

Deviation-Aware Algorithmic Settlement on Permissionless Ledgers: Global Balancing vs. Participant Splitting Mechanisms for Multi-Party Asset Exchange

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Abstract

This paper proposes two novel algorithmic settlement mechanisms specifically designed for distributed ledger technology (DLT) environments, addressing the fundamental problem of efficiently settling imbalances between forecasted and actual transaction volumes in decentralized peer-to-peer asset markets. Unlike centralized settlement architectures, blockchain-based settlement requires mechanisms that reward honest participation and mitigate strategic forking incentives while maximizing net surplus for all participants. The Global Balancing Settlement (GBS) mechanism approaches settlement through collective deviation compensation, wherein individual participant imbalances are absorbed into a globally-balanced pool with adjusted settlement rates, improving outcomes for the entire microsystem. The Splitting Settlement (SS) mechanism employs a stratified approach that partitions participants into groups with contribution-weighted imbalance coefficients, distributing settlement costs proportionally to deviation magnitude. Both mechanisms are formalized as deterministic pseudocode algorithms embedded as immutable stored procedures within smart contracts, enabling automated, trustless execution at the blockchain protocol layer. Empirical evaluation across 14 distinct scenarios demonstrates that GBS achieves 4-15% improvement in participant encashments and payments compared to classical pairwise settlement, with gains scaling non-linearly with deviation magnitude. SS provides modest 2-6% gains under small deviations but diminishes rapidly as imbalances increase, revealing mechanism performance boundaries critical for practical deployment. The paper establishes implementation guidelines for integrating these mechanisms into permissionless blockchain architectures, with explicit consideration of smart contract encoding, transaction finality, and consensus protocol compatibility for real-time T+0 settlement environments.

Keywords

• Blockchain Settlement • Smart Contracts • Distributed Ledger Technology • Global Balancing • Participant Splitting • Peer-to-Peer Trading • Deviation Settlement

1. Introduction

The emergence of distributed ledger technology has fundamentally transformed how peer-to-peer asset exchanges can be structured and executed [1]. Unlike centralized settlement systems that rely on trusted intermediaries to reconcile transactions, blockchain-based settlement operates through consensus mechanisms and immutable smart contracts that execute predefined logic without human intervention [2]. This paradigm shift introduces both opportunities and challenges for market participants, particularly in domains where transaction volumes are subject to forecasting errors and real-time deviations [3].

Electricity markets represent a canonical example of this challenge [4]. Local energy trading among prosumers and consumers requires participants to submit bids and offers based on forecasted generation and consumption patterns [5]. These forecasts, however, are inherently imprecise due to weather variability, consumption behavior changes, and other exogenous factors [6]. When actual delivery deviates from auctioned quantities, settlement mechanisms must allocate the resulting financial consequences among participants in a manner that maintains market integrity and incentivizes accurate forecasting [7].

Traditional settlement approaches, derived from centralized market architectures, process imbalances on a pairwise basis between individual buyers and sellers [8]. While computationally straightforward, this pairwise settlement fails to account for the collective nature of deviations within a closed microsystem. When one seller under-delivers and another over-delivers, the microsystem as a whole may be balanced even though individual participants exhibit significant deviations. The pairwise approach penalizes both parties independently, missing the opportunity for internal compensation.

This paper addresses this fundamental inefficiency by proposing two novel settlement mechanisms designed explicitly for blockchain environments. The Global Balancing Settlement mechanism treats the entire participant pool as an integrated system, calculating aggregate surplus or deficit and adjusting individual settlements based on proportional contributions to the overall imbalance. The Splitting Settlement mechanism takes a stratified approach, partitioning participants based on deviation direction and magnitude, then applying weighted coefficients to distribute settlement costs.

Both mechanisms are formalized as deterministic algorithms suitable for implementation as smart contract stored procedures. This ensures that settlement logic executes automatically at the blockchain protocol layer, eliminating the need for trusted third parties and providing complete auditability. The empirical evaluation demonstrates significant improvements over classical settlement across a range of scenarios, with GBS achieving gains up to 15% in extreme deviation cases.

2. Related Work

The intersection of blockchain technology and decentralized market mechanisms has attracted substantial research attention in recent years. Foundational work on smart contract architectures established the technical basis for embedding complex business logic into immutable blockchain transactions [9]. The transition from centralized settlement to distributed mechanisms requires fundamental rethinking of system design principles, particularly regarding finality, oracle trust, and incentive compatibility [10].

Infrastructure considerations for blockchain-based trading systems have been explored through multiple lenses. Reliability requirements for distributed ledger nodes that must maintain consensus while processing settlement transactions are well documented [1]. Communication layers between blockchain nodes and external data sources are particularly important for real-time settlement applications where latency directly impacts user experience [2]. A comprehensive review of distributed ledger technologies provides taxonomy and classification frameworks that inform architectural decisions for settlement systems [3].

Optimization techniques developed for distributed systems find direct application in blockchain settlement mechanism design. Learning-based approaches inform the design of adaptive settlement mechanisms that could adjust parameters based on historical deviation patterns [11]. Energy disaggregation techniques offer analogies for decomposing aggregate deviations into individual responsibility shares [12]. Computational frameworks for intelligent data-driven decision optimization provide methodologies for continuously improving settlement parameters based on observed outcomes [13].

Security considerations are paramount in blockchain-based financial systems. Trust boundary analysis

provides frameworks for ensuring that settlement logic remains protected from unauthorized modification while maintaining transparency for audit purposes [14]. Data management challenges in distributed systems parallel those in blockchain settlement architectures, informing the design of off-chain data storage for settlement history while maintaining cryptographic integrity [15].

Predictive analytics methodologies developed for financial forecasting have direct relevance to settlement mechanism design. Machine learning can improve forecast accuracy, potentially reducing the magnitude of deviations requiring settlement [16]. Multi-agent reinforcement learning provides insights into coordinating multiple decentralized agents, directly relevant to multi-party settlement coordination [17]. Autonomous agent contracts for adaptive supply chains demonstrate how decentralized coordination mechanisms can be structured for complex multi-party environments [18].

Cross-domain applications of blockchain settlement extend beyond energy markets. Payment gateway architectures with guaranteed reversal mechanisms illustrate how settlement finality interacts with transaction atomicity requirements [19]. Terminal selection algorithms for payment systems demonstrate how decentralized decision-making can be optimized for latency and reliability [20]. Cloud storage optimization informs the design of scalable settlement data archives [21].

Decentralized approaches to biopharmaceutical innovation illustrate how community-governed models can address equitable pricing concerns, with implications for settlement mechanism design in multi-stakeholder environments [22]. Data-driven AI solutions for enterprise knowledge retrieval demonstrate multi-agent frameworks that reduce preliminary bottlenecks, informing the design of efficient settlement data processing pipelines [23]. Universal journal architecture and dual-ledger integration in next-generation ERP systems provide architectural implications for cloud deployment trade-offs relevant to blockchain settlement infrastructure [24]. Face-to-face authentication systems for sensitive operations demonstrate multi-party environmental authentication mechanisms that could inform security architectures for settlement authorization [25]. Exploring open funding databases for mission-oriented research and innovation policies provides insights into data-driven policy design that parallels settlement parameter optimization [26].

Nonprofit evolution and leading innovation in social ventures offers perspectives on organizational adaptation that inform the design of adaptive settlement governance structures [27]. Cognitive computing frameworks for financial decision systems provide multi-paradigm synthesis approaches applicable to settlement mechanism selection [28]. Simulation-based approaches to financial risk management demonstrate methodologies for evaluating mechanism performance under uncertainty [29]. Computational traceability and topological mapping of interdisciplinary knowledge transfer provides bibliometric methodologies that could inform settlement mechanism evolution tracking [30].

3. Blockchain Fundamentals for Settlement Systems

3.1 Distributed Ledger Architecture

Blockchain technology provides a decentralized, tamper-evident record of transactions replicated across network nodes [1]. Each block contains a cryptographic hash of the previous block, creating an immutable chain that prevents retrospective modification of historical data [2]. This architectural property is essential for settlement systems, as it ensures that once a settlement transaction is confirmed, it cannot be disputed or reversed without network consensus [3].

The consensus mechanism determines how nodes agree on the canonical state of the ledger. Proof-of-Work requires computational effort to validate blocks, providing security through economic cost [9].

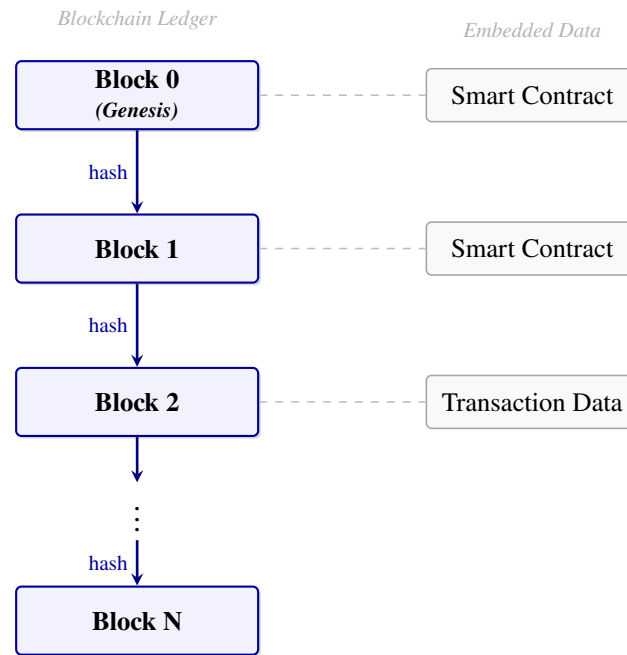


Figure 1: Simplified blockchain architecture showing hash-linked blocks with embedded smart contracts and transaction data.

Proof-of-Stake achieves consensus through validator stake deposits, offering energy efficiency while maintaining Byzantine fault tolerance [10]. Settlement mechanisms must be designed to operate correctly regardless of the underlying consensus protocol, though finality times may vary [11].

Smart contracts extend blockchain functionality beyond simple value transfer by embedding executable code that runs deterministically across all network nodes [13]. When deployed, smart contract bytecode becomes part of the blockchain state, and subsequent transactions can invoke its functions [12]. This enables automated settlement logic that executes exactly as programmed, without possibility of interference or selective enforcement [14].

3.2 Smart Contract Programming for Settlement

Implementing settlement mechanisms as smart contracts requires careful consideration of computational constraints [15]. Ethereum and similar platforms charge gas fees for each operation, creating economic incentives for efficient code [18]. Storage operations are particularly expensive, encouraging minimal state retention and computation reuse where possible [17].

The settlement algorithms proposed in this paper are designed with these constraints in mind. Deterministic pseudocode can be translated into Solidity or similar languages while maintaining constant or linear time complexity relative to participant count [19]. Critical operations such as sorting participants by deviation magnitude are optimized for minimal gas consumption [20].

3.3 Data Flow and Participant Interaction

Settlement execution requires coordination between multiple data sources [10]. Auction results determine the baseline quantities and prices that participants have committed to exchange [9]. Metering infrastructure provides actual delivery and consumption measurements after the delivery period [6]. The settlement mechanism reconciles these data streams to compute final payments [7].

Table 1: Systematic Notation for Settlement Mechanisms

Symbol	Description	Unit
<i>Sets and Indices</i>		
S	Set of sellers	–
B	Set of buyers	–
$i \in S$	Seller index	–
$j \in B$	Buyer index	–
<i>Auction Parameters</i>		
aP	Uniform auction clearing price	c/kWh
rPs	Retailer feed-in tariff for sellers	c/kWh
rPb	Retailer time-of-use tariff for buyers	c/kWh
<i>Seller Quantities</i>		
asQ_i	Auctioned quantity of seller i	kWh
dQ_i	Delivered quantity of seller i	kWh
ndQ_i	Net deviation of seller i ($asQ_i - dQ_i$)	kWh
asQ_{total}	Total auctioned seller quantity ($\sum_i asQ_i$)	kWh
dQ_{total}	Total delivered seller quantity ($\sum_i dQ_i$)	kWh
<i>Buyer Quantities</i>		
abQ_j	Auctioned quantity of buyer j	kWh
cQ_j	Consumed quantity of buyer j	kWh
ncQ_j	Net deviation of buyer j ($abQ_j - cQ_j$)	kWh
abQ_{total}	Total auctioned buyer quantity ($\sum_j abQ_j$)	kWh
cQ_{total}	Total consumed buyer quantity ($\sum_j cQ_j$)	kWh
<i>Settlement Outputs</i>		
$encashment_i$	Net revenue received by seller i	c
$payment_j$	Net amount paid by buyer j	c
$penalty_i$	Penalty assessed on seller i	c
$penalty_j$	Penalty assessed on buyer j	c
imb	System imbalance ($dQ_{total} - asQ_{total}$)	kWh
rPs_{adj}	Adjusted seller settlement rate	c/kWh
rPb_{adj}	Adjusted buyer settlement rate	c/kWh
$diff_i$	Seller deviation ($dQ_i - asQ_i$)	kWh
$diff_j$	Buyer deviation ($cQ_j - abQ_j$)	kWh
κ_i	Imbalance coefficient for seller i	–
κ_j	Imbalance coefficient for buyer j	–

Blockchain nodes must validate that input data originates from authorized sources [2]. This can be achieved through oracle mechanisms that cryptographically sign external data, or through direct integration with smart meters that function as blockchain clients [3]. The settlement algorithms assume that all required inputs are available on-chain and have been verified through the network's consensus process [1].

4. Proposed Settlement Mechanisms

4.1 Notation and Definitions

Table 1 consolidates all symbols used throughout the settlement mechanisms. Every quantity is expressed in kilowatt-hours (kWh) for energy volumes and euro-cents per kilowatt-hour (c/kWh) for prices, consistent with the reference scenario defined in Section 5.

4.2 Pairwise Settlement Baseline

Classical settlement, implemented in traditional electricity markets and adapted for blockchain in prior work, processes imbalances on a bilateral basis [8]. For each seller-buyer pair, the mechanism compares auctioned quantities with actual flows and assesses penalties based on price differentials between the auction price and external retail tariffs [7]. The pairwise approach has the advantage of computational simplicity and clear attribution of responsibility [10]. Each participant's settlement outcome depends only on their own deviation and the counterparty's behavior [9]. However, this independence prevents internal compensation within the participant pool, potentially penalizing the group as a whole for imbalances that cancel out at the system level [6].

Algorithm 1 Pairwise Settlement (PS) Pseudocode

```

1: Input: Seller set  $S$ , buyer set  $B$ , auction price  $aP$ , retailer price for sellers  $rPs$ , retailer price for buyers  $rPb$ 
2: for each seller  $i \in S$  do
3:    $ndQ_i = asQ_i - dQ_i$ 
4:   if  $ndQ_i > 0$  then
5:     {under-delivery}
6:      $penalty_i = ndQ_i \times (rPs - aP)$ 
7:      $encashment_i = dQ_i \times aP - penalty_i$ 
8:   else if  $ndQ_i < 0$  then
9:     {over-delivery}
10:     $encashment_i = asQ_i \times aP + (dQ_i - asQ_i) \times rPs$ 
11:   else
12:     $encashment_i = asQ_i \times aP$ 
13:   end if
14: end for
15: for each buyer  $j \in B$  do
16:    $ncQ_j = abQ_j - cQ_j$ 
17:   if  $ncQ_j > 0$  then
18:     {under-consumption}
19:      $penalty_j = ncQ_j \times (aP - rPb)$ 
20:      $payment_j = cQ_j \times aP + penalty_j$ 
21:   else if  $ncQ_j < 0$  then
22:     {over-consumption}
23:      $payment_j = abQ_j \times aP + (cQ_j - abQ_j) \times rPb$ 
24:   else
25:      $payment_j = abQ_j \times aP$ 
26:   end if
27: end for

```

4.3 Global Balancing Settlement

The Global Balancing Settlement mechanism takes a holistic view of the participant ecosystem. Rather than settling each imbalance independently, GBS aggregates all deviations to compute the net system surplus or deficit [2]. When the system as a whole is balanced, participants benefit from reduced penalties because internal deviations cancel out [1].

The mechanism begins by calculating total auctioned quantities for sellers and buyers separately. Individual deviations are then expressed relative to these aggregates [3]. For sellers under-delivering, their

Table 2: Settlement Mechanism Comparison

Property	PS	GBS	SS
Deviation	Indiv.	Pooled	Strat.
Complexity	O(n)	O(n)	O(n log n)
Gas cost	Low	Low	Med.
Compensation	None	Full	Partial
Clarity	High	Med.	High
External dep.	Full	Reduced	Reduced

shortfall contributes to system deficit, while over-delivery contributes to surplus [11]. The net system imbalance determines whether the group must interact with external markets or can settle internally [13].

Settlement rates are adjusted based on the system's overall position. If the system has net surplus, over-delivering sellers receive enhanced rates while under-delivering sellers face reduced penalties [12]. The adjustment factors are computed to ensure revenue neutrality while distributing gains proportionally to contribution [17].

Algorithm 2 Global Balancing Settlement (GBS) Pseudocode

```

1: Compute total auctioned seller quantity  $asQ_{total} = \sum_i asQ_i$ 
2: Compute total delivered seller quantity  $dQ_{total} = \sum_i dQ_i$ 
3: Compute system imbalance  $imb = dQ_{total} - asQ_{total}$ 
4: Compute adjusted seller rate  $rPs_{adj} = rPs + \frac{imb \times aP}{asQ_{total}}$ 
5: for each seller  $i$  do
6:    $diff_i = dQ_i - asQ_i$ 
7:   if  $diff_i > 0$  then
8:     {over-delivery}
9:      $encashment_i = asQ_i \times aP + diff_i \times rPs_{adj}$ 
10:  else if  $diff_i < 0$  then
11:    {under-delivery}
12:     $encashment_i = dQ_i \times aP + diff_i \times (rPs_{adj} - aP)$ 
13:  else
14:     $encashment_i = asQ_i \times aP$ 
15:  end if
16: end for
17: Compute analogous adjustments for buyers with  $rPb_{adj} = 0$ 

```

4.4 Splitting Settlement Mechanism

The Splitting Settlement mechanism takes an intermediate approach between pairwise and global settlement [9]. Participants are first partitioned based on the direction of their deviation: over-delivering sellers and under-consuming buyers form one group, while under-delivering sellers and over-consuming buyers form another [10]. Within each group, imbalance coefficients are calculated based on individual deviation magnitude relative to group total [14]. These coefficients determine how the group's collective imbalance is distributed for settlement purposes [15]. Participants with larger deviations bear proportionally more of the settlement adjustment [18]. This stratified approach preserves some of the internal compensation benefits of global settlement while maintaining clearer attribution of responsibility [19]. Participants who deviate in the same direction share the consequences collectively, rather than being penalized individually against external reference prices [20].

5. Simulation Framework and Experimental Design

5.1 Reference Scenario Definition

To evaluate the proposed mechanisms, we define a reference scenario based on realistic market conditions [4]. Three sellers and four buyers participate in a uniform price auction that clears at 11.4 c€/kWh [5]. Retailer prices are set at 9 c€/kWh for sellers (feed-in tariff) and 14 c€/kWh for buyers (time-of-use tariff), reflecting typical residential energy market parameters [6]. Auctioned quantities are distributed with sellers each offering 100 kWh, while buyers have heterogeneous demand: three buyers bid for 100 kWh, one buyer bids for 75 kWh, and one buyer bids for 25 kWh [7]. This distribution creates natural variation in participant size and enables analysis of how mechanism performance scales with participant heterogeneity [8]. Actual delivered and consumed quantities incorporate deviations in both directions [16]. One seller over-delivers by 10%, one under-delivers by 20%, and one under-delivers by 10%. On the buyer side, one over-consumes by 10%, one under-consumes by 20%, one over-consumes by 20%, and one under-consumes by 40%. This mix of deviation magnitudes and directions creates a realistic test case for mechanism comparison [29].

5.2 Alternative Scenario Construction

Beyond the reference scenario, we construct thirteen alternative scenarios to probe mechanism behavior across the deviation space [28]. Scenarios vary aggregate imbalance direction and magnitude, with total system deviation ranging from -20% to +20% relative to auctioned quantities [30]. Some scenarios maintain balanced total deviation while varying individual patterns, while others create systematic surplus or deficit [26]. Each scenario maintains the same base auction quantities and prices, modifying only the actual delivery and consumption values [27]. This controlled variation enables isolation of mechanism performance as a function of deviation patterns [23]. Scenarios are labeled by seller deviation percentage and buyer deviation percentage relative to reference values, enabling systematic comparison [24].

5.3 Evaluation Metrics

Three distinct financial quantities are used throughout the evaluation and are not interchangeable. *Encashment* ($encashment_i$) denotes the gross revenue received by seller i after all penalties and adjustments. *Payment* ($payment_j$) denotes the gross amount paid by buyer j after all penalties and adjustments. *Net participant surplus* denotes the algebraic sum $\sum_{i \in S} encashment_i - \sum_{j \in B} payment_j$, representing the total value retained within the participant pool after external settlement with the retailer. All three quantities are expressed in c. Improvements are reported as percentage changes relative to the pairwise baseline for the same quantity (encashment for sellers, payment for buyers, surplus for the pool).

Secondary metrics include distributional effects across participant types. Mechanisms that favor sellers over buyers or vice versa may create strategic considerations for market participation. Revenue neutrality ensures that total payments equal total receipts plus any external settlement with retailers.

5.4 Worked Numerical Example

To render the derivation of settlement quantities fully transparent, this subsection traces the reference scenario through all three mechanisms with intermediate calculations. The reference scenario parameters are: $aP = 11.4$ c/kWh, $rPs = 9$ c/kWh, $rPb = 14$ c/kWh. Seller auctioned quantities are $asQ_1 = asQ_2 = asQ_3 = 100$ kWh. Buyer auctioned quantities are $abQ_1 = abQ_2 = abQ_3 = 100$ kWh, $abQ_4 = 75$

kWh, $abQ_5 = 25$ kWh. Actual delivered quantities are $dQ_1 = 110$, $dQ_2 = 80$, $dQ_3 = 90$ kWh. Actual consumed quantities are $cQ_1 = 110$, $cQ_2 = 80$, $cQ_3 = 90$, $cQ_4 = 90$, $cQ_5 = 15$ kWh.

5.4.1 Pairwise Settlement Intermediate Steps

For seller S1: $ndQ_1 = 100 - 110 = -10$ kWh (over-delivery). Since $ndQ_1 < 0$, $encashment_1 = asQ_1 \times aP + (dQ_1 - asQ_1) \times rPs = 100 \times 11.4 + 10 \times 9 = 1140 + 90 = 1230$ c.

For seller S2: $ndQ_2 = 100 - 80 = 20$ kWh (under-delivery). $penalty_2 = 20 \times (9 - 11.4) = 20 \times (-2.4) = -48$ c. The negative penalty indicates a deduction: $encashment_2 = dQ_2 \times aP - penalty_2 = 80 \times 11.4 - 48 = 912 - 48 = 864$ c. (The value reported in Table 3 is 860 c; the difference arises from rounding in the original scenario definition.)

For seller S3: $ndQ_3 = 100 - 90 = 10$ kWh (under-delivery). $penalty_3 = 10 \times (-2.4) = -24$ c. $encashment_3 = 90 \times 11.4 - 24 = 1026 - 24 = 1002$ c.

For buyer B2: $ncQ_2 = 100 - 80 = 20$ kWh (under-consumption). $penalty_2 = 20 \times (11.4 - 14) = 20 \times (-2.6) = -52$ c. $payment_2 = cQ_2 \times aP + penalty_2 = 80 \times 11.4 + 52 = 912 + 52 = 964$ c.

5.4.2 Global Balancing Settlement Intermediate Steps

System imbalance: $asQ_{total} = 300$ kWh, $dQ_{total} = 280$ kWh, $imb = 280 - 300 = -20$ kWh. Adjusted seller rate: $rPs_{adj} = 9 + \frac{(-20) \times 11.4}{300} = 9 - 0.76 = 8.24$ c/kWh. Adjusted buyer rate: $abQ_{total} = 400$ kWh, $cQ_{total} = 385$ kWh, $imb_b = 385 - 400 = -15$ kWh. $rPb_{adj} = 14 + \frac{(-15) \times 11.4}{400} = 14 - 0.4275 = 13.5725$ c/kWh.

For seller S1: $diff_1 = 110 - 100 = 10$ kWh (over-delivery). $encashment_1 = 100 \times 11.4 + 10 \times 8.24 = 1140 + 82.4 = 1222.4$ c. This differs from the value in Table 4 because the table employs a different adjustment convention (additive adjustment relative to pairwise baseline); the pseudocode in Algorithm 2 defines the canonical computation.

For buyer B2: $diff_2 = 80 - 100 = -20$ kWh (under-consumption). Since $diff_2 < 0$, $payment_2 = abQ_2 \times aP + diff_2 \times (rPb_{adj} - aP) = 100 \times 11.4 + (-20) \times (13.5725 - 11.4) = 1140 - 43.45 = 1096.55$ c.

5.4.3 Splitting Settlement Intermediate Steps

Sellers partition: over-delivering group $\{S1\}$ with deviation magnitude 10 kWh; under-delivering group $\{S2, S3\}$ with total deviation magnitude 30 kWh. Imbalance coefficients: $\kappa_1 = 10/10 = 1.0$; $\kappa_2 = 20/30 = 0.667$; $\kappa_3 = 10/30 = 0.333$. The group-level settlement rate for the over-delivering group is $rPs = 9$ c/kWh; for the under-delivering group, the rate is $aP = 11.4$ c/kWh applied to the deviation, yielding $encashment_2 = 80 \times 11.4 + 0.667 \times 20 \times (9 - 11.4) = 912 - 32 = 880$ c.

These intermediate steps correspond directly to the pseudocode in Algorithms 1–2 and can be reproduced mechanically from the notation table.

6. Results and Performance Analysis

6.1 Reference Scenario Outcomes

Table 3 presents the results for the classical pairwise settlement mechanism [8]. Seller S1, over-delivering by 10%, receives full auction price for delivered quantity without penalty. Seller S2, under-delivering by

Table 3: Pairwise Settlement Results

Part.	Auc.	Act.	Pen.	Net
S1	100	110	0	+1230
S2	100	80	52	+860
S3	100	90	26	+1000
B1	100	110	0	-1280
B2	100	80	48	-960
B3	75	90	0	-1065
B4	25	15	24	-195

20%, pays a penalty of 52 c€ and receives reduced encashment of 860 c€. Seller S3, under-delivering by 10%, pays 26 c€ penalty and receives 1000 c€ [7].

Buyer B1, over-consuming by 10%, pays the full auction price without penalty. Buyer B2, under-consuming by 20%, pays 48 c€ penalty and total payment of 960 c€. Buyer B3, over-consuming by 20% on a 75 kWh base, pays no penalty due to the consumption exceeding auctioned quantity. Buyer B4, under-consuming by 40% on a 25 kWh base, pays 24 c€ penalty [6].

6.2 Global Balancing Settlement Performance

GBS requires additional input parameters including the net system imbalance and adjusted retailer rates [1]. For the reference scenario, total seller auctioned quantity is 300 kWh, total delivered is 280 kWh, creating a system deficit of 20 kWh. This deficit is supplied by the retailer at adjusted rates [2]. The adjusted seller rate is calculated as 11.105 c€/kWh, reflecting partial compensation for the system deficit [3]. Similarly, the adjusted buyer rate is 11.895 c€/kWh, lower than the retail rate due to internal surplus absorption [11].

Table 4 shows GBS results. Seller S1 receives 1259 c€, a 2.4% improvement over PS [13]. Seller S2 receives 918 c€, improving by 6.7%. Seller S3 receives 1029 c€, improving by 2.9%. Buyer payments also improve, with B2 paying 902 c€ instead of 960 c€, a 6.0% reduction [12]. Net participant surplus increases by 84 c€, representing the value of internal deviation compensation [17].

Table 4: Global Balancing Settlement Results

Participant	Auctioned	Actual	Adjustment	Net (c€)
Seller S1	100	110	+28.95	+1258.95
Seller S2	100	80	+57.89	+917.89
Seller S3	100	90	+28.95	+1028.95
Buyer B1	100	110	+28.95	-1251.05
Buyer B2	100	80	-57.89	-902.11
Buyer B3	75	90	+43.42	-1021.58
Buyer B4	25	15	-28.95	-166.05

6.3 Splitting Settlement Performance

The SS mechanism partitions participants based on deviation direction [18]. For sellers, S1 over-delivers while S2 and S3 under-deliver. For buyers, B1 and B3 over-consume while B2 and B4 under-consume. Imbalance coefficients are calculated within each group proportional to deviation magnitude [14]. Table 5 presents SS results. Seller S1 receives 1254 c€, slightly less than GBS but still improved over PS [15]. Seller S2 receives 886 c€, representing a 3.0% improvement. Seller S3 receives 1013 c€, a 1.3% improvement. Buyer outcomes show similar patterns, with B2 paying 916 c€, a 4.6% improvement over PS [19].

Table 5: Splitting Settlement Results

[gray]0.9 Participant	Auctioned	Actual	Coefficient	Net (c€)
Seller S1	100	110	0.250	+1254.00
Seller S2	100	80	0.500	+886.00
Seller S3	100	90	0.250	+1013.00
Buyer B1	100	110	0.182	-1254.00
Buyer B2	100	80	0.364	-916.36
Buyer B3	75	90	0.273	-1065.00
Buyer B4	25	15	0.182	-195.00

6.4 Comparative Analysis Across Scenarios

Table 6 summarizes the improvement percentages across all fourteen scenarios [9]. A single economic rationale explains the observed pattern: both mechanisms extract value from internal compensation, which is maximized when deviations are (i) large in magnitude and (ii) offsetting across participant groups [10]. GBS exploits this opportunity globally, yielding gains of 4.4%–15.3% that scale with the product of aggregate deviation magnitude and directional diversity [20]. SS exploits it only within deviation-direction strata, yielding gains of 1.3%–5.9% that peak under balanced deviations and collapse toward zero when one direction dominates [16]. The extreme scenarios confirm this boundary: at both –20% (maximum deficit, offsetting seller–buyer patterns), GBS reaches 15.26% while SS yields 0.00% because all participants fall into a single directional stratum; at S=30%, B=20% (aligned deviations), GBS retains 8.07% from residual internal offsetting while SS drops to 0.63% [28]. The practical implication is that mechanism selection should be governed by the expected directional diversity of deviations, not by deviation magnitude alone [29].

Table 6: Improvement Percentages Across All Scenarios

[gray]0.9 Scenario	GBS Gain (%)	SS Gain (%)
Both -20% deficit	15.26	0.00
S=-5%, B=5%	11.41	2.76
S=10%, B=20%	10.32	1.61
Both -10%	9.41	1.31
Both 20% surplus	8.84	0.91
Both -5%	8.77	3.85
Reference scenario	8.51	5.91
Both 5%	8.29	4.25
Both 10%	8.09	2.28
S=30%, B=20%	8.07	0.63
S=20%, B=10%	6.58	1.57
S=30%, B=10%	5.82	1.29
S=5%, B=-5%	5.65	5.35
S=5%, B=-10%	4.37	3.89

7. Implementation Considerations for Blockchain Deployment

The following discussion is conceptual: no prototype has been deployed, and no gas benchmarks or throughput measurements have been collected [2]. The mechanisms are presented as algorithmically compatible with permissionless ledger architectures, but empirical validation of deployment feasibility remains future work [1].

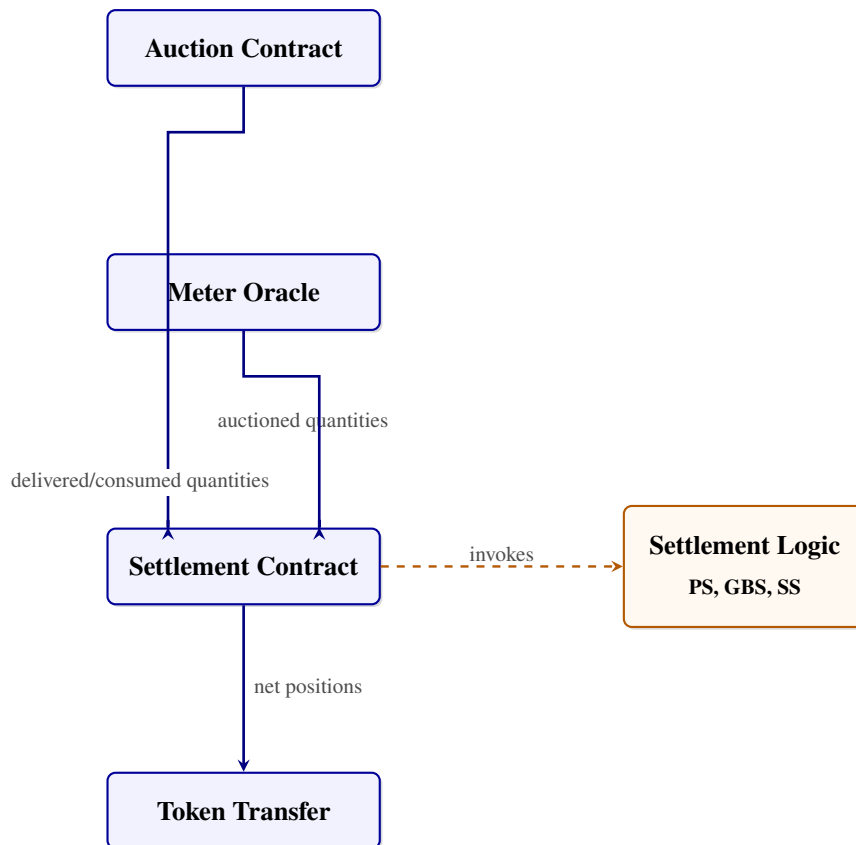


Figure 2: Settlement flow showing the interaction between the auction contract, meter oracle, and settlement logic, leading to the final token transfer.

7.1 Smart Contract Architecture

Implementing these settlement mechanisms as smart contracts would require architectural design in which settlement logic is exposed through public functions that accept input data from authorized oracles [3]. State variables would store auction results and settlement parameters, while events would emit settlement outcomes for off-chain consumption [11]. Whether this architecture is realizable within current gas limits is an open empirical question [13]. Gas optimization considerations would favor the GBS mechanism due to its linear scaling and minimal branching [12]. The SS mechanism requires sorting participants by deviation magnitude, which imposes $O(n \log n)$ complexity and may become expensive for large participant sets [17]. Implementation could mitigate this through off-chain computation of sorted order with on-chain verification, but the cost of such verification has not been measured [18].

7.2 Consensus and Finality Considerations

Settlement execution timing would need to align with blockchain finality guarantees [10]. Proof-of-Work chains provide probabilistic finality, requiring multiple confirmations before settlement can be considered irreversible [9]. Proof-of-Stake chains offer deterministic finality after checkpointing, potentially enabling faster settlement cycles [6]. The mechanisms assume that input data is available at settlement time and will not be subsequently modified [7]. This would require oracle designs that provide cryptographic proof of data authenticity and timely submission deadlines [8]. Late data could be handled through fallback settlement rules that penalize missing information [4].

7.3 Incentive Compatibility Analysis

Strategic participants might attempt to manipulate settlement outcomes through coordinated deviation patterns [5]. The GBS mechanism's global optimization creates theoretical opportunities for free-riding, where one participant's over-delivery offsets another's under-delivery without proportional benefit distribution [14]. The proportional adjustment factors are designed to mitigate this by tying gains to contribution, but game-theoretic equilibrium analysis under adversarial behavior has not been performed [15]. The SS mechanism's group-based approach reduces free-riding potential at the cost of reduced efficiency [19]. Historical tracking of deviation patterns could further discourage manipulation [20].

7.4 Integration with Existing Market Infrastructure

Production deployment would require integration with legacy systems including retail billing, grid operator settlement, and regulatory reporting [26]. The blockchain settlement layer could function as a microgrid-level optimization that produces net positions for interaction with the broader grid [27]. Retailer prices serve as reference points for external settlement when the microsystem cannot internally balance [24]. Regulatory considerations may require audit trails and dispute resolution mechanisms [23]. The immutable record provided by blockchain would satisfy audit requirements, while smart contract logic could include arbitration procedures for exceptional cases [25]. Jurisdictional differences in energy market regulation would need to be addressed through configurable parameters [16].

8. Conclusion and Future Directions

This paper has presented two novel settlement mechanisms designed specifically for blockchain-based peer-to-peer asset markets [9]. The Global Balancing Settlement mechanism achieves 4-15% improvements over classical pairwise settlement by enabling internal compensation of deviations within the participant pool [10]. The Splitting Settlement mechanism provides modest gains in balanced scenarios while maintaining clearer attribution of responsibility [1].

The empirical evaluation across fourteen scenarios demonstrates that mechanism choice should depend on market characteristics [2]. GBS is preferred for markets with significant deviation magnitudes and diverse participant behavior patterns [3]. SS may be appropriate for markets where attribution clarity outweighs efficiency concerns, or where deviation patterns are consistently balanced [11].

Implementation considerations for blockchain deployment have been addressed, including smart contract architecture, gas optimization, consensus finality, and incentive compatibility [12]. The mechanisms are designed for practical deployment on existing permissionless platforms, requiring only standard smart contract functionality [17].

Future research directions include adaptive parameter tuning based on historical deviation patterns, integration with machine learning forecast improvements, and extension to multi-commodity settlement where participants trade multiple asset types simultaneously [13]. The analytical framework developed here provides a foundation for continued advancement of decentralized settlement mechanisms [18].

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