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HBSBA: Design of a Hybrid Bio-Swarm model for enhancing Blockchain miner performance through resource Augmentation techniques

Ms. Mona Mulchandani

Research Scholar, Computer Science & Engineering, Medi-caps University,
Indore, MP, India
mona.mulchandani@gmail.com

Dr. Pramod S. Nair

Professor & Head,Computer Science & Engineering, Medi-caps University,
Indore, MP, India
pramods.nair@medicaps.ac.in

Abstract

Blockchain mining is a power &resource consuming task, which requires multiple-levels of optimization, both at resource &task level. Over the years, a wide variety of mining optimization models are proposed by researchers, but most of them are applicable only to a subset of mining types. For instance, mining models used for Proof-of-Work (PoW) consensus-based mining, are not applicable for Delegated Proof-of-Stake (DPoS), and other consensus types. This limits the scalability of these models, which reduces their adoptability for dynamic blockchain systems (DBSes). These DBSes utilize different consensus models as per context of data storage, and are widely used by blockchain designers to deploy high-efficiency, and low delay storage solutions. A standard mining optimization solution is not available for such scenarios, due to which researchers & system designers opt for deployment-specific optimizations, which need to be redesigned for each blockchain system. To remove this drawback, a standard blockchain mining optimization model is proposed in this text. This model uses a combination of Genetic Algorithm (GA) & Particle Swarm Optimization (PSO) for solving two different issues. The GA model is used to optimize miner set selection, which will be used for consensus, while the PSO model optimizes the responses from these miner sets depending upon their temporal mining performance. Due to optimum miner set selection, only higher efficiency miner nodes are used for mining the blockchain. While due to performance optimization of these miner nodes, their internal mining efficiency is improved.This efficiency is evaluated in terms of delay & power needed for single block mining w.r.t. blockchain length. It was observed that a combination of these models is capable of enhancing mining speed, with reduced power consumption, and higher mining throughput. Due to this improvement the proposed HBSBA model outperforms most of the recently proposed blockchain mining models. The model was evaluated on DPoS, Proof-of-Authority (PoA), Proof-of-Stake (PoS), and PoW based consensus models, and a delay reduction of 14.5%, throughput improvement of 8.3%, and reduction in energy consumption by 4.6% when compared with various state-of-the-art models. Due to this improvement, the proposed model is applicable for a wide variety of medium to large scaled blockchain mining applications.

***Keywords*: Blockchain, Mining, Time, Cost, Speed, Scalability, Consensus.**

1. Introduction

Designing a blockchain-based storage model requires drafting of block structure, consensus modelling, hash rules, blockchain visibility rules, etc. A typical blockchain storage model is depicted in figure 1, wherein identification of storage goals, platform selection, ideation of blockchain, minimum viable product (MVP) design, technical design & testing, development, deployment and upgrade phases can be observed. During the initial design phase, finalization of block structure, its consensus type, and miner selection models are decided. These decisions are based on identification of blockchain platform, which can either be public, private or consortium, depending upon visibility of the chain [1]. Once these parameters are finalized, then internal design processes are deployed, which assist in modelling of consensus rules, splitting of central chain into multiple sidechains, etc. Combination of these models form an initial MVP blockchain, which is scaled via development & design processes.

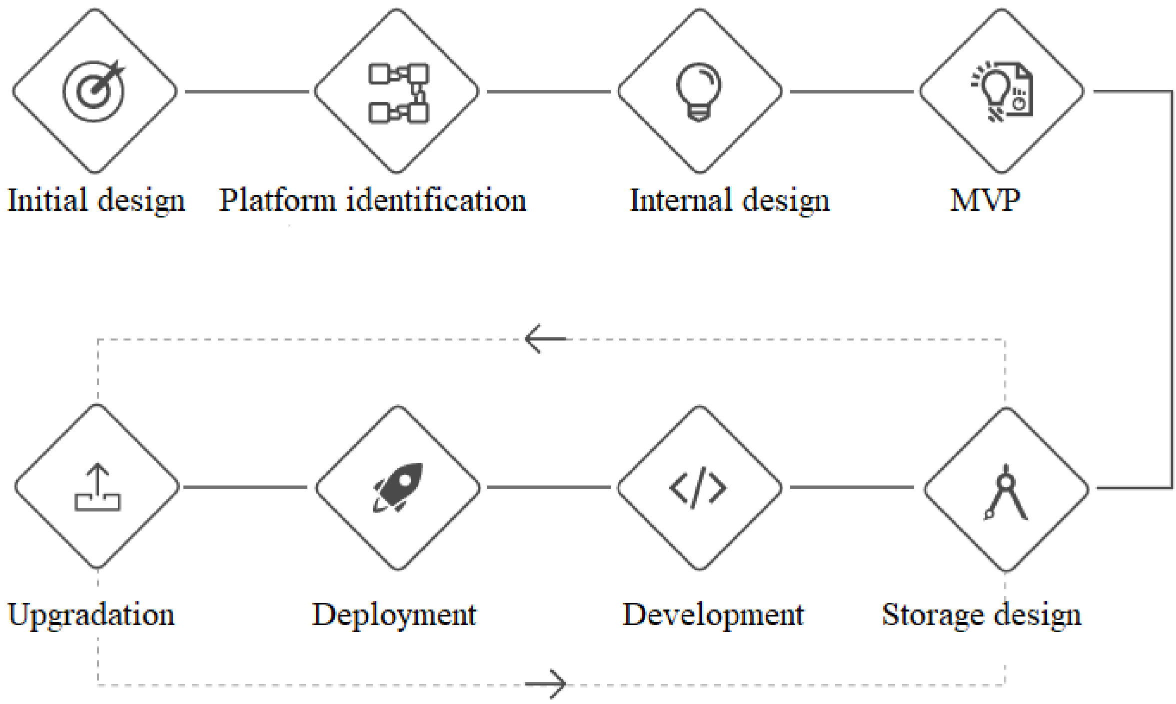

Fig 1. Typical design process for blockchain storage models

Once these processes are tuned, and performance validation is completed, then the blockchainis deployed for real-time data storage, and upgraded as per model’s design requirements. Out of these blocks, the ‘*initial design block’* is of primary importance, because it decides block structure, and consensus parameters [2]. Various approaches are proposed by researchers for improving efficiency of this block, and each of them varies in terms of computational complexity, scalability, internal structure design, performance metrics, etc. Survey of these approaches is discussed in the next section, which assists in identification of most optimum consensus models for different blockchain applications. Based on this review, it is observed that very few approaches are proposed for improving blockchain mining performance, because most of the mining models are non-standardized. To overcome this drawback, section 3 proposes design of a hybrid bio-swarm model for enhancing blockchain miner performance via resource augmentation techniques. Performance of this model was evaluated in section 4, and was compared with various state-of-the-art approaches w.r.t. mining delay, efficiency of resource utilization, energy requirement, and throughput. Based on this performance it was observed that the proposed model had lower delay, lower energy requirement, & better throughput when compared with state-of-the-art approaches, which assists in enhancing its deployment capabilities. Finally, this text concludes with some interesting observations about the proposed miner performance optimization model, and recommends various methods to improve its performance.

2. Literature Review

A wide variety of blockchain miner selection models are proposed by researchers, and each of these models vary in terms of mining efficiency metrics including delay, energy needed for mining, throughput, etc. For instance, work in [3, 4, 5, 6] proposes use of reputation-based Miner Node selection (RMN), honesty-based Miner Node selection, PoS based on-chain time synchronization, and auction approach for Miner Node selection (AAMN), which assist in improving efficiency of application-specific blockchains. To improve scalability of these models, work in [7] proposes intelligent Mining pool selection approach, that can work under different types of attacks. This approach is useful when a large number of VMs are available for mining, and their grouping is needed under attack-based scenarios. Similar Models are proposed in [8, 9, 10], wherein PoW based Mining pool selection, machine learning for Mining pool selection, and evaluation of incentivizing Miners for Mining are proposed. These models aim at selection of the best Miners from a given pool, which assists in reducing delay of mining, and enhancing mining throughput.

Approaches that use smart contracts-based random Oracles [11], blockchain Mining based on drones [12], software defined networks (SDNs) for optimization of Mining performance [13], and deep learning based honestly evaluation (DLH) [14] are discussed by researchers. These models aim at optimizing miner selection process via reducing redundant miner nodes that have lower capacities, and low availability then other nodes. Based on these approaches work in [15, 16, 17, 18] propose use of reputation &contract theory, privacy-preserving Reputation schemes, dynamic selection of Mining pools via Reward sharing strategies, and distributed transaction validation for high-throughput, and low delay consensus designs. These models utilize miner level optimizations to reduce dependency during mining process. Similarly, work in [19, 20, 21, 22] propose non patience models, Game theory based pooling models, deep Reinforcement learning models, and Adaptive Broadcast Routing Assignment for improving efficiency of miner node selection & control. These models aim at improving capacity of miners via parametric augmentation, but can be applied to only a fixed type of consensus applications, which limits their scalability. To improve this scalability, next section proposes design of ahybrid bio-swarm model for enhancing blockchain miner performance via resource augmentation techniques, and evaluates its performance w.r.t. various state-of-the art approaches.

3. Design of the proposed hybrid bio-swarm model for enhancing blockchain miner performance via resource augmentation techniques

Based on the literature survey, it can be observed that very few approaches have been proposed by researchers for blockchain mining optimization & enhancement of miner performance. This is because consensus models have highly irregular designs, which limits their performance &scalability when applied to larger blockchains. To standardize this performance, a Novel GA model is used to optimize miner set selection, and is combined with a PSO model that optimizes responses from these miner sets based upon their temporal mining performance.

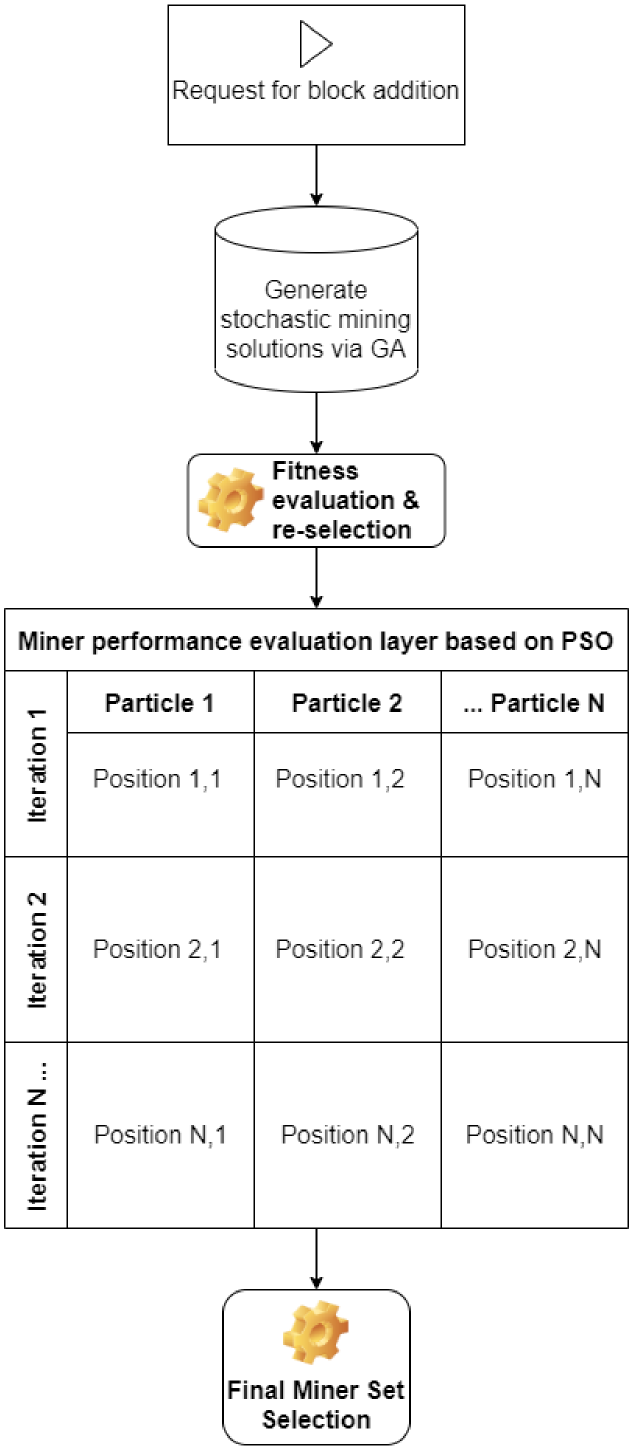

Fig 2. Overall flow of the proposed model

Overall flow of the proposed miner optimization model is depicted in figure 2, wherein combination of PSO & GA can be observed.From this flow, it can be observed that initially requests for block addition are input to the system model, which activates a GA based miner resource selection layer. This layer assists in identification of most optimum resource configuration of miners, that is required to mine the underlying blockchain type. These miners are re-visited via a miner performance evaluation layer based on PSO, that assists in identification of the most optimum miners that can perform underlying consensus with high efficiency, and low overheads. Based on this selection, a final miner set is generated, which can be used for mining blocks with high performance. Design of the complete model is divided into sub-tasks, and each of these tasks are discussed in different sub-sections of this text. Researchers can implement these tasks in part(s) or as a whole depending upon their model requirements.

3.1. Design of the GA model for miner performance optimization

The GA model is used to optimize miner performance, which assists in identification of miner parameters to reduce delay needed for consensus. Each mining node is evaluated in terms of its capacity, delay needed for mining one block, and user preferences. This capacity is maximized via the following process,

- Initialize GA parameters,
  - Number of iterations (N_i)
  - Number of solutions (N_s)
  - Learning rate (L_r)
  - Number of resources per miner (N_r)
  - Number of computational cycles needed for mining a block (N_c)
  - Maximum number of dummy blocks to be mined (Max_B)
- Initially mark all solutions as 'to be mutated'
- For each iteration in 1 to N_i
  - For each solution in 1 to N_s
    - If the solution is marked as 'not to be mutated', then go to the next solution.
    - Else, generate a new solution via the following process,
      - Select random miner resources ($M_{resources}$) via equation 1,

$$M_{resources} = Random(1, N_r) \dots (1)$$

      - Select random number of dummy blocks to for mining via equation 2,

$$Blocks_{dummy} = Random(1, Max_B) \dots (2)$$

      - Evaluate capacity of miner node via equation 3,

$$Cap(Miner) = \left[\sum_{i=1}^{M_{resources}} \frac{PE_i}{Max(PE)} + \frac{RAM_i}{Max(RAM)} + \frac{BW_i}{Max(BW)} + \frac{MIPS_i}{Max(MIPS)}\right] * \frac{Blocks_{dummy}}{Max_B} \dots (3)$$

Where, $PE, RAM, BW, \& MIPS$ represents number of processing elements, RAM Memory, bandwidth, and capacity of VM in terms of millions of instructions per second respectively.

      - Evaluate the number of cycles needed to mine the blocks via equation 4,

$$N_c = \frac{\sum_{i=1}^{Blocks_{dummy}} [D_{read_i} + D_{write_i} + D_{hash_i} + D_{validate_i}]}{4 * Max(Delay)} \dots (4)$$

Where, $D_{read}, D_{write}, D_{hash}, and D_{validate}$ represents delays to read the block, write the block, hash the block, and validate the block in the blockchain. To normalize these delays, they are quantized with maximum delay needed for mining each block.

      - Blocks that require lowest cycles are mined with higher priority, while blocks that require larger cycles are mined with lower priority.
      - To perform this task, blocks with higher N_c values are assigned to miners with lower values of $Cap(Miner)$
      - Based on this assignment, solution fitness is evaluated via equation 5,

$$f_i = \frac{\sum_{i=1}^{Blocks_{dummy}} D(mining)}{Blocks_{dummy}^2} * Max_B \dots (5)$$

Where, $D(mining)$ represents delay of mining the blocks.

    - Fitness for all solutions is evaluated, and a fitness threshold is evaluated via equation 6 as follows,

$$f_{th} = \sum_{i=1}^{N_S} f_i * \frac{L_r}{N_s} \dots (6)$$

- Solutions with fitness lower than f_{th} are marked as 'not to be mutated', while others are marked as 'to be mutated'
- Repeat this process for all iterations, and select the solution with lowest value of fitness.

The selected solution with consist of internal configuration of miners which must be used for effective blockchain mining purposes. These configurations are given to a PSO model for selection of the best miners to perform consensus, based on their temporal mining performance. Design of this PSO model is described in the next sub-section of this text.

3.2. Design of the PSO model for miner selection

Once configuration of miners is selected, then each miner is evaluated via a PSO model.This model uses their temporal mining performance to identify best miners suited for the current mining scenario. This PSO model works using the following process,

- Initialize PSO parameters,
  - Number of particles (N_p)
  - Cognitive learning rate (L_c)
  - Social learning rate (L_s)
  - Number of iterations N_i
- Initialize each particle randomly, where each particle consists of a group of miner nodes, which were evaluated from section 3.1.
- For each iteration in 1 to N_i
  - Find velocity of each solution via equation 7,

$$V_i = \frac{\sum_{j=1}^{N(miners)} \sum_{l=1}^{N_{blocks}} D(mining)_l}{N(miners)_i} \dots (7)$$

Where, N_{blocks}, and D(mining) represents number of blocks currently mined by the miner, and delay needed for mining these blocks.

  - Find global best miner position via equation 8,

$$G_{best} = Min\left(\bigvee_{i=1}^{N_p} V_i\right) \dots (8)$$

  - Update velocity of current solution via equation 9,

$$New_v = Old_v * r + L_c[Old_v - Best_v] + L_s[Old_v - G_{best}] \dots (9)$$

  - Where, Old_v, $Best_v$, and r represents old velocity, current best velocity of the particle, and a random number used to make the process stochastic.
  - Based on this new value of velocity, add or remove miners from current solution.
  - Repeat this process for all solutions, and identify solution with minimum velocity to perform final mining process
  - Using this model, particle with minimum velocity is selected, which assists in selection of a group of miners with low consensus delays, and better temporal performance. Based on this miner selection, various types of blockchainswere mined, and their performance was evaluated in the next section. This performance was compared with various state-of-the-art methods, and evaluated in terms of mining delay, energy requirement, and mining throughput for DPoS, PoA, PoS, and PoW based consensus models.

4. Result evaluation & comparison

The proposed HBSBA model uses a combination of GA & PSO for effective blockchain miner resource utilization& selection based on their temporal mining performance. To evaluate parametric performance of the proposed model, Crypto Mining dataset from Google Cloud (https://cloud.google.com/blog/products/data-analytics/introducing-six-new-cryptocurrencies-in-bigquery-public-datasets-and-how-to-analyze-them), Kaggle (https://www.kaggle.com/amritpal333/crypto-mining-data), and Data Word repository (https://data.world/cnoza/cryptocurrencies), were used. These datasets were combined to form 1 million cryptocurrency transactions, out of which 70% were used for training the GA & PSO model, while the remaining 30% were used for model evaluation. Based on this strategy, average mining delay (D), energy consumed during mining (E), & mining throughput in blocks mined per second (T) were evaluated, and compared with the mining optimization models proposed in RMN [3], AAMN [6], and DLH [14]. Evaluation of mining delay is tabulated w.r.t. number of blocks used for mining (NBM) in table 1, wherein DPoS consensus model was used.

NBM	**D (s) RMN [3]**	**D (s) AAMN [6]**	**D (s) DLH [14]**	**D (s) HBS BA**
10k	1.50	1.40	1.93	1.38
20k	2.60	2.20	3.20	2.29
30k	4.90	2.90	5.20	3.71
40k	9.25	4.10	8.90	6.36
50k	15.60	5.20	13.87	9.90
60k	19.90	15.90	23.87	17.05
70k	25.80	29.30	34.44	25.58
80k	33.90	46.50	50.25	37.33
90k	46.20	39.76	53.72	39.91
120k	44.83	45.61	56.53	41.99
140k	50.25	51.45	63.57	47.22
160k	55.67	57.30	70.61	52.45
180k	61.09	63.15	77.65	57.68
200k	66.51	69.00	84.70	62.92
220k	71.93	74.85	86.34	66.61
240k	77.35	80.70	92.97	71.72
260k	82.77	86.55	99.60	76.83
275k	88.19	92.40	106.23	81.95
290k	93.61	98.25	112.85	87.06
300k	99.03	104.09	119.48	92.17

Table 1. Average mining delay for DPoS consensus w.r.t. number of blocks in the blockchain

From this evaluation, it can be observed that the proposed model is 10% faster than RMN [3], 14% faster than AAMN [6], and 18% faster than DLH [14] for DPoS based consensus. This is because of optimum miner selection, and improving the mapping efficiency of capacity to blockchain mining resource requirements. Similarly, average mining delay taken for PoS, PoW, and PoA based consensus models was evaluated, and can be observed from table 2 as follows,

NBM	**D (s) RMN [3]**	**D (s) AAMN [6]**	**D (s) DLH [14]**	**D (s) HBS BA**
10k	2.05	1.80	2.57	1.83
20k	3.75	2.55	4.20	3.00
30k	7.08	3.50	7.05	5.04
40k	12.43	4.65	11.38	8.13
50k	17.75	10.55	18.87	13.48
60k	22.85	22.60	29.15	21.31
70k	29.85	37.90	42.34	31.46
80k	40.05	43.13	51.99	38.62
90k	45.52	42.68	55.12	40.95
120k	47.54	48.53	60.05	44.61
140k	52.96	54.38	67.09	49.84
160k	58.38	60.23	74.13	55.07
180k	63.80	66.08	81.17	60.30
200k	69.22	71.93	85.52	64.76
220k	74.64	77.77	89.66	69.16
240k	80.06	83.62	96.28	74.28
260k	85.48	89.47	102.91	79.39
275k	90.90	95.32	109.54	84.50
290k	96.32	101.17	116.17	89.62
300k	101.74	107.02	131.20	97.13

Table 2. Average mining delay for PoS, PoA, and PoW consensus w.r.t. number of blocks in the blockchain

From this evaluation, it can be observed that the proposed model is 8% faster than RMN [3], 10% faster than AAMN [6], and 15% faster than DLH [14] for PoS, PoA and PoW based consensus. This is because of optimum miner selection, and improving the mapping efficiency of capacity to blockchain mining resource requirements. Similarly, evaluation of energy needed for mining is tabulated w.r.t. number of blocks used for mining (NBM) in table 3, wherein DPoS consensus model was used.

NBM	E (mJ) RMN [3]	E (mJ) AAMN [6]	E (mJ) DLH [14]	E (mJ) HBS BA
10k	0.75	0.70	0.97	0.65
20k	1.30	1.10	1.60	1.14
30k	2.45	1.45	2.60	1.86
40k	4.63	2.05	4.45	3.18
50k	7.80	2.60	6.93	4.95
60k	9.95	7.95	11.93	8.52
70k	12.90	14.65	17.22	12.79
80k	16.95	23.25	25.13	18.66
90k	23.10	19.88	26.86	19.95
120k	22.42	22.80	28.26	21.00
140k	25.13	25.73	31.78	23.61
160k	27.84	28.65	35.31	26.23
180k	30.55	31.58	38.83	28.84
200k	33.26	34.50	42.35	31.46
220k	35.97	37.43	43.17	33.30
240k	38.67	40.35	46.48	35.86
260k	41.38	43.27	49.80	38.42
275k	44.09	46.20	53.11	40.97
290k	46.80	49.12	56.43	43.53
300k	49.51	52.05	59.74	46.09

Table 3. Average mining energy needed by DPoS consensus w.r.t. number of blocks in the blockchain

From this evaluation, it can be observed that the proposed model has5% lower energy consumption than RMN [3], 10.5% lower energy consumption than AAMN [6], and 16.5% lower energy consumption than DLH [14] for DPoS based consensus. This is because of optimum miner selection, and improving the mapping efficiency of capacity to blockchain mining resource requirements. Similarly, average mining energy needed for PoS, PoW, and PoA based consensus models was evaluated, and can be observed from table 4 as follows,

NBM	**E (mJ) RMN [3]**	**E (mJ) AAMN [6]**	**E (mJ) DLH [14]**	**E (mJ) HBS BA**
10k	1.03	0.90	1.28	0.90
20k	1.88	1.28	2.10	1.50
30k	3.54	1.75	3.53	2.52
40k	6.21	2.33	5.69	4.07
50k	8.88	5.28	9.43	6.74
60k	11.43	11.30	14.58	10.66
70k	14.93	18.95	21.17	15.73
80k	20.03	21.56	25.99	19.31
90k	22.76	21.34	27.56	20.47
120k	23.77	24.27	30.02	22.30
140k	26.48	27.19	33.54	24.92
160k	29.19	30.11	37.07	27.53
180k	31.90	33.04	40.59	30.15
200k	34.61	35.96	42.76	32.38
220k	37.32	38.89	44.83	34.58
240k	40.03	41.81	48.14	37.14
260k	42.74	44.74	51.46	39.69
275k	45.45	47.66	54.77	42.25
290k	48.16	50.58	58.08	44.81
300k	50.87	53.51	65.60	48.57

Table 4. Average mining energy needed for PoS, PoA, and PoW consensus w.r.t. number of blocks in the blockchain

From this evaluation, it can be observed that the proposed model has 6% lower energy consumption than RMN [3], 9.4% lower energy consumption than AAMN [6], and 15.5% lower energy consumption than DLH [14] for PoS, PoW, and PoA based consensus. Similarly, evaluation of average throughput in blocks mined per minute is tabulated w.r.t. number of blocks used for mining (NBM) in table 5, wherein DPoS consensus model was used.

NBM	T (bpm) RMN [3]	T (bpm) AAMN [6]	T (bpm) DLH [14]	T (bpm) HBS BA
10k	40.00	42.86	31.03	43.45
20k	23.08	27.27	18.75	26.25
30k	12.24	20.69	11.54	16.15
40k	6.49	14.63	6.74	9.44
50k	3.85	11.54	4.33	6.06
60k	3.02	3.77	2.51	3.52
70k	2.33	2.05	1.74	2.35
80k	1.77	1.29	1.19	1.61
90k	1.30	1.51	1.12	1.50
120k	1.34	1.32	1.06	1.43
140k	1.19	1.17	0.94	1.27
160k	1.08	1.05	0.85	1.14
180k	0.98	0.95	0.77	1.04
200k	0.90	0.87	0.71	0.95
220k	0.83	0.80	0.69	0.90
240k	0.78	0.74	0.65	0.84
260k	0.72	0.69	0.60	0.78
275k	0.68	0.65	0.56	0.73
290k	0.64	0.61	0.53	0.69
300k	0.61	0.58	0.50	0.65

Table 5. Average throughput for DPoS consensus w.r.t. number of blocks in the blockchain

From this evaluation, it can be observed that the proposed model is 9% better throughput than RMN [3], 15% better throughput than AAMN [6], and 16.5% better throughput than DLH [14] for DPoS based consensus. This is because of optimum miner selection, and improving the mapping efficiency of capacity to blockchain mining resource requirements. Similarly, average throughput for PoS, PoW, and PoA based consensus models was evaluated, and can be observed from table 4 as follows,

NBM	**T (bpm) RMN [3]**	**T (bpm) AAMN [6]**	**T (bpm) DLH [14]**	**T (bpm) HBS BA**
10k	29.27	33.33	23.38	32.73
20k	16.00	23.53	14.29	20.00
30k	8.48	17.14	8.51	11.91
40k	4.83	12.90	5.27	7.38
50k	3.38	5.69	3.18	4.45
60k	2.63	2.65	2.06	2.81
70k	2.01	1.58	1.42	1.91
80k	1.50	1.39	1.15	1.55
90k	1.32	1.41	1.09	1.47
120k	1.26	1.24	1.00	1.35
140k	1.13	1.10	0.89	1.20
160k	1.03	1.00	0.81	1.09
180k	0.94	0.91	0.74	1.00
200k	0.87	0.83	0.70	0.93
220k	0.80	0.77	0.67	0.87
240k	0.75	0.72	0.62	0.81
260k	0.70	0.67	0.58	0.76
275k	0.66	0.63	0.55	0.71
290k	0.62	0.59	0.52	0.67
300k	0.59	0.56	0.46	0.62

Table 6. Average throughput for PoS, PoA, and PoW consensus w.r.t. number of blocks in the blockchain

From this evaluation, it can be observed that the proposed model is 4.9% better throughput than RMN [3], 6.5% better throughput than AAMN [6], and 10.5% better throughput than DLH [14] for PoA, PoW, and PoS based consensus. Due to these improvements, the proposed model showcases high scalability, and better mining performance. This ensures that the model is applicable for high-speed, low energy, and high throughput application scenarios.

5. Conclusion and future scope

The proposed HBSBA model uses a combination of GA & PSO based approaches for high-throughput, low delay, and low-energy mining operations. This is because of the incorporation of average mining delay during miner node grouping, and internal resource selection processes. The model was tested on various consensus methods, and it was observed that HBSBA outperformed RMN [3], AAMN [6], and DLH [14] models in terms of mining delay, throughput, and energy requirement parameters. The proposed model was observed to be 9.4% faster than RMN [3], 10.5% faster than AAMN [6], and 14.6% faster than DLH [14], while the proposed model had6.5% lower energy consumption than RMN [3], 8.9% lower energy consumption than AAMN [6], and 14.1% lower energy consumption than DLH [14]when averaged forDPoS, PoS, PoW, and PoA based consensus. Due to this improvement in performance, the proposed model is useful for a wide variety of high-speed, and low-energy blockchain storage applications. In future, researchers can further optimize model's performance via use of deep learning for miner node selection, and incorporation of other QoS parameters like computational complexity, resource utilization, and fault tolerance during the mining process. Furthermore, researchers can also explore utilization of Q-learning based approaches, which will assist in application of reward-based miner selection, to achieve better mining performance under different network scenarios.

References

[1] S. Dos Santos, C. Chukwuocha, S. Kamali and R. K. Thulasiram, "An Efficient Miner Strategy for Selecting Cryptocurrency Transactions," 2019 IEEE International Conference on Blockchain (Blockchain), 2019, pp. 116-123, doi: 10.1109/Blockchain.2019.00024.

[2] K. Wang and H. S. Kim, "FastChain: Scaling Blockchain System with Informed Neighbor Selection," 2019 IEEE International Conference on Blockchain (Blockchain), 2019, pp. 376-383, doi: 10.1109/Blockchain.2019.00058.

[3] S. R. Maskey, S. Badsha, S. Sengupta and I. Khalil, "Reputation-Based Miner Node Selection in Blockchain-Based Vehicular Edge Computing," in IEEE Consumer Electronics Magazine, vol. 10, no. 5, pp. 14-22, 1 Sept. 2021, doi: 10.1109/MCE.2020.3048312.

[4] I. Makhdoom, F. Tofigh, I. Zhou, M. Abolhasan and J. Lipman, "PLEDGE: A Proof-of-Honesty based Consensus Protocol for Blockchain-based IoT Systems," 2020 IEEE International Conference on Blockchain and Cryptocurrency (ICBC), 2020, pp. 1-3, doi: 10.1109/ICBC48266.2020.9169406.

[5] A. Hartl, T. Zseby and J. Fabini, "BeaconBlocks: Augmenting Proof-of-Stake with On-Chain Time Synchronization," 2019 IEEE International Conference on Blockchain (Blockchain), 2019, pp. 353-360, doi: 10.1109/Blockchain.2019.00055.

[6] A. Devi, G. Rathee and H. Saini, "Using Optimization and Auction Approach: Security provided to Vehicle network through Blockchain Technology," 2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC), 2020, pp. 476-480, doi: 10.1109/PDGC50313.2020.9315804.

[7] K. Fujita, Y. Zhang, M. Sasabe and S. Kasahara, "Intelligent Mining Pool Selection in the Case of Unobservable Block Withholding Attack," 2021 IEEE International Conference on Blockchain and Cryptocurrency (ICBC), 2021, pp. 1-4, doi: 10.1109/ICBC51069.2021.9461125.

[8] K. Fujita, Y. Zhang, M. Sasabe and S. Kasahara, "Mining Pool Selection Problem in the Presence of Block Withholding Attack," 2020 IEEE International Conference on Blockchain (Blockchain), 2020, pp. 321-326, doi: 10.1109/Blockchain50366.2020.00047.

[9] R. Qin, Y. Yuan and F. -Y. Wang, "Research on the Selection Strategies of Blockchain Mining Pools," in IEEE Transactions on Computational Social Systems, vol. 5, no. 3, pp. 748-757, Sept. 2018, doi: 10.1109/TCSS.2018.2861423.

[10] B. G. Gebraselase, B. E. Helvik and Y. Jiang, "Effect of Miner Incentive on the Confirmation Time of Bitcoin Transactions," 2021 IEEE International Conference on Blockchain (Blockchain), 2021, pp. 521-529, doi: 10.1109/Blockchain53845.2021.00079.

[11] N. S. Patel, P. Bhattacharya, S. B. Patel, S. Tanwar, N. Kumar and H. Song, "Blockchain-Envisioned Trusted Random Oracles for IoT-Enabled Probabilistic Smart Contracts," in IEEE Internet of Things Journal, vol. 8, no. 19, pp. 14797-14809, 1 Oct.1, 2021, doi: 10.1109/JIOT.2021.3072293.

[12] J. Kang, Z. Xiong, D. Niyato, S. Xie and D. I. Kim, "Securing Data Sharing from the Sky: Integrating Blockchains into Drones in 5G and Beyond," in IEEE Network, vol. 35, no. 1, pp. 78-85, January/February 2021, doi: 10.1109/MNET.011.2000183.

[13] Y. Yahiatene and A. Rachedi, "Towards a Blockchain and Software-Defined Vehicular Networks Approaches to Secure Vehicular Social Network," 2018 IEEE Conference on Standards for Communications and Networking (CSCN), 2018, pp. 1-7, doi: 10.1109/CSCN.2018.8581756.

[14] Rakkini, M.J.J., Geetha, K. Deep learning classification of bitcoin miners and exploration of upper confidence bound algorithm with less regret for the selection of honest mining. *J Ambient Intell Human Comput* (2021). https://doi.org/10.1007/s12652-021-03527-9.

[15] J. Kang, Z. Xiong, D. Niyato, D. Ye, D. I. Kim and J. Zhao, "Toward Secure Blockchain-Enabled Internet of Vehicles: Optimizing Consensus Management Using Reputation and Contract Theory," in IEEE Transactions on Vehicular Technology, vol. 68, no. 3, pp. 2906-2920, March 2019, doi: 10.1109/TVT.2019.2894944.

[16] Z. Geng, Y. He, C. Wang, G. Xu, K. Xiao and S. Yu, "A Blockchain based Privacy-Preserving Reputation Scheme for Cloud Service," ICC 2021 - IEEE International Conference on Communications, 2021, pp. 1-6, doi: 10.1109/ICC42927.2021.9500841.

[17] C. Xu, K. Zhu, R. Wang and Y. Xu, "Dynamic Selection of Mining Pool with Different Reward Sharing Strategy in Blockchain Networks," ICC 2020 - 2020 IEEE International Conference on Communications (ICC), 2020, pp. 1-6, doi: 10.1109/ICC40277.2020.9149279.

[18] A. S. M. S. Hosen et al., "Blockchain-Based Transaction Validation Protocol for a Secure Distributed IoT Network," in IEEE Access, vol. 8, pp. 117266-117277, 2020, doi: 10.1109/ACCESS.2020.3004486.

[19] H. Shi, S. Wang and Y. Xiao, "Queuing Without Patience: A Novel Transaction Selection Mechanism in Blockchain for IoT Enhancement," in IEEE Internet of Things Journal, vol. 7, no. 9, pp. 7941-7948, Sept. 2020, doi: 10.1109/JIOT.2020.2996614.

[20] X. Liu, W. Wang, D. Niyato, N. Zhao and P. Wang, "Evolutionary Game for Mining Pool Selection in Blockchain Networks," in IEEE Wireless Communications Letters, vol. 7, no. 5, pp. 760-763, Oct. 2018, doi: 10.1109/LWC.2018.2820009.

[21] N. C. Luong, T. T. Anh, H. T. ThanhBinh, D. Niyato, D. I. Kim and Y. -C. Liang, "Joint Transaction Transmission and Channel Selection in Cognitive Radio Based Blockchain Networks: A Deep Reinforcement Learning Approach," ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 8409-8413, doi: 10.1109/ICASSP.2019.8683228.

[22] F. Y. -S. Lin, C. -H. Hsiao, Y. -F. Wen and Y. -C. Su, "Adaptive Broadcast Routing Assignment Algorithm for Blockchain Synchronization Services," 2018 Tenth International Conference on Ubiquitous and Future Networks (ICUFN), 2018, pp. 487-492, doi: 10.1109/ICUFN.2018.8436814.

Authors Profile

Ms. Mona Mulchandani,is currently working as HOD, Computer Science and Engineering, at Jhulelal Institute of Technology, Nagpur-India having 18 years of Experience in teaching. His research areas include Blockchain, Machine learning, and programming.

Dr Pramod S. Nair, is currently working as Professor & Head, Computer Sicence and Engineering, at Medi –Caps University Indore-India. He had received B. Tech, M. Tech and Ph.D in Computer Science. His research spanned over Business Intelligence, Data Mining, Machine Learning, Big Data, Computer Networks, Data Science, Artificial Intelligence and IoT. He has the right blend of 23 years of Experience spanned across industry and academia. Published many papers in peer reviewed journals.