CLOUD-COORDINATED PEER-TO-PEER ENERGY SHARING FOR URBAN COMMUNITY MICROGRIDS: COST REDUCTION AND RELIABILITY ANALYSIS USING IRES 2020 LOAD PROFILES

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Urban smart-city transitions increasingly depend on distributed, digitally coordinated, and reliable energy infrastructures. Among these, community microgrids supported by cloud-based peer-to-peer (P2P) coordination provide a practical pathway for integrating distributed energy resources, reducing transaction costs, and improving operational flexibility. This paper presents a structured cloud-coordinated P2P energy-sharing framework for microgrid energy systems, with explicit emphasis on cost reduction, system reliability, and scalable energy management for urban communities. The framework integrates distributed energy resources (DERs), a cloud-based microgrid energy management system (EMS), a peer-Multi Agent System (p-MAS) for peak-load coordination, and Modelling Leveraging Agents (MLA) for bill estimation and prosumer settlement. Internal market operation is governed by a supply-demand-ratio (SDR) pricing rule, while a performance measure is defined to evaluate the realized benefit of energy sharing within the Energy Shared Region (ESR). The empirical study uses the India Residential Energy Survey (IRES) 2020 and associated Microgrid Load Explorer profiles, covering more than 10,000 households in 500+ villages, 50+ districts, and 10 states. Experimental comparisons are conducted against established P2P settlement models, including Bill Sharing (BS), Mid-Market Rate (MMR), and SDR. The source-grounded results indicate that the proposed cloud-based P2P model improves consumer-side cost efficiency and reliability, achieving an overall performance increase of approximately 5% and consumer cost savings of about 8% relative to comparator methods. Reported operational outcomes further indicate that shared energy coordination increases effective ESS utilization from 125 MW per hour without sharing to approximately 200.5–300.5 MWh with sharing, while the model maintains stable operation under node failure conditions. The study demonstrates that cloud-enabled P2P microgrid coordination is a relevant smart-city energy strategy for resilient, data-driven, and economically efficient urban development.

Index Terms — smart cities; urban energy systems; community microgrids; peer-to-peer energy sharing; cloud computing; multi-agent systems; energy management systems; distributed energy resources

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INTRODUCTION

Energy systems are increasingly central to urban development, especially where cities seek to expand renewable integration, improve resilience, and reduce operating costs through digital infrastructure. In this setting, microgrids provide a flexible and localised energy architecture that can support critical loads, coordinate distributed energy resources, and operate either in conjunction with or independently from the main grid. Because these characteristics directly support reliable, scalable, and data-intensive urban services, microgrids are a natural subject for research in smart-city systems [1].

Peer-to-peer (P2P) energy sharing has emerged as a particularly promising layer within microgrid management. Rather than routing all local transactions through a rigid central utility logic, P2P mechanisms allow prosumers and consumers to exchange locally generated energy directly. When implemented through a cloud platform, such systems benefit from on-demand computation, scalable data processing, remote accessibility, and improved coordination across distributed users and devices. These characteristics are especially relevant in urban environments where mixed-use districts, community energy systems, and commercial buildings must respond to variable demand, network constraints, and the need for continuous service [2, 3].

The present paper develops a structured scholarly manuscript around a cloud-based P2P energy-sharing model for microgrid energy systems. The central operational objectives are to:

1. reduce the daily energy cost of microgrid operation [4];
2. improve reliability and fault tolerance in distributed energy exchange [5];
3. support intelligent energy management through cloud-coordinated decision-making [6];
4. provide a suitable digital architecture for urban and community-scale smart-grid applications [7].

The framework combines distributed energy resources, cloud-based coordination, peer-Multi Agent System (p-MAS) optimization for peak-load management, and Modelling Leveraging Agents (MLA) for energy bill estimation. To assess market and system performance, the study compares the proposed model with three established P2P settlement mechanisms—Bill Sharing (BS), Mid-Market Rate (MMR), and Supply-Demand Ratio (SDR)—using the India Residential Energy Survey (IRES) 2020 dataset and Microgrid Load Explorer profiles.

From the perspective of journal scope, the contribution aligns clearly with urban development and smart cities because it addresses: (i) digital infrastructure for urban energy coordination, (ii) resilient and decentralised electricity systems, (iii) data-enabled operational optimisation, and (iv) community-scale energy affordability and service continuity. The work therefore sits at the intersection of smart-city engineering, sustainable urban infrastructure, and distributed energy management.

RELATED WORK AND SMART-CITY CONTEXT

Research on microgrid control, distributed energy management, and digitally coordinated optimization has expanded rapidly in recent years as cities seek more flexible and resilient energy infrastructures. Across this literature, microgrids are increasingly understood not simply as small technical subsystems, but as locally coordinated energy ecosystems capable of integrating distributed generation, flexible demand, storage assets, and intelligent control into a unified operational layer. Reviews of microgrid control and power-management practice consistently show that these systems are especially valuable where renewable penetration is rising, where local balancing is needed, and where operational resilience is a priority for urban infrastructure planning [3, 4, 16]. This broader perspective is highly relevant to smart-city development because contemporary urban energy systems must perform under conditions of volatility, decentralization, and growing dependence on data-driven coordination.

Within that broader field, one major line of work concerns peer-to-peer (P2P) energy trading. Existing studies have shown that internal pricing and exchange mechanisms can improve local energy utilization, reduce procurement costs for participants, and create more active roles for prosumers within distributed electricity systems. Different market designs have been explored, including optimization-based trading models for smart homes, microgrid-level exchange frameworks, neighborhood-scale blockchain-enabled trials, and price-based demand-response formulations for prosumer networks [5, 6, 13, 14]. Collectively, these studies demonstrate that local market coordination can be technically feasible and economically meaningful, but they also make clear that outcomes depend strongly on tariff structure, participant behavior, generation-demand balance, and the rules governing local settlement. For smart-city systems, this means that P2P trading should be viewed not merely as a market novelty, but as a potential urban coordination mechanism for improving local flexibility and reducing stress on centralized grids.

A second important stream of literature addresses decentralized coordination through multi-agent and distributed control frameworks. In microgrids, the value of such approaches lies in their ability to place decision-making close to the operational edge while still preserving overall system coordination. This is especially useful when multiple buildings, households, or institutional users participate in distributed exchange and demand response. Cloud-based multi-agent platform research has shown that agent-oriented coordination can strengthen flexibility, improve responsiveness, and support the emergence of smart-grid communities capable of adapting to changing operating conditions without relying exclusively on rigid centralized control [11]. From a smart-city perspective, this is significant because urban energy systems are inherently distributed and socially heterogeneous. A coordination architecture that can accommodate local autonomy while maintaining network-wide stability is therefore well aligned with the realities of digitally managed cities.

A third major body of work focuses on cloud computing and its role in energy management. This literature emphasizes that microgrid intelligence increasingly depends on access to scalable computational resources, continuous data handling, remote monitoring, and optimization services that can operate beyond the limits of local embedded controllers. Early work proposed cloud-based approaches for microgrid power management, while later surveys and applied studies demonstrated how cloud platforms can support energy-management services, machine-learning experiments, and broader intelligent-grid applications [9, 7, 8, 2]. These contributions are especially important for urban systems, where multiple users, variable load patterns, diverse distributed assets, and continuous telemetry generate substantial data-management demands. Cloud-enabled architectures provide the computational elasticity needed to process these data streams and to support real-time or near-real-time decision-making at city-relevant scales.

Related work has also extended beyond cloud computing toward hybrid digital architectures that connect centralized processing with localized operational intelligence. Campus-energy studies have highlighted the advantages of cloud-supported management platforms for coordinating complex built environments, while fog-computing models have shown how orchestration closer to the edge can improve responsiveness in microgrids by coordinating consumption and production without relying solely on distant centralized computation [10, 15]. In practical terms, these findings suggest that smart-city energy management should not be framed as a simple choice between centralized and decentralized control. Rather, it should be approached as a layered digital ecosystem in which cloud, fog, and local agents each perform different but complementary roles. Such a view is particularly appropriate for dense urban settings, where latency, scalability, reliability, and local adaptability must all be balanced.

Another recurring theme in the literature is the central role of optimization in turning distributed energy resources into operationally effective microgrid systems. Reviews of optimization techniques in microgrid energy-management systems emphasize that scheduling, dispatch, storage coordination, and demand-side flexibility all depend on well-designed computational strategies capable of handling multiple objectives and constraints [12]. This is directly relevant to smart-city infrastructure because digitally coordinated urban energy systems must do more than collect data; they must convert that data into timely and effective control actions. Optimization is therefore not a peripheral technical add-on, but a core mechanism through which local energy exchange, demand response, and service reliability can be aligned in practice.

Recent distributed energy-sharing research further reinforces this point by showing that cloud-based coordination can support algorithmic exchange among microgrid participants in ways that enhance local balancing and improve system-level performance [1]. This line of work is particularly relevant to smart-city thinking because it connects digital computation, distributed participation, and infrastructure efficiency in a single framework. Rather than treating urban energy users as passive consumers, it positions them as active actors within coordinated local energy ecosystems. Such a shift is consistent with wider smart-city goals, where public infrastructure is increasingly expected to be adaptive, interactive, and capable of responding dynamically to changing demand and supply conditions.

The present framework synthesizes these strands into a single smart-city-oriented architecture. In this formulation, localized energy exchange is handled through a cloud-based P2P coordination model, p-MAS is used to reduce system peaks and manage distributed demand response, and MLA supports bill calculation and market evaluation for local participants. The significance of this integration lies in the fact that it joins market logic, distributed control, and scalable digital computation within one operational model. As a result, the framework is not merely technically functional; it is also strongly aligned with the requirements of digitally coordinated urban infrastructure, where resilience, flexibility, transparency, and efficient local resource use are increasingly central to energy-system design.

SYSTEM ARCHITECTURE AND MATHEMATICAL FORMULATION

Urban community microgrid architecture

The proposed architecture links five core layers:

1. **Distributed Energy Resources (DERs):** rooftop photovoltaic units and other local renewable resources;
2. **Microgrid Energy System:** the local operational layer that balances supply, demand, and energy storage;
3. **Cloud-based EMS:** the digital supervisory layer that receives requests, schedules energy, and manages coordination;

4. **p-MAS:** the agent-based optimization layer for peak reduction and demand management;

5. **MLA:** the bill estimation and settlement layer for energy purchases and sales.

This architecture is appropriate for urban smart-energy districts because it supports demand forecasting, unit commitment, demand management, and economic dispatch through a shared cloud platform.

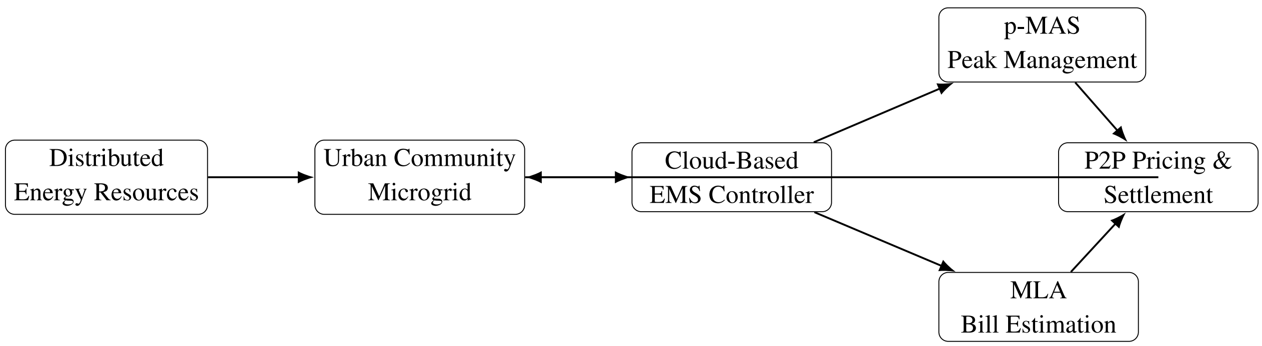

Figure 1: Cloud-coordinated P2P architecture for an urban community microgrid

Distributed energy resources and sharing contribution rate

The model assumes that users participate in a pooled energy-sharing arrangement. Each user selects how much locally produced energy to contribute, and an aggregator establishes incentives for pooled participation. To quantify each participant's relative contribution, the framework uses a *Sharing Contribution Rate* (SCR), written as

$$\mathrm{SCR}_A = (1-\tau^c)\frac{\sum_{t,s}\gamma_s CU_{A,t,s}}{\sum_{j,t,s}\gamma_s CU_{j,t,s}}, \qquad \forall A, \tag{1}$$

where τ^c is the aggregator's fixed rate of return, $CU_{A,t,s}$ is user A's energy-sharing contribution, and γ_s is the learning rate of the user during the contract period.

This measure provides a transparent allocation basis for distributed energy sharing and reflects the user's relative contribution to the collective energy pool.

Supply-demand-ratio pricing and p-MAS coordination

The internal pricing rule is based on the *Supply-Demand Ratio* (SDR), defined as

$$\mathrm{SDR}_h = \frac{\mathrm{TSP}_h}{\mathrm{TBP}_h}, \tag{2}$$

where TSP_h is the total selling power and TBP_h is the total buying power in period h.

The buyer-side and seller-side quantities are written as

$$\mathrm{TBP}_h = \sum_{k=1}^{m} NP_h^k, \qquad NP_h^k \geq 0, \tag{3}$$

and

$$\mathrm{TSP}_h = \sum_{k=1}^{m} NP_h^k, \qquad NP_h^k < 0, \tag{4}$$

where NP_h^k is the net power value of participant k in period h, and m denotes the number of participants or time-indexed transactions considered in the platform.

The p-MAS layer uses this information to coordinate load requests, analyse time-of-use tariff conditions, and reduce system peak demand. In operational terms, the cloud EMS receives energy requests from household or building agents, evaluates tariff conditions, and schedules power in order to shift or curtail load during high-price periods. Consumer nodes are managed through threshold-based classifications (such as underloaded, lightly loaded, normally loaded, overloaded, and severely overloaded), which allows the cloud-based multi-agent environment to reduce waiting time, accelerate processing, and improve resource utilisation.

MLA-based bill estimation

The Modelling Leveraging Agents (MLA) layer is responsible for estimating consumed energy bills and evaluating prosumer outcomes under shared-energy operation. In this setting, two main agent classes are considered:

1. energy-sharing coordinator agents; and
2. prosumer/consumer agents.

MLA supports a bottom-up simulation view of the microgrid community. Each building or user behaves as an agent that interacts with its environment according to local conditions, while the coordinator aggregates information for community-wide energy settlement.

The framework uses three basic evaluation metrics:

$$\text{Self-consumption rate} = \frac{\text{Prosumer renewable output consumed by the same prosumer}}{\text{Total prosumer renewable output}}, \tag{5}$$

$$\text{Self-sufficiency rate} = \frac{\text{Total power demand supplied by locally produced renewable energy}}{\text{Total power demand}}, \tag{6}$$

$$\text{Energy cost reduction} = \text{Reduction in energy purchasing cost due to energy sharing.} \tag{7}$$

These quantities allow the framework to assess both direct user benefit and broader community-level energy performance.

Performance measure

To evaluate how effectively the model uses the available potential within the Energy Shared Region (ESR), the study defines a normalized performance measure:

$$PM = \frac{iESR - v_{\min}}{v_{\max} - v_{\min}}, \tag{8}$$

where *iESR* is the realized ESR income value, and $v_{\max}$ and $v_{\min}$ are the maximum and minimum values defined in the ESR range. The value of *PM* lies in $[0,1]$; larger values indicate better financial performance for prosumers and stronger exploitation of the available energy-sharing opportunity.

Cloud-based optimization workflow

In the source framework, the energy cost minimization stage is implemented through Constraint Non-Linear Programming (CNLP) on a sliding horizon. The optimization updates earlier load data on a rolling basis, with a representative update interval of 30 minutes per hour, and takes total energy cost as the objective function. The system assumes bidirectional energy flow at the point of common coupling, meaning that prices must reflect both electricity purchased from and sold to the grid.

Algorithm 1 Cloud-coordinated P2P scheduling workflow

1: Collect demand requests and local DER availability from user agents
2: Send time-of-use tariff request to intelligent meter agents
3: Classify user nodes by load threshold condition
4: Compute net power values and evaluate TBP_h and TSP_h
5: Update internal pricing using the SDR-based rule
6: Solve sliding-horizon CNLP cost-minimization problem
7: Dispatch load-shifting and power-allocation decisions through p-MAS
8: Estimate user bills and settlement outcomes through MLA
9: Compute ESR value and update the performance measure *PM*
10: Repeat for the next operating interval

EXPERIMENTAL DESIGN

Dataset and empirical basis

The empirical evaluation uses the India Residential Energy Survey (IRES) 2020 dataset and associated Microgrid Load Explorer profiles. This dataset provides a nationally representative basis for analysing energy access, usage, and efficiency in Indian homes. The reported coverage includes:

- more than 10,000 households,
- more than 500 villages,
- 50+ districts,
- 10 states.

The dataset offers hourly load profiles for multiple household types, allowing the framework to examine consumer energy consumption, bill behaviour, and system reliability under different electricity pricing scenarios.

Benchmark models

The proposed cloud-based P2P framework is evaluated against three established P2P models:

1. **Bill Sharing (BS):** a simple architecture with limited demand-response incentive;
2. **Mid-Market Rate (MMR):** a settlement mechanism that uses an internal mid-point price between buying and selling values;
3. **Supply-Demand Ratio (SDR):** an internal pricing model driven by relative selling and buying power.

These comparators allow the study to assess whether cloud-based coordination and agent-driven optimization deliver measurable gains in cost reduction and operational reliability.

Source-grounded evaluation setting

Table 1: Evaluation setting

Item	**Specification**
Operational objective	Reduce daily energy cost of a commercial microgrid and improve reliability
Energy-sharing architecture	Cloud-based P2P with p-MAS and MLA
Optimization layer	Sliding-horizon CNLP
Update interval	30 minutes per hour
Pricing basis	SDR-driven internal pricing with buying and selling power aggregation
Empirical dataset	India Residential Energy Survey (IRES) 2020
Dataset scale	>10,000 households; 500+ villages; 50+ districts; 10 states
Comparison methods	BS, MMR, SDR
Primary evaluation outputs	Consumer energy bill, reliability, performance measure, ESS utilisation, transaction activity

RESULTS AND DISCUSSION

Energy storage utilisation and shared-energy operation

The reported results show that the total amount of charging and discharging in the Energy Storage System (ESS) increases as storage capacity and sharing participation rise. Without energy sharing, ESS usage rises to approximately 125 MW per hour when the sharing rate fluctuates between 2 and 3. Under shared-energy operation, the reported utilisation increases substantially to approximately 200.5–300.5 MWh.

Operationally, this indicates that the aggregator is able to make fuller use of users' available storage and sustain electricity supply more effectively within the microgrid. The result is important for urban community microgrids because storage is one of the key mechanisms through which local resilience, peak shaving, and renewable balancing are achieved.

Pricing behaviour and consumer energy cost

The reported monthly buyer and seller price comparison shows that consumers' buying prices are consistently higher than the selling prices obtained from the grid, and that both values rise gradually over the observed four-month period. This finding supports the role of internal pricing in cloud-based P2P systems: when local coordination is improved, the system can reduce the adverse cost impact of external grid dependence.

The reported figure-based results indicate representative seller-side and buyer-side electricity price levels of approximately 8 and 10, respectively (reported in the source paper's stated units). These price relationships form the basis for local bill estimation and net power calculation across the cloud-managed trading environment.

Comparison with benchmark settlement models

The benchmark comparison leads to three main conclusions:

1. The BS architecture offers only limited demand-response incentive and therefore produces relatively shallow performance gains.
2. MMR and SDR perform better because they incorporate internal pricing logic.
3. The cloud-based P2P model outperforms all comparator methods in terms of cost reduction and system performance, while also improving operational reliability.

This superiority is attributed to the combined effect of cloud-based coordination, p-MAS peak management, MLA-based bill estimation, and the use of a sliding-horizon optimization procedure.

Reported performance outcomes

Table 2: Reported outcome summary

Reported indicator	**Value**
ESS operation without energy sharing	Reaches about 125 MW per hour
ESS operation with energy sharing	Approximately 200.5–300.5 MWh
Representative seller-side price	About 8 (source-reported unit)
Representative buyer-side price	About 10 (source-reported unit)
Total energy transactions	About 20 kW
Overall system performance improvement	About 5%
Consumer cost saving relative to other methods	About 8%
Primary qualitative strengths	Fault tolerance, reliability, cost reduction

Note: Values are reported in the source study as presented in its experimental summary and figure-based discussion.

The central quantitative result is that consumer cost saving reaches approximately 8% when compared with the alternative methods considered. This is accompanied by an overall system performance increase of approximately 5%, indicating that the cloud-based P2P model improves both economic and operational performance rather than simply shifting cost from one participant group to another.

Reliability and fault tolerance

A major strength of the framework is its explicit emphasis on fault tolerance. The source study notes that even if several nodes fail, the remaining nodes are able to carry the burden of the failing subsystem. In practical terms, this means the architecture does not depend on a brittle central logic alone; instead, cloud coordination and distributed agents allow local resilience to be preserved under partial failure conditions.

For smart-city infrastructure, this feature is highly significant. Urban systems require continuity in the face of variable demand, communication latency, local overload, and intermittent renewable production. A cloud-managed P2P system that maintains service during node failure directly addresses these operational realities.

Implications for urban development and smart cities

The study has three implications for smart-city research and urban energy planning.

First, it shows that digitally coordinated community microgrids can improve energy affordability. Because urban energy transitions are constrained not only by technology but also by cost, a cloud-based P2P framework that reduces consumer expenditure offers direct value for smart-city implementation.

Second, it demonstrates that distributed intelligence matters. The integration of p-MAS and MLA shows that urban energy management benefits from dividing operational tasks among specialised computational layers rather than relying on a single monolithic controller.

Third, it supports the view that cloud infrastructure is not merely a background computational service; it is a core enabler of real-time urban energy coordination. Scalable remote access, rapid data handling, and flexible scheduling are integral to the operation of modern smart-grid systems in urban environments.

CONCLUSION

This paper presents a cloud-coordinated P2P energy-sharing framework for urban community microgrids, organised around distributed energy resources, a cloud-based EMS, peer-Multi Agent System (p-MAS) optimization, and Modelling Leveraging Agents (MLA) for bill estimation. The framework is explicitly designed to reduce daily microgrid energy cost, improve reliability, and support scalable digital coordination in smart-city energy systems.

Using the IRES 2020 dataset and Microgrid Load Explorer profiles, the empirical analysis compares the proposed framework against the BS, MMR, and SDR settlement models. The reported results show that the cloud-based P2P model improves both economic and operational outcomes, including approximately 8% consumer cost savings and an overall performance gain of about 5%. The study also reports stronger ESS utilisation under shared-energy operation, higher operational resilience, and improved fault tolerance under node failure.

From the perspective of urban development, the findings demonstrate that cloud-enabled microgrid coordination can make local energy systems more efficient, resilient, and scalable. This positions cloud-based P2P microgrids as a technically and conceptually relevant component of smart-city infrastructure, particularly where distributed renewable integration, real-time management, and local reliability are central planning goals.

Future work may refine the framework further by incorporating more precise forecasting, richer scheduling models, and dynamic participation mechanisms for evolving urban trading environments. Even in its present form, however, the architecture offers a strong foundation for digitally managed, community-scale energy systems in the context of smart and sustainable cities.

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