots, N_n$
Output: Improve the reliable communication

1: Begin

2:　　　　**For each node** 'N_i'

3:　　　　Construct 'm' number of weak learners

4:　　　　**Analyze the** features E, SS_r, B

5.　　　　**if** $((E > T_E)\ and\&\ \&\&\ (SS_r > T_{SS_r})\&\&\ and\ (B > T_B))$ **then**

6:　　　　　　Node is said to efficient for communication

7:　　　　**else**

8:　　　　　Node is said to inefficient for communication

9:　　　**end if**

10:　　　Combine all weak learner outputs $Z = \sum_{i=1}^{m} H_i$

11:　　**For each H_i**

12:　　　Apply votes 'β'

13:　　　Find majority vote $arg \max_{m} \beta (H_i)$

14:　　　Attain strong classification results

15:　　End for

16: **End for**

17: End

Algorithm 1 describes the Bivalence Fuzzified Decision Stump bootstrap aggregative model for identifying the efficient nodes. The proposed ensemble technique constructs the number of weak learners as a Bivalence Fuzzified Decision Stump. For each node, the energy, signal strength, and bandwidth are measured. Then the estimated values are given to root node of decision stump. Then root node analyzes values with the threshold value using fuzzy rules. The node that has higher energy, signal strength, and bandwidth are considered as efficient node. Otherwise, node is not efficient for better communication. The weak learner's results are combined into strong by applying the voting scheme. The results with majority votes are obtained as strong results. With the classified node, the 6G architecture needs to be done to obtain reliable communication with minimum cost.

3. Simulation settings

Simulation of BFDSBAmodel and MRDSASL [1] hybrid NOMA [2] are conducted in Network Simulator (NS3). 500 sensor nodes are deployed in a network size of $1000 * 1000$. The simulation is conducted using a Deep slice & secure 5G-5G LTE Wireless dataset obtained from https://www.kaggle.com/anuragthantharate/deepslice to execute 6G communication. Data packets are taken in the ranges from 30, 60, 90,120, 150,180, 210, 240, 270, and 300. Totally ten iterations are performed for each method with a number of nodes and data packets. The hardware requirement is listed in table 1.

Table 1 hardware requirement

Hardware	Specification
Operating system	Windows 10
Processor	Core i3-4130 3.40 GHz
RAM	4GB RAM
Hard disk	1 TB

4. Simulation results and discussions

The performance analysis of three different methods namely BFDSBAmodel and existing MRDSASL [1] and hybrid NOMA [2] are described with different metrics.

4.1 Impact of energy consumption

Energy consumption is measured as amount of energy taken by nodes to transmit the data packets. The energy consumption is mathematically estimated as given below,
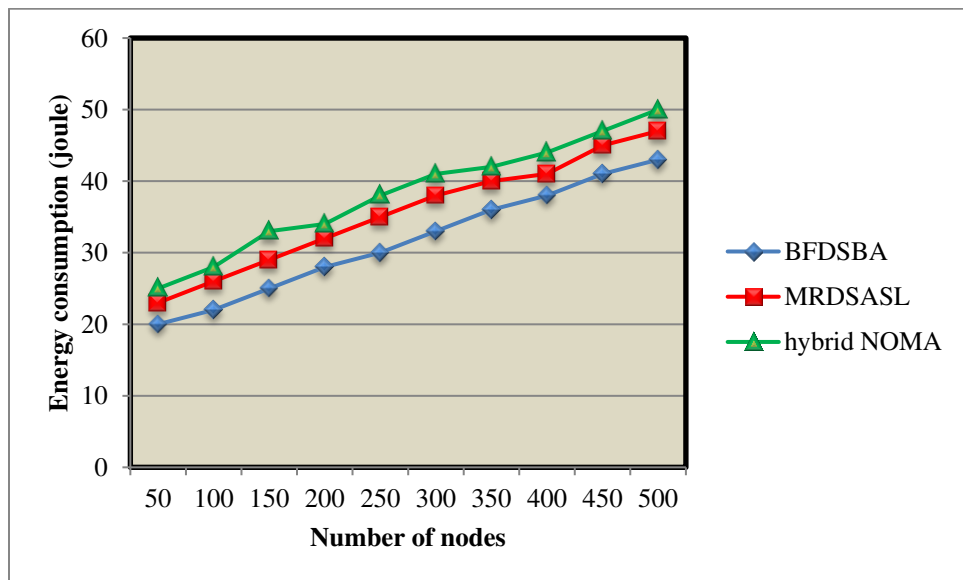
$$E_C = number\ of\ nodes * [E_C(single\ node)] \quad (7)$$

Where, E_C denotes an energy consumption and it is measured in the unit of joule (J).

Table 2 comparative analysis of Energy consumption

Number of nodes	Energy consumption (joule)		
	BFDSBG	MRDSASL	hybrid NOMA
50	20	23	25
100	22	26	28
150	25	29	33
200	28	32	34
250	30	35	38
300	33	38	41
350	36	40	42
400	38	41	44
450	41	45	47
500	43	47	50

Table 2 demonstrates the performance of energy consumption of nodes that delivered data packets to destination. The estimated results confirm that the BFDSBAtechnique minimizes the energy consumption as compared to MRDSASL [1] and hybrid NOMA [2]. For each method, ten runs are carried out with different numbers of nodes. The performance of BFDSBA is compared to the other two methods. The comparison results prove that the energy consumption of the BFDSBA model is considerably minimized by 12%, and 18% when compared to MRDSASL [1] and hybrid NOMA [2].

Figure 6 numbers of nodes versus energy consumption

Figure 6 portrays energy consumption with number of nodes. From figure 6, energy consumption for all three methods gets enhanced. Among three methods, proposed BFDSBA minimizes overall energy consumption. This is due to BFDSBAuses the Bivalence Fuzzified Decision Stump Bootstrap Aggregating model discovers energy-efficient nodes to participatein data transmission process. This minimizes overall energy consumption during the data transmission from one to another.

4.2 Impact of packet delivery ratio

Packet delivery ratio is calculated as ratio of number of data packets correctly received to total number of packets sent. Packet delivery ratio is calculated as follows,

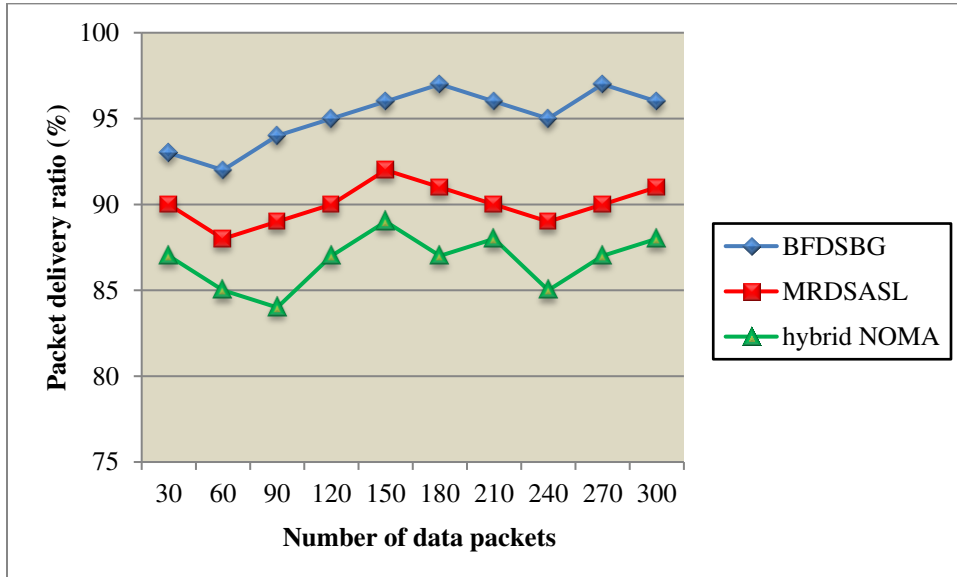$$DR = \left[\frac{packet\ received}{packet\ sent}\right] * 100 \qquad (8)$$

WhereDR is a Packet delivery ratio measured in percentage (%).

Table 3 comparative analysis of packet delivery ratio

Number of data packets	Packet delivery ratio (%)		
	BFDSBA	**MRDSASL**	**hybrid NOMA**
30	93	90	87
60	92	88	85
90	94	89	84
120	95	90	87
150	96	92	89
180	97	91	87
210	96	90	88
240	95	89	85
270	97	90	87
300	96	91	88

Table 3 reports the performance of packet delivery ratio withnumber of data packets. Observed results indicate that the BFDSBA model achieves greater packet delivery ratio than other two models. Let us consider 30 data packets sent. By applying the BFDSBA model, 28 data packets are send and delivery ratio is 93%. The number of packets delivered 27 and 26 data packets are successfully send and delivery ratio of the MRDSASL [1] and hybrid NOMA [2] are 90%, 87%.

The average of comparison results inthe BFDSBA model enhances packet delivery ratio by 6% and 10% than the [1] and [2].

Figure 7 numbers of nodes versus packet delivery ratio

Figure 7 illustrates results of packet delivery ratio forthree models. Observed results prove that the BFDSBA model achieves a higher data delivery ratio. The BFDSBA model finds the higher energy, signal strength, and bandwidth nodes to carry out communication. This assists to enhance data transmission and reduces packet drop.

4.3 **Impact of cost**

Cost is a metric measured in terms of delay during the data transmission. The delay is measured as difference amongtime for data packet arrival and transmitting from node. It s mathematically formulated as given below,

$$delay = [AT_p] - [TT_p] \qquad (9)$$

Where,AT_p denotes a data arrival time, TT_pindicates the transmission time. Delay is calculated in milliseconds (ms).

Table 4 comparative analysis of cost

Number of data packets	Cost (ms)		
	BFDSBG	MRDSASL	hybrid NOMA
30	0.23	0.27	0.3
60	0.25	0.3	0.35
90	0.28	0.32	0.36
120	0.32	0.37	0.4
150	0.35	0.4	0.44
180	0.38	0.42	0.45
210	0.4	0.44	0.47
240	0.42	0.48	0.52
270	0.48	0.53	0.56
300	0.54	0.58	0.6

Figure 8 numbers of data packets versus Cost

Table 4 and figure 8 portrays results of cost in terms of delay withnumber of data packets. For the different counts of the data packets, the delay of three methods gets increased for all three methods. But comparatively, the BFDSBA model reduces the delay. The reason for this accomplishment is to select energy-efficient, higher signal strength nodes. The higher energy and efficient signal strength of the nodes increases the speed of the data transmission from one node to another. Let us consider '30 data packets to conduct the simulation in the first iteration. The delay of the BFDSBA model was observed '$0.23ms$' and $0.27ms$' '$0.3ms$''delay was observed

using MRDSASL [1] and hybrid NOMA [2]. The delay is comparatively reduced by 12% and 19% when compared [1] [2].

5. Conclusion

A novel machine learning technique called BFDSBA is introduced in this paper to forecast the energy and cost-aware communication in 6G network. BFDSBA uses the Bootstrap Aggregating ensemble technique to find the efficient devices for communication by constructing the weak learners. The Bivalence Fuzzified Decision Stump is a tree to analyze the energy level, signal strength, and bandwidth using fuzzy conditions and returns the output. The nodes that have better resources are considered to perform the data communication in the future 6G networks. It will help to improve reliable data communication with lesser cost in6G network. Assessment results demonstrateefficiency of BFDSBA model is better in terms of delivery ratio, energy consumption and cost.

Conflict of Interests

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Data Availability statement:

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Code Availability

Not Applicable.

References

[1]Sekaran, R., Ramachandran, M., Patan, R., & Al-Turjman, F. (2021). Multivariate regressive deep stochastic artificial learning for energy and cost efficient 6G communication. Sustainable Computing: Informatics and Systems, 30, 100522.

[2]Li, H., Fang, F., & Ding, Z. (2020). Joint resource allocation for hybrid NOMA-assisted MEC in 6G networks. Digital Communications and Networks, 6(3), 241-252.

[3] Yang, P., Xiao, Y., Xiao, M., & Li, S. (2019). 6G wireless communications: Vision and potential techniques. IEEE Network, 33(4), 70-75.

[4]Shakeel, P. M., Baskar, S., Fouad, H., Manogaran, G., Saravanan, V., & Xin, Q. (2020). Creating Collision-Free Communication in IoT with 6G Using Multiple Machine Access Learning Collision Avoidance Protocol. Mobile Networks and Applications, 1-12.

[5]Chowdhury, M. Z., Shahjalal, M., Ahmed, S., & Jang, Y. M. (2020). 6G wireless communication systems: Applications, requirements, technologies, challenges, and research directions. IEEE Open Journal of the Communications Society, 1, 957-975.

[6] Viswanathan, H., &Mogensen, P. E. (2020). Communications in the 6G era. IEEE Access, 8, 57063-57074.

[7]Wild, T., Braun, V., &Viswanathan, H. (2021). Joint Design of Communication and Sensing for Beyond 5G and 6G Systems. IEEE Access, 9, 30845-30857.

[8]Qi, Q., Chen, X., Zhong, C., & Zhang, Z. (2020). Integration of energy, computation and communication in 6G cellular internet of things. IEEE Communications Letters, 24(6), 1333-1337.

[9]Sheth, K., Patel, K., Shah, H., Tanwar, S., Gupta, R., & Kumar, N. (2020). A taxonomy of AI techniques for 6G communication networks. Computer Communications, 161, 279-303.

[10]Faisal, A., Alghamdi, R., Dahrouj, H., Sarieddeen, H., Saeed, N., Al-Naffouri, T. Y., &Alouini, M. S. (2021). Diversity Schemes in Multi-hop Visible Light Communications for 6G Networks. Procedia Computer Science, 182, 140-149.

[11] Zhang, S., Zhang, H., & Song, L. (2020). Beyond D2D: Full dimension UAV-to-everything communications in 6G. IEEE Transactions on Vehicular Technology, 69(6), 6592-6602.

[12]Janbi, N., Katib, I., Albeshri, A., &Mehmood, R. (2020). Distributed artificial intelligence-as-a-service (daiaas) for smarter ioe and 6g environments. Sensors, 20(20), 5796.

[13]You, X., Wang, C. X., Huang, J., Gao, X., Zhang, Z., Wang, M., ... & Liang, Y. C. (2021). Towards 6G wireless communication networks: Vision, enabling technologies, and new paradigm shifts. Science China Information Sciences, 64(1), 1-74.

[14]Nawaz, S. J., Sharma, S. K., Wyne, S., Patwary, M. N., &Asaduzzaman, M. (2019). Quantum machine learning for 6G communication networks: State-of-the-art and vision for the future. IEEE Access, 7, 46317-46350.

[15]Kaur, J., Khan, M. A., Iftikhar, M., Imran, M., &Haq, Q. E. U. (2021). Machine learning techniques for 5g and beyond. *IEEE Access*, *9*, 23472-23488.

[16]Yuan, Y., Zhao, Y., Zong, B., &Parolari, S. (2020). Potential key technologies for 6G mobile communications. Science China Information Sciences, 63, 1-19.

[17]Chen, Y., Liu, W., Niu, Z., Feng, Z., Hu, Q., & Jiang, T. (2020). Pervasive intelligent endogenous 6G wireless systems: Prospects, theories and key technologies. Digital Communications and Networks, 6(3), 312-320.

[18]Basar, E. (2020). Reconfigurable intelligent surface-based index modulation: A new beyond MIMO paradigm for 6G. IEEE Transactions on Communications, 68(5), 3187-3196.

[19]Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial-Intelligence-Enabled Intelligent 6G Networks. IEEE Network, 34(6), 272-280.

[20]Tang, F., Kawamoto, Y., Kato, N., & Liu, J. (2019). Future intelligent and secure vehicular network toward 6G: Machine-learning approaches. Proceedings of the IEEE, 108(2), 292-307.
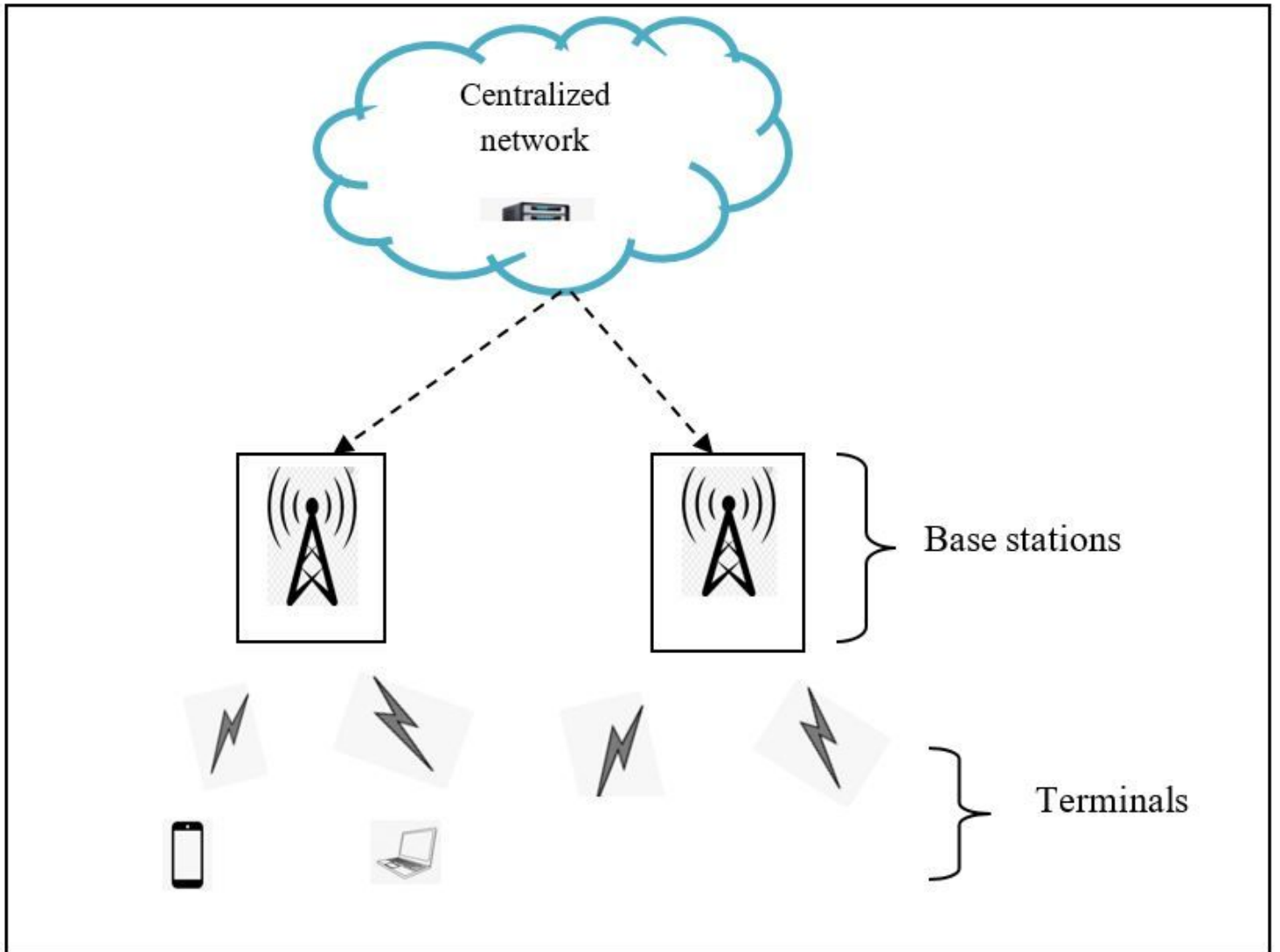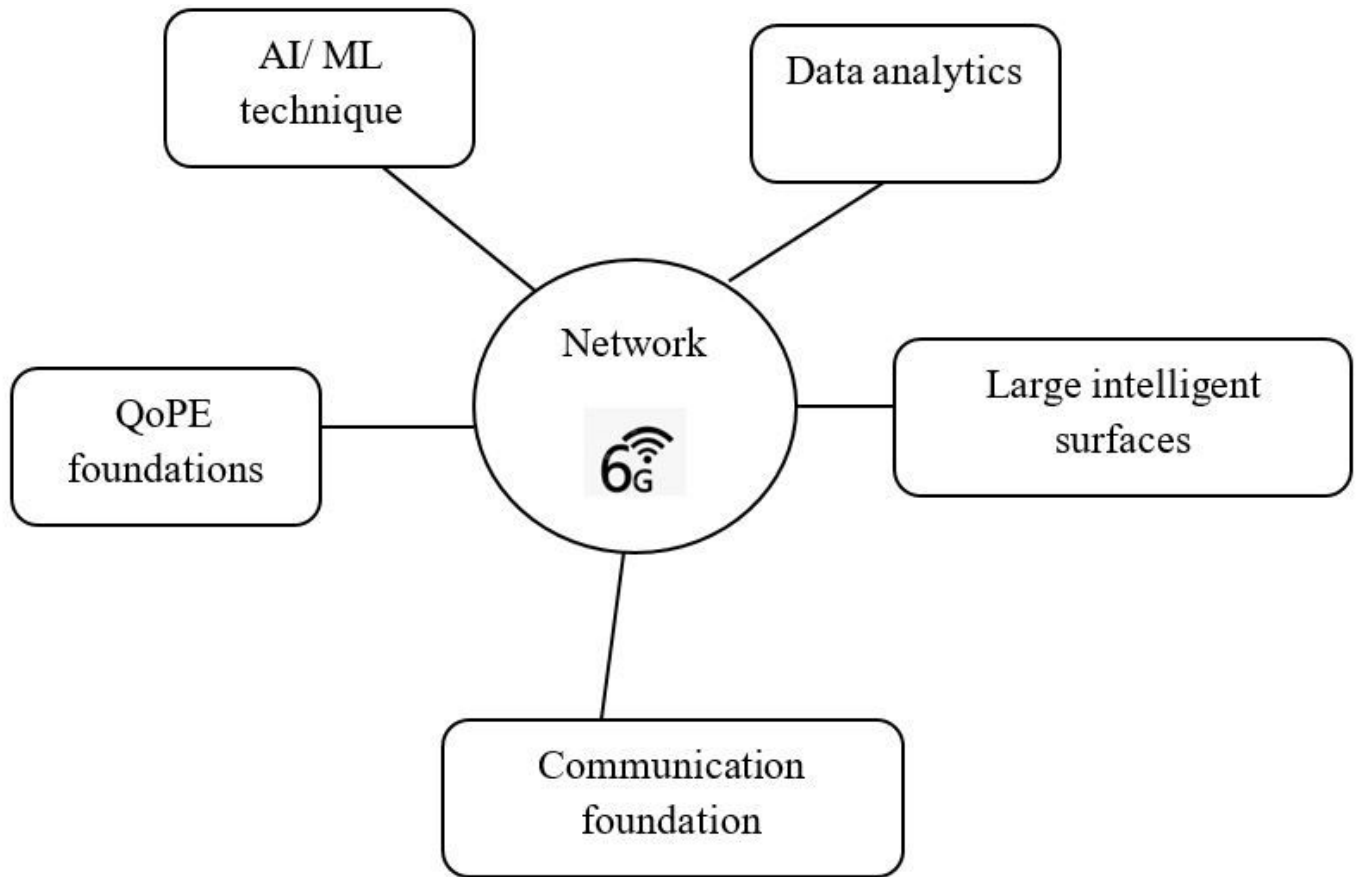
Figures

Figure 1

service aware architecture of 6G network

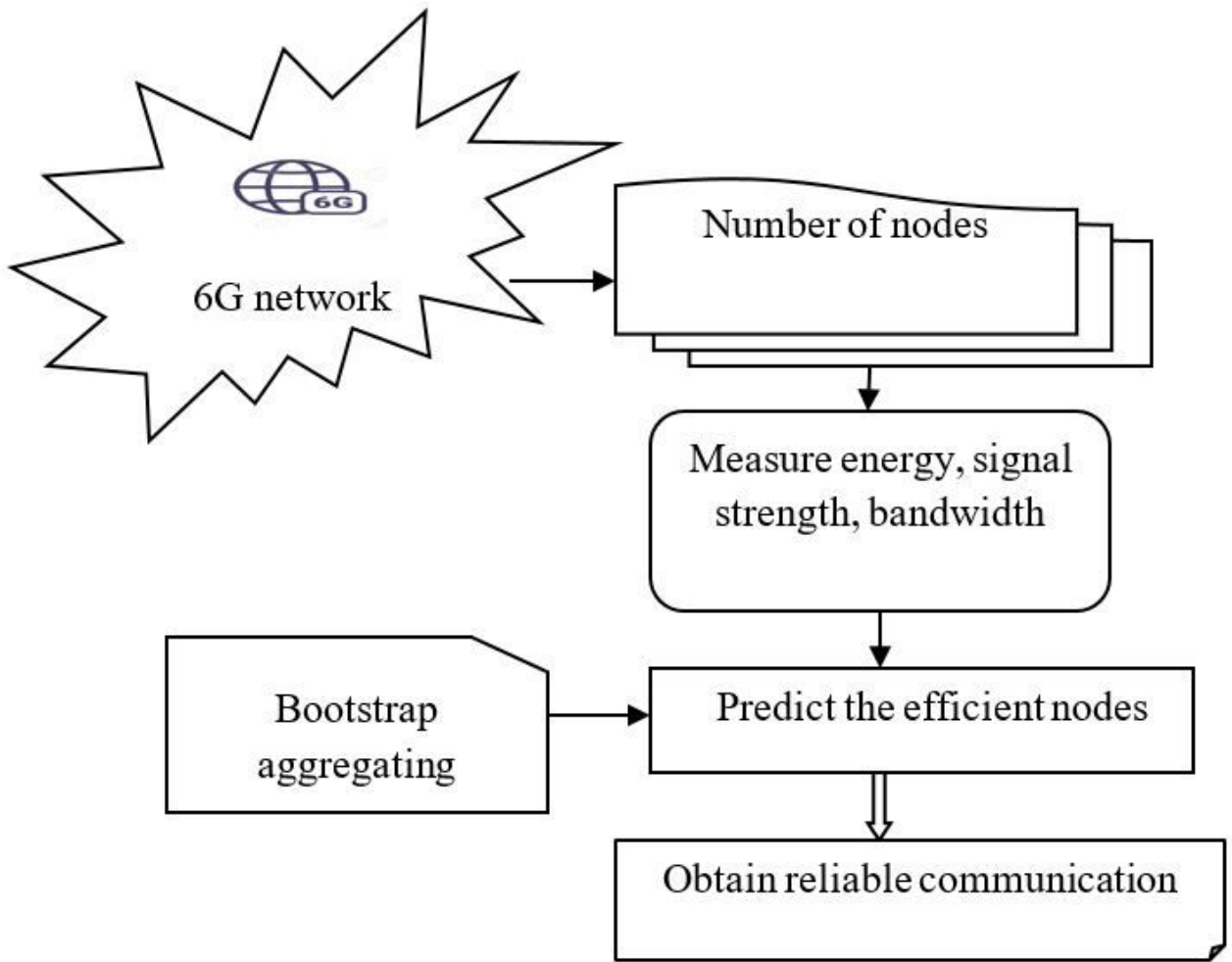**Figure 2**

analytical foundations for 6G

Figure 3

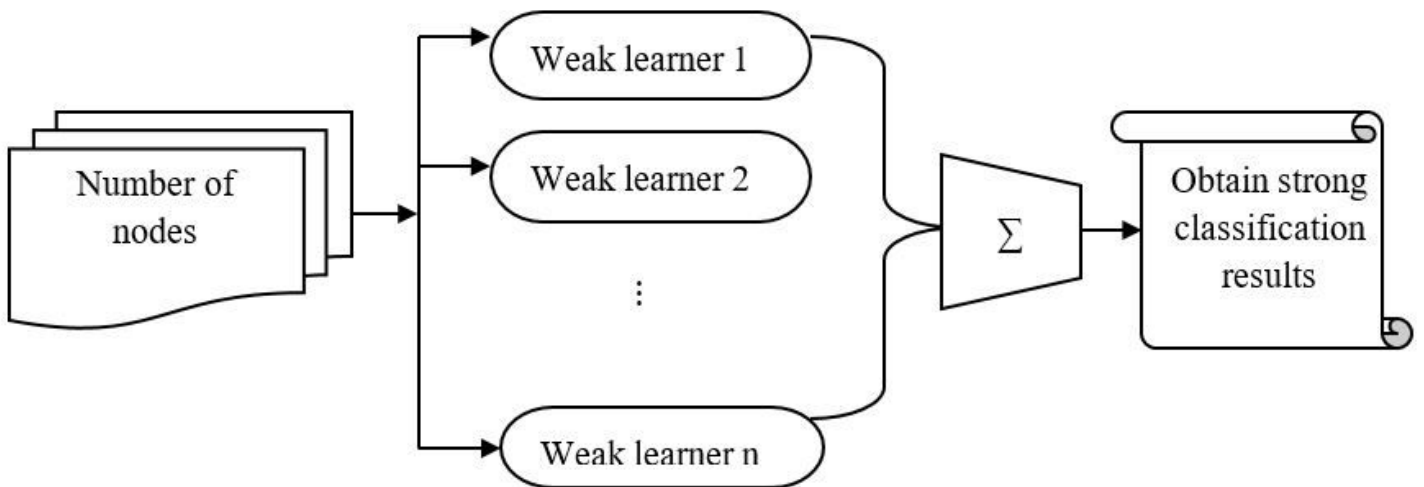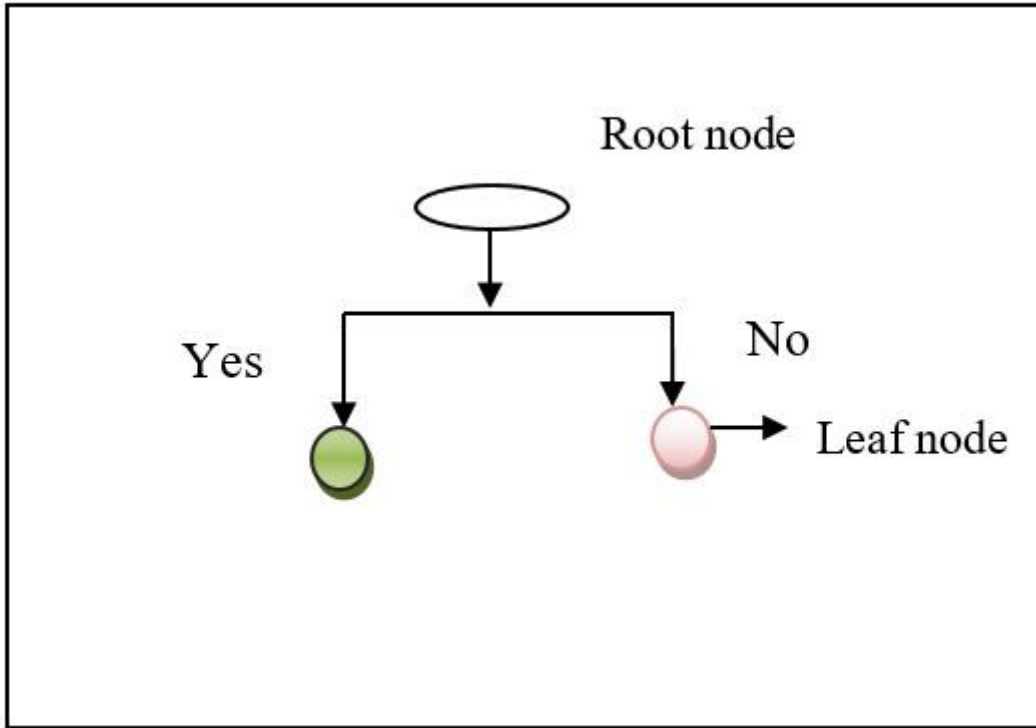architecture of the BFDSBA model

Figure 4

block diagram of Bootstrap aggregating

Figure 5
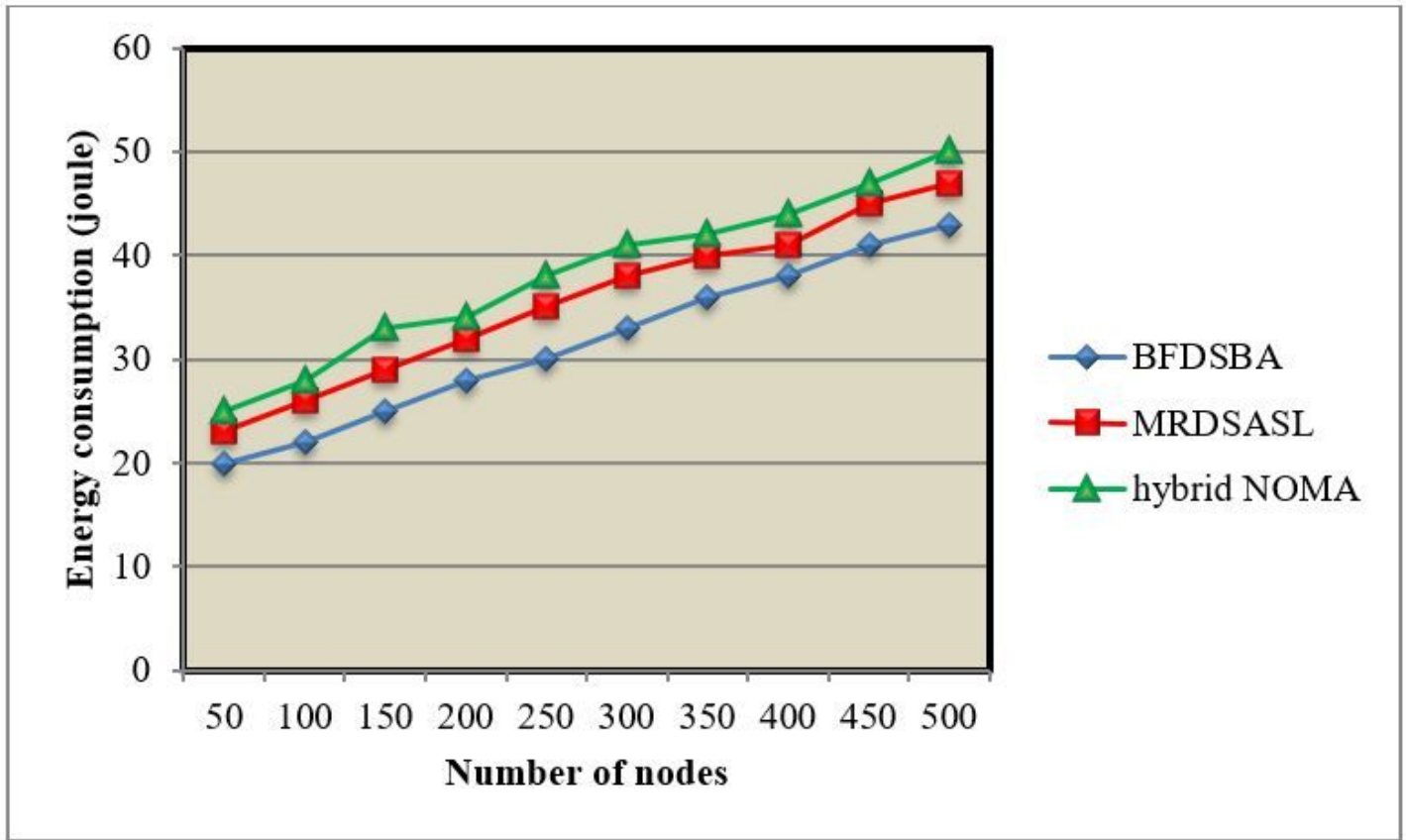
Bivalence Fuzzified Decision Stump based classification

Figure 6
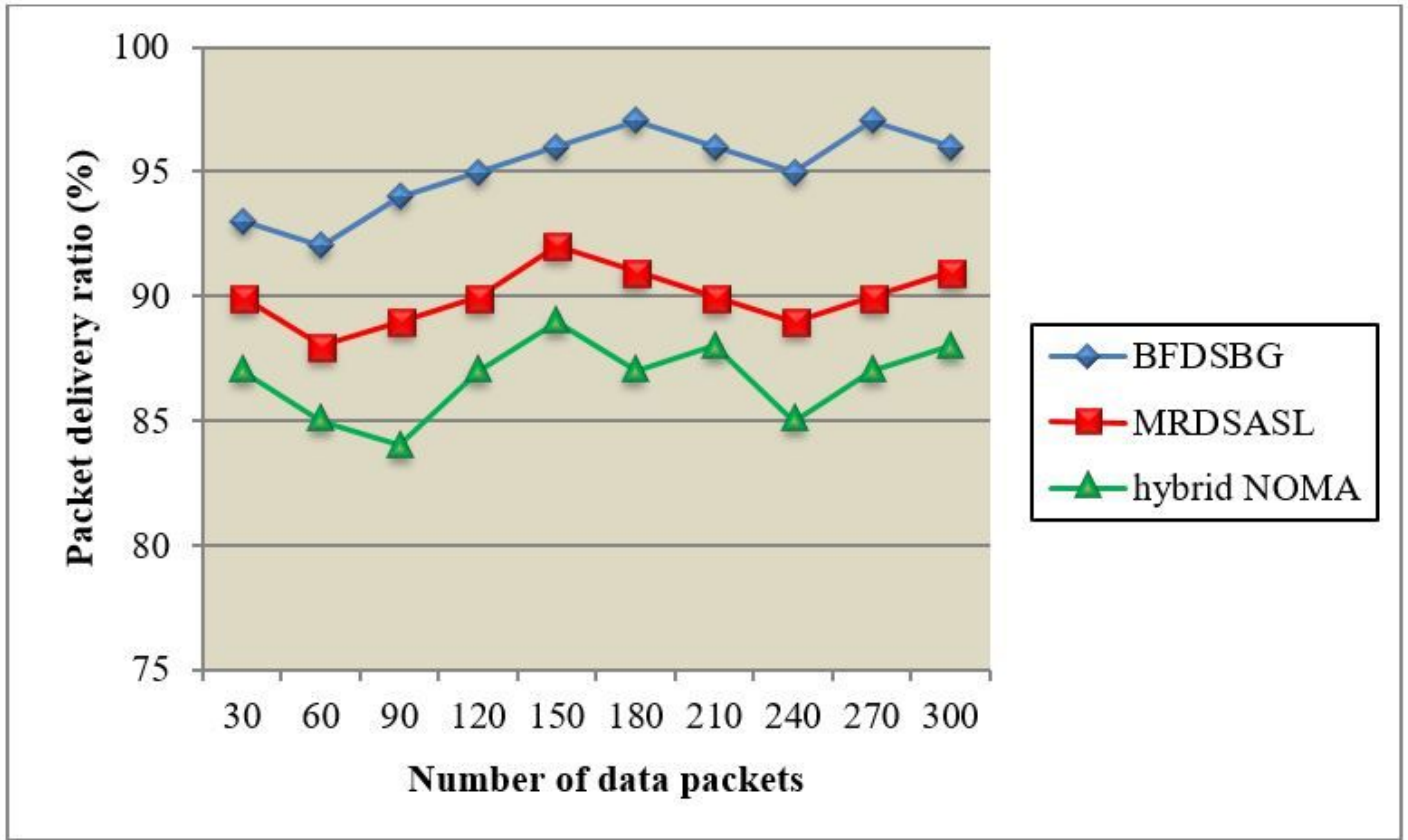
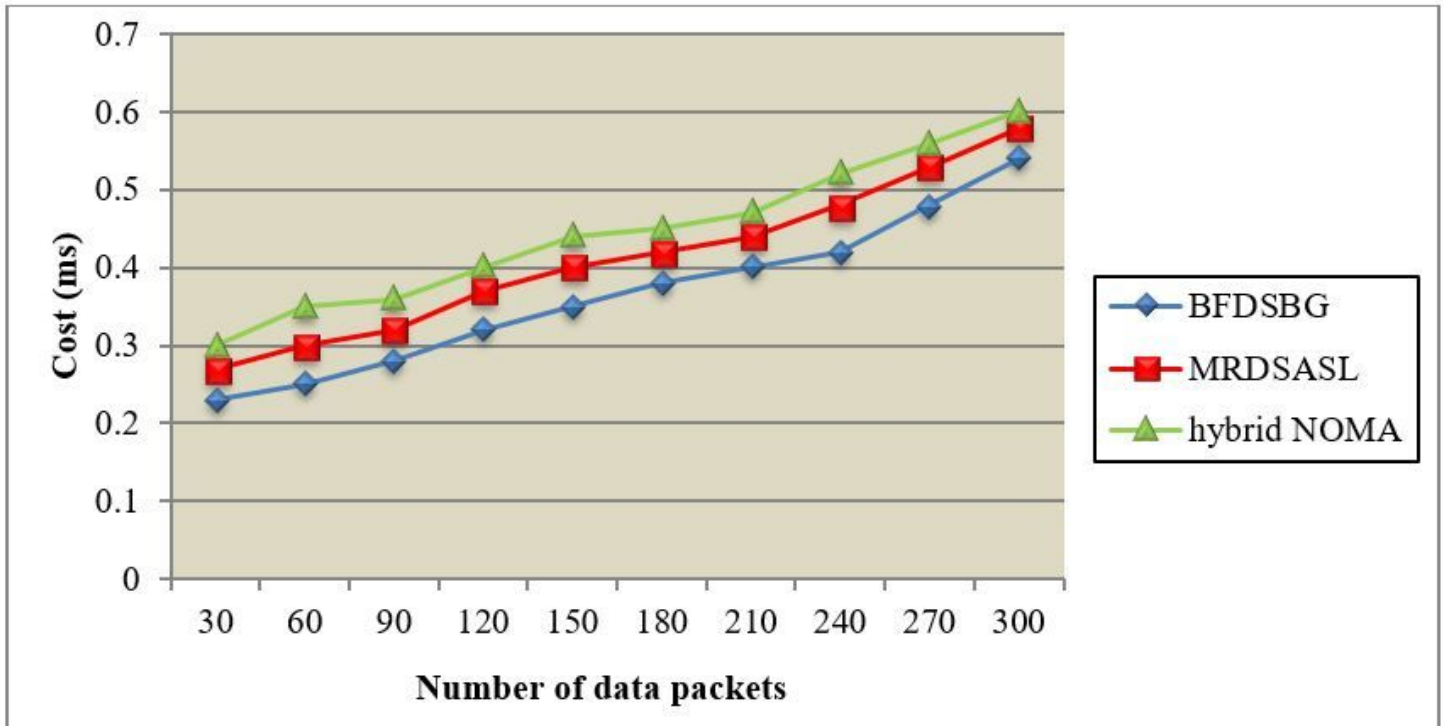numbers of nodes versus energy consumption

Figure 7

numbers of nodes versus packet delivery ratio

Figure 8

numbers of data packets versus Cost