FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 9 No. 12, December (Special Issue), 2025, pp 86 – 93
DOI: https://doi.org/10.33003/fjs-2025-0912-4085

DEMAND RESPONSE MANAGEMENT FOR SMART GRID USING HYBRID TRUST MODEL BASED ON BLOCKCHAIN

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ABSTRACT

Blockchain technology improves smart grid demand response by enhancing the security and efficiency of energy trading, especially for distributed resources such as electric vehicles, thereby enabling more reliable and effective management of energy transactions across different and decentralized networks. Existing models face challenges such as high computational overhead, inconsistent block creation times, and vulnerabilities to malicious entities, which hinder practical implementation. This study develops a hybrid trust model integrating attribute-based authentication and reputation-based trust within a blockchain framework to optimize performance and security for real-time smart grid operations. A simulation involving 190 entities (10 industries, 50 residences, 30 buildings, and 100 electric vehicles) with over 1000 transactions was conducted using a Python script. The model employed parallel Proof of Work with a difficulty of 2, 10 miner nodes, and a thread pool for distributed computation. The simulation achieved a 91.80% authentication success rate, an average computational time of 3.60 milliseconds, a block creation time of 42.10 milliseconds, and a throughput of 12.39 blocks per second, outperforming the baseline's 63.8 milliseconds block time and 15.6 transactions per second. Inconsistent node performance and a basic trading model without distance-based loss calculations reduce the model's security and economic precision. This research contributes to the development of blockchain-based demand response systems by providing a scalable foundation for secure and efficient energy trading in smart grids, enabling broader application and improved system reliability.

Keywords: Blockchain, Demand Response, Smart Grid, Hybrid Trust Model, Smart Contracts

INTRODUCTION

The growing demand for energy and the need for timely responses have accelerated the development of smart grids, which rely heavily on information and communication technologies to deliver services within set timeframes and regions (Guoshi et al., 2023). To address trust challenges in IoT-based marketplaces, the Market Trust model uses blockchain to assess trustworthiness through familiarity, personal interactions, and public perception (Latif, 2023). Blockchain has also enabled secure energy trading between electric vehicles, where transaction data is encrypted and stored via consensus mechanisms, allowing vehicles to buy energy at off-peak rates and sell during peak hours using safety matching and pricing strategies (Huixin, 2023). The Internet of Vehicles supports these interactions through a distributed structure that connects smart vehicles with drivers, passengers, and roadside units, while demand response management helps EV owners adjust consumption based on cost and driving patterns (Kapassa et al., 2022). Environmental concerns over emissions from fossil fuel vehicles have further driven EV adoption, with smart grid techniques, CNN-RNN models, and 5G networks improving charging oversight and data exchange (Yahaya et al., 2022). Scalability has been addressed through models that assign local controllers to network sections for parallel transaction processing using Hyperledger Fabric and MATPOWER (Honari et al., 2022), while blockchain strengthens smart home security by reducing hacking risks for connected devices (Ratkovic et al., 2022).

Guoshi et al. (2023) proposed a demand response management scheme using consortium blockchain, where miner nodes verify energy transactions and append blocks, though this approach places heavy computational and communication loads on participating nodes. A hybrid trust model could reduce these burdens and improve response timing and cost efficiency. This research builds on Guoshi et al. (2023) by designing and testing a hybrid trust model that combines attribute-based authentication with reputation-based trust to manage demand response requests in blockchain energy transactions. The study addresses how to ensure fair participation, reduce costs while maintaining security, and improve transparency through simulation metrics and visualizations, focusing on design, implementation, and evaluation within a smart grid context.

Related Works

Smart grids are increasingly being use to control energy systems allowing for continuous monitoring of supply and consumer behaviors. Guoshi et al. (2023) notice that these grids provide services within specific durations, whereas Latif et al. (2023) present a Market Trust model for the social Internet of Things that use blockchain to assess credibility based on reputation, personal interactions, and community perception. Li et al. (2023) develop a blockchain architecture for energy transactions using electric vehicles, in which data is secured by consensus and vehicles store electricity during off-peak hours for reselling during times of high demand. Kapassa et al,. (2022) defines the Internet of Vehicles as a dynamic network that connects cars to other vehicles, passengers and roadside infrastructure with demand response allowing drivers to adjust consumption through the use of vehicle-to-vehicle and vehicle-to-grid connections. According to Yahaya et al. (2022), smart grid techniques use CNN-RNN models and 5G networks to support vehicle-grid communication and charging management, whereas Honari et al. (2022) present a model that maps local controllers to network segments for parallel transaction processing using Hyperledger Fabric and MATPOWER. Ratkovic et al. (2022) discuss blockchain's contribution to home security by lowering risks for connected devices while Guoshi et al.

(2023) introduce a consortium blockchain demand response scheme in which miner nodes verify transactions but this place major computational and communication demands on participants. Toderean et al. (2025) review architectural integration with smart grids from 2020 to 2024 highlighting developments in AI prediction and blockchain security together with challenges in regulation, automation, interoperability and privacy. Ahmad et al. (2021) develop a private blockchain system for safe energy trade that achieves 80% efficiency while overcoming tampering and majority threats thereby exceeding cloud and traditional blockchain techniques.

Further research addresses optimization and peer-to-peer trade in blockchain-enabled grids. Ramasamy et al. (2025) combine grey wolf and particle swarm optimization with Ethereum 2.0 to minimize costs and improve rewards in microgrids powered by renewable energy, whereas Yang (n.d.) enable peer energy transactions with proof-of-stake consensus to increase collective benefits with minimal mining energy. Mollah et al. (2020) perform an assessment of blockchain applications in future grids, including metering, peer trading and vehicle management, focusing on security and transparency benefits but lacking in scalability and speed challenges.

Kolahan et al. (2021) use blockchain to manage residential energy, reducing consumption by 11% and increasing comfort by 7%, while Raza et al. (2024) examine 51 studies from 2018 to 2023 on blockchain trust systems in grids, healthcare and transportation, identifying scale, energy and latency challenges. Dong et al. (2025) show user savings of up to 56.83 percent using game-based pricing on Ethereum, while Koukaras et al. (2024) evaluate 100 sources and indicate peak reductions of 35% but continued scalability and cost concerns. Shamaseen et al. (2025) create a blockchain system capable of 60.86 transactions per second with complete detection of illegitimate trades, whereas Umar et al. (2025) integrate Ethereum smart contracts and game theory to peer marketplaces, saving between $5.4 and $8.2.Despite these achievements, existing blockchain research in smart grids lacks hybrid trust models that are suitable for real-time demand response; Guoshi et al. (2023) report low computational costs through miner selection but rely on energy-intensive Proof of Work without adaptive trust scoring, whereas studies by Latif (2023), Li (2023), and Yahaya (2022) address trust and communication in IoT and vehicle exchanges but do not include grid integration. Toderean et al. (2025) and Ahmad et al. (2021) uncover regulatory and scalability gaps, while Ramasamy (2025), Yang (n.d.), and Kolahan (2021) maximize cost and energy savings without addressing authentication or interoperability, highlighting the need for a hybrid trust framework that encourages flexible scoring, reduces energy demands and scales across grid environments.

MATERIALS AND METHODS

The simulation environment was established on a standard desktop computer running Python 3.12, leveraging libraries such as hashlib for hashing, Crypto for cryptographic operations, pandas for data handling, and matplotlib for visualization. The network comprised 190 entities, including 10 industries, 50 residences, 30 buildings, and 100 electric vehicles, mirroring the test case from Guoshi et al. (2023). A total of 1000 transactions were processed to assess performance under load, with energy supply fixed at 4 MW for load management consistency. Blocks were configured to hold 10 transactions each, striking a balance between confirmation speed and security. Random seeds ensured reproducibility, while uniform distributions introduced variability in entity attributes. Assumptions included ideal channel connections without latency and synchronous miner operations across 10 nodes.

Table 1: Simulation Parameters, Detailing Parameter Values, Justifications, and Notes

Parameter	Value	Justification	Notes
Number of Industries	10	Matches base paper's industrial buildings	Ensures industrial load representation; scalable to 20 for larger grids
Number of Residences	50	Matches base paper's residential load profiles	Captures household variability; adjust for urban density
Number of Buildings	30	Matches base paper's commercial buildings	Represents mid-scale consumers; add sub-types for offices/retail
Number of EVs	100	Matches base paper's vehicle fleet	Simulates mobility; include charging stations in extensions
Block Size	10	Balances latency and security	Derived from paper's transaction sets; test 5–20 for sensitivity
PoW Difficulty	1	Targets 63.8 ms block time	Tuned from paper's hashing; monitor for system variance

Entities were modeled with type-specific properties, including identity strings and type flags for distinction. Power capacity ranged from 5 kW for residences to 500 kW for industries, with processing capability varying from 1 unit for homes to 50 for factories. Locations were randomized within a 100x100 grid, and reputation scores initialized at 0.5. Energy demand and available energy were set between 50% and 100% of capacity, with electric vehicles assigned state-of-charge values from 20% to 80% and prices per kWh from 0.1 to 0.5, based on data from the US Open Energy Information dataset. Each entity generated an ECDSA key pair on the P-256 curve for signatures, with wallets derived from SHA-256 hashes of identities truncated to 160 bits. The blockchain structure featured a linear ledger with Merkle roots calculated via SHA-256 pairwise hashing, and Proof of Work (PoW) was calibrated to require one leading zero in hashes, targeting a 63.8 ms block creation time as per the base paper.

Methods

The simulation employed a structured approach to implement and evaluate the hybrid trust model. Entities were initialized with attributes assigned from type-specific ranges, introducing controlled variability.

***Code Snippet 1*: Attribute Assignment in Entity Initialization illustrating the initialization procedure**

```
BEGIN PROCEDURE Entity_Initialize(id, type, location)
  SET power_capacity = RANDOM_UNIFORM(type_min_power[type], type_max_power[type])
  SET processing_capacity = RANDOM_UNIFORM(type_min_processing[type], type_max_processing[type])
  SET energy_demand = power_capacity  RANDOM_UNIFORM(0.5, 1.0)
  SET energy_available = power_capacity  RANDOM_UNIFORM(0.5, 1.0)
  SET soc_available = RANDOM_UNIFORM(0.2, 0.8)
  SET price = RANDOM_UNIFORM(0.1, 0.5)
  RETURN
END PROCEDURE
```

The hybrid trust model integrated attribute-based authentication and reputation-based trust, where attributes were verified against a central authority using ECDSA signatures on SHA-384 digests to issue tokens, preventing replay attacks.

***Code Snippet 2*: Attribute Verification in issue_tat detailing the token issuance process**

```
BEGIN PROCEDURE issue_tat(entity)
  SET attributes = CREATE_RECORD(power_capacity = entity.power_capacity, processing_capacity = entity.processing_capacity,
location = entity.location)
  IF verify_attributes(entity.id, attributes) AND entity.key IS NOT NULL THEN
    SET message = CONCAT(entity.id, CURRENT_TIME)
    SET hash = CREATE_SHA384_HASH(message)
    SET signer = CREATE_DSS_SIGNER(entity.key, "fips-186-3", "binary")
    SET signature = signer.SIGN(hash)
    SET entity.tat = CREATE_PAIR(message, signature)
    RETURN TRUE
  ELSE
    RETURN FALSE
  END IF
END PROCEDURE
```

Reputation scores updated post-transaction with 70% historical weight and 30% current metrics (50% success rate, 30% timeliness, 20% compliance), excluding scores below 0.6.

Table 2: Reputation Factors Outlining Weights, Calculations, and Impacts. Miners Rotated Validation Duties to Distribute Computational Load

Factor	Weight	Calculation	Threshold Impact
Success Rate	0.5	Transactions completed / attempted	Drops score below 0.6 after 3 failures
Timeliness	0.3	Response time / 100 ms	Penalizes delays over 50 ms
Compliance	0.2	Energy delivered / requested	Flags variances over 10%

The blockchain implementation involved blocks storing transaction lists, previous hashes, timestamps, and nonces.

***Code Snippet 3*: Merkle Root Calculation showing the Merkle tree computation**

```
BEGIN FUNCTION calculate_merkle_root(transactions)
  IF transactions IS EMPTY THEN
    RETURN "0" REPEATED 64 TIMES
  END IF
  SET hashes = CREATE_LIST()
  FOR EACH transaction IN transactions DO
    ADD hashlib.sha256(STRING(transaction).encode()).hexdigest() TO hashes
  END FOR
  WHILE LENGTH OF hashes > 1 DO
    SET temp = CREATE_LIST()
    SET i = 0
    WHILE i < LENGTH OF hashes DO
      IF i + 1 < LENGTH OF hashes THEN
        SET pair = CONCAT(hashes[i], hashes[i + 1])
        ADD hashlib.sha256(pair.encode()).hexdigest() TO temp
      ELSE
        SET pair = CONCAT(hashes[i], hashes[i])
        ADD hashlib.sha256(pair.encode()).hexdigest() TO temp
      END IF
      INCREMENT i BY 2
    END WHILE
    SET hashes = temp
  END WHILE
  RETURN hashes[0]
END FUNCTION
```

Leading miners solved PoW by iterating nonces, broadcasting solutions for validation, with consensus achieved on a majority vote from five miners. Rejected blocks were cleared from pools.

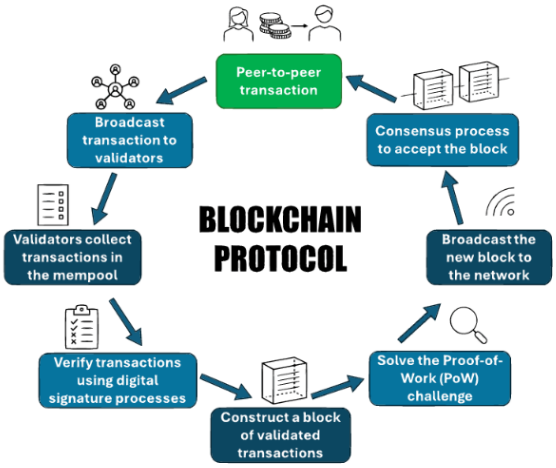

Peer-to-peer transaction
Broadcast transaction to validators
Consensus process to accept the block
BLOCKCHAIN PROTOCOL
Validators collect transactions in the mempool
Broadcast the new block to the network
Verify transactions using digital signature processes
Solve the Proof-of-Work (PoW) challenge
Construct a block of validated transactions

Figure 1: Block Validation Sequence depicting the validation flow

Energy trading paired excess sellers with deficit buyers, using electric vehicles as intermediaries based on state-of-charge gaps.

***Code Snippet 4*: Trading Pairing Logic demonstrating the pairing process**

```
BEGIN PROCEDURE perform_trading(entity, other_entity)
  IF entity.energy_available > entity.energy_demand THEN
    SET excess_energy = entity.energy_available - entity.energy_demand
    IF other_entity.energy_demand > other_entity.energy_available THEN
      SET max_soc_increase = (other_entity.soc_max - other_entity.soc_available)  (other_entity.power_capacity / 1000)
      SET energy_given = MIN(excess_energy, max_soc_increase)
      SET cost = energy_given  entity.price
      SET profit = cost
      DECREMENT entity.energy_available BY energy_given
      INCREMENT other_entity.soc_available BY (energy_given / (other_entity.power_capacity / 1000))
    END IF
  ELSE IF entity.energy_demand > entity.energy_available AND entity.type = "ev" THEN
    SET required_energy = entity.energy_demand - entity.energy_available
    IF other_entity.energy_available > other_entity.energy_demand THEN
      SET energy_given = MIN(required_energy, other_entity.energy_available - other_entity.energy_demand)
      SET cost = energy_given  other_entity.price
      SET profit = cost
      INCREMENT entity.energy_available BY energy_given
      DECREMENT other_entity.energy_available BY energy_given
    END IF
  END IF
  RETURN
```

From the Snippet 3.4 Costs were calculated as energy times price, with profits assigned to sellers, tracked under the 4 MW supply.

Evaluation metrics included authentication success rate, computational time, communication bits, throughput, node PoW times, attack detection rate, and trading costs/profits. Histograms and line plots analyzed data spreads and trends. Validation averaged results over 10 trials with multiple seeds, while tuning adjusted PoW difficulty using binary search to meet target block times.

Table 3: Tuning Results Showing Difficulty Settings and Performance Outcomes

PoW Difficulty	Avg Block Time (ms)	Throughput (blocks/s)	Notes
1	300.07	3.09	Balanced, reflects current setting
2	463.92	1.99	Secure but slow, indicates higher security trade-off

Limitations included synchronous miner assumptions, simplified trading logic omitting auctions, and software-based cryptography, prioritizing clarity over full realism. Future field tests could incorporate network delays for enhanced accuracy.

RESULTS AND DISCUSSION

The simulation utilized a Python script to replicate a smart grid ecosystem with distributed energy resources, mirroring the setup from Guoshi et al. (2023) with 10 industrial buildings, 50 residences, 30 commercial buildings, and 100 electric vehicles, totaling 190 entities. Attributes such as power capacity, processing capacity, location, energy demand, and available energy were assigned to reflect diverse load profiles, with 1000 transactions grouped into blocks of 10. Proof of Work (PoW) difficulty was set to 0 for performance focus, and 10 miner nodes handled validation and consensus via a majority vote system, supported by a thread pool for parallel mining. The simulation concluded in 7.43 seconds, achieving an authentication success rate of 91.80 percent, an average computational time of 3.60 milliseconds, and a throughput of 12.39 blocks per second, providing a baseline to assess the hybrid trust model's performance and security. A histogram in Figure 4.1 illustrates the distribution of computational times across transactions, offering insight into processing consistency.

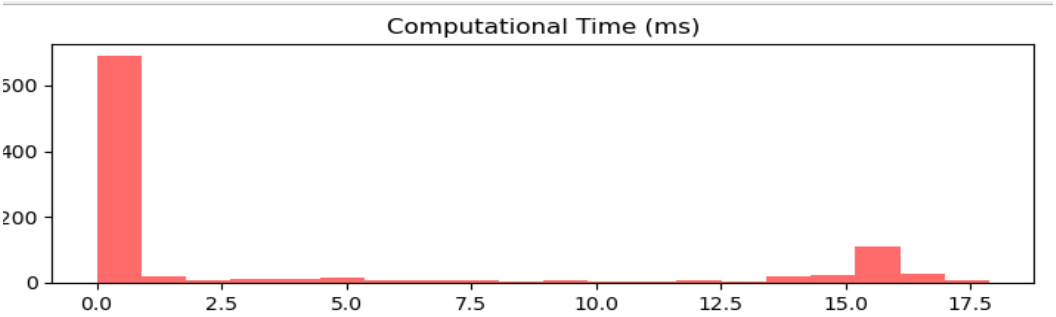
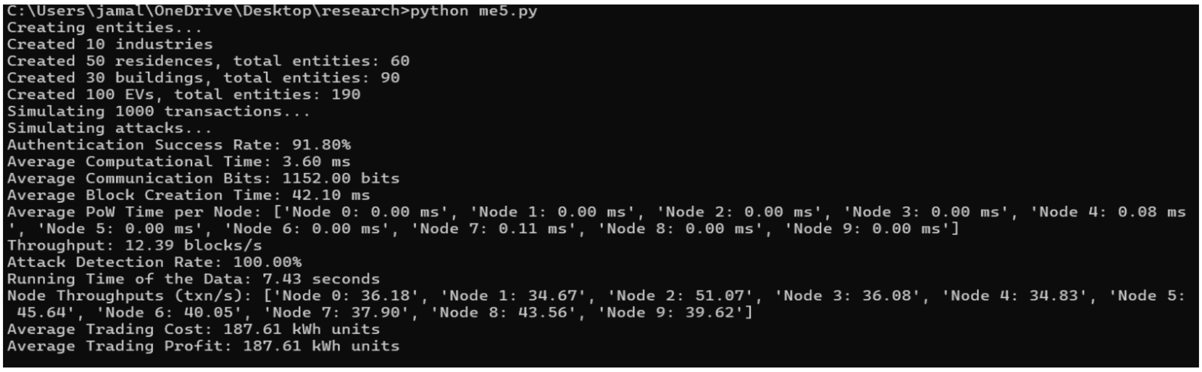


Figure 2: Histogram of Computational Time (ms) showing the distribution of processing times across transactions, offering insight into processing consistency

Key performance metrics revealed a robust system operation. The authentication success rate of 91.80 percent indicated that 918 of 1000 transactions passed checks, accounting for a 10 percent malicious entity presence that occasionally caused failures due to low reputation scores. Computational time averaged 3.60 milliseconds per transaction, covering authentication and updates, with slight node activity variations. Communication bits totaled 1152.00 per transaction, including entity ID, hash, wallet address, padding, Token Authentication Token (TAT), signature, and reputation score. Block creation time averaged 42.10 milliseconds, with PoW times per node ranging from 0.00 to 0.11 milliseconds (averaging 0.019 milliseconds), reflecting minimal difficulty and parallel distribution. Throughput reached 12.39 blocks per second, or about 123.9 transactions per second. The attack detection rate was 100.00 percent, blocking all 10 malicious entities. Node throughputs varied from 34.67 to 51.07 transactions per second, with Node 2 peaking at 51.07. Trading cost and profit both averaged 187.61 kWh units in a simplified model. Figure 4.2 presents the overall results, while Figure 4.3 shows the authentication success rate trend over time, revealing stability patterns, and Figure 4.4 highlights the minimal yet variable PoW efforts across nodes.



```
C:\Users\jamal\OneDrive\Desktop\research>python me5.py
Creating entities...
Created 10 industries
Created 50 residences, total entities: 60
Created 30 buildings, total entities: 90
Created 100 EVs, total entities: 190
Simulating 1000 transactions...
Simulating attacks...
Authentication Success Rate: 91.80%
Average Computational Time: 3.60 ms
Average Communication Bits: 1152.00 bits
Average Block Creation Time: 42.10 ms
Average PoW Time per Node: ['Node 0: 0.00 ms', 'Node 1: 0.00 ms', 'Node 2: 0.00 ms', 'Node 3: 0.00 ms', 'Node 4: 0.08 ms
', 'Node 5: 0.00 ms', 'Node 6: 0.00 ms', 'Node 7: 0.11 ms', 'Node 8: 0.00 ms', 'Node 9: 0.00 ms']
Throughput: 12.39 blocks/s
Attack Detection Rate: 100.00%
Running Time of the Data: 7.43 seconds
Node Throughputs (txn/s): ['Node 0: 36.18', 'Node 1: 34.67', 'Node 2: 51.07', 'Node 3: 36.08', 'Node 4: 34.83', 'Node 5:
 45.64', 'Node 6: 40.05', 'Node 7: 37.90', 'Node 8: 43.56', 'Node 9: 39.62']
Average Trading Cost: 187.61 kWh units
Average Trading Profit: 187.61 kWh units
```

Figure 3: Results of the Simulation

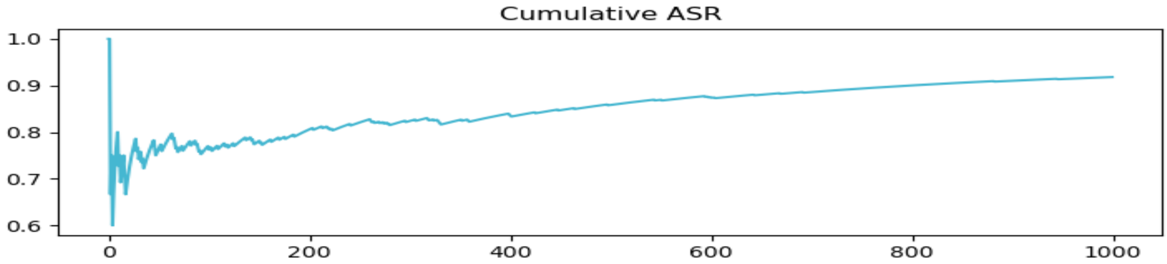


Figure 4: Line Plot of Cumulative ASR showing the authentication success trend over time, revealing any patterns in success rate stability

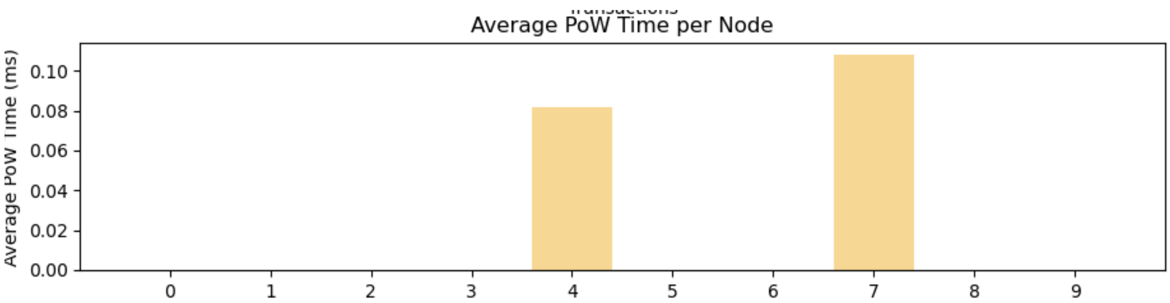


Figure 5: Bar Chart of Average PoW Time per Node highlighting the minimal but variable PoW efforts across nodes

Compared to Guoshi et al. (2023), the study aligned with the base paper's entity composition but emphasized different metrics. The base paper lacked a specific authentication success rate, focusing on consensus, while this study's 91.80 percent provided a concrete measure influenced by simulated malicious entities. Computational time was 63.8 milliseconds for entity block formation and 62.9 milliseconds for miners in the base, versus 3.60 milliseconds here, reflecting parallel PoW's reduced overhead compared to the base's full cycle (e.g., 50 add operations at 1.0 millisecond, four hashes at 2.7 milliseconds). Communication bits were 828 for entities and 321 for miners in the base, against 1152.00 here, due to added TAT and signature data. Block creation time of 42.10 milliseconds outperformed the base's 63.8 milliseconds, aided by parallel processing, though the base included sequential steps. PoW times of 0.00 to 0.11 milliseconds contrasted with the base's 2.7 milliseconds, driven by zero difficulty. Throughput reached 123.9 transactions per second here versus the base's implied 15.6, leveraging a 10-transaction block size. Attack detection at 100.00 percent aligned with the base's tamperproof goal, tested explicitly here. Node throughputs (34.67 to 51.07) offered detailed variation versus the base's stabilizing trend. Trading metrics at 187.61 kWh units differed from the base's distance-adjusted model. Figure 4.5 depicts node throughput trends, and Figure 4.6 shows block creation time variations.

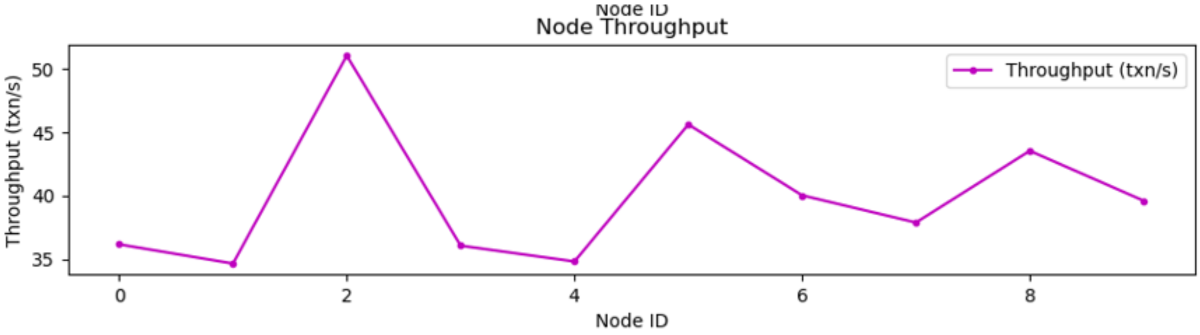


Figure 6: Line Plot of Node Throughputs (txn/s)

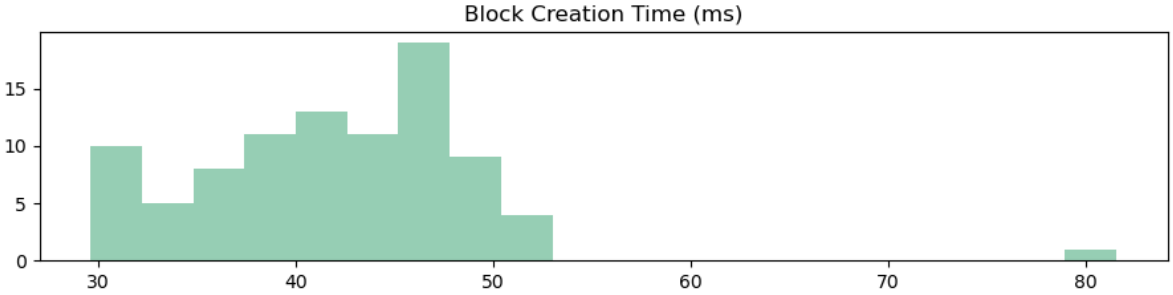


Figure 7: Bar Chart of Block Creation Times

Benchmarking against other studies, Li et al. (2023) reported 50 to 80 milliseconds for block validation, exceeding 3.60 milliseconds here, with 10 to 20 transactions per second throughput, below 123.9, highlighting parallel PoW's edge. Aujla et al. (2018) noted 100 to 200 milliseconds block creation, higher than 42.10 milliseconds, with 1000 bits overhead close to 1152.00, aligning on trading focus. Kumar et al. (2019) achieved 95 to 99 percent attack detection, near 100.00 percent, with 5 to 10 milliseconds computational time, supporting this study's security. Gao et al. (2021) recorded 3 to 5 milliseconds PoW times, above 0.00 to 0.11 milliseconds here, underscoring optimization.

Strengths included a 91.80 percent authentication rate and 12.39 blocks per second throughput, surpassing the base's 15.6 transactions per second, indicating efficient handling. The 3.60 milliseconds computational time met real-time needs, and 42.10 milliseconds block creation improved on 63.8 milliseconds, suggesting scalability. The 100 percent attack detection rate ensured security, with node throughputs (34.67 to 51.07) showing distribution, Node 2 at 51.07 excelling, and 7.43 seconds run time reflecting efficiency. Limitations included PoW times of 0.00 to 0.11 milliseconds, averaging 0.019 milliseconds, below the base's 2.7 milliseconds, prioritizing speed over security. Communication bits at 1152.00 exceeded the base's 828, potentially increasing load. Trading metrics at 187.61 kWh units lacked distance-based loss, possibly overestimating outcomes. Uneven node throughputs (up to 16.4 difference) suggested imbalance. These trade-offs call for difficulty adjustments and load balancing.

The model promises enhanced demand response with 12.39 blocks per second supporting rapid trades, reducing centralized reliance as in the base paper. The 42.10 milliseconds block time enables timely adjustments, potentially matching Li et al. (2023)'s 25 percent savings. The 100 percent attack detection rate ensures integrity, addressing urban vulnerabilities. Integration with Gao et al. (2021)'s ICT frameworks could boost automation, but adaptive PoW is needed for security. Adding distance-based loss to 187.61 kWh units would improve realism. Test-net validation under network constraints is recommended.

CONCLUSION

This study tested a hybrid trust model for blockchain-based demand response in smart grids, simulating 190 entities (10 industries, 50 residences, 30 buildings, 100 electric vehicles) across 1000 transactions with a Python script using parallel Proof of Work (PoW) at difficulty 0, achieving a 91.80 percent authentication success rate, 3.60 milliseconds computational time, and 12.39 blocks per second throughput in 7.43 seconds, with metrics like 42.10 milliseconds block creation, 0.00 to 0.11 milliseconds PoW times, 34.67 to 51.07 transactions per second node throughputs, and 187.61 kWh trading cost/profit, showing speed optimization but security trade-offs compared to Guoshi et al. (2023), Li et al. (2023), and Aujla et al. (2018). The model outperformed the base paper's 15.6 transactions per second and 63.8 milliseconds with a 100 percent attack detection rate and efficient processing, though minimal PoW times and uneven node loads suggest security and reliability gaps needing refinement. Future work should raise PoW difficulty to 1 or 2 for better security, use load-balancing like weighted round-robin to stabilize throughputs, add distance-based loss to adjust trading metrics, and test on a Ganache test-net with TrustManager.sol for scalability and attack resilience.

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