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Chapter 1

Introduction

Peer-to-peer (P2P) energy trading has emerged as a promising solution for distributed energy resource (DER) management, allowing prosumers to actively participate in the energy market. With increasing adoption of renewable energy sources, the need for efficient energy allocation and distribution has become essential. This project presents a decentralized P2P energy trading platform, leveraging Python Django and a multi-objective optimization framework, to optimize transactions between prosumers while ensuring network stability. The platform dynamically matches energy supply and demand, balances real-time deviations with the grid, and performs financial settlements on a monthly basis.

1.1 Motivation

The global energy landscape is rapidly shifting towards renewable energy, with more individuals generating electricity through solar and wind sources. This decentralization introduces challenges in energy management, distribution, and ensuring grid stability. Traditional centralized models are not equipped to handle the variability and unpredictability of renewable energy generation, leading to the necessity of P2P energy trading platforms. This project seeks to address these challenges by offering a system that ensures efficient energy trading while maintaining grid stability.

1.2 Problem Definition

Renewable energy generation, being inherently intermittent, creates a complex environment for energy trading. In a P2P energy market, ensuring a fair and efficient match between buyers and sellers while maintaining system stability is crucial. The main problem lies in optimizing energy transactions between prosumers such that both seller and buyer welfare is maximized, while also ensuring that network stability is maintained through continuous monitoring and corrective actions using load flow analysis.

1.3 Objectives

- Develop a decentralized platform for energy trading among prosumers.
- Implement a multi-objective optimization framework that maximizes the conflicting welfares of both sellers and buyers.
- Perform backward-forward sweep (BFS) flow analysis after each iteration of the optimization algorithm to ensure network stability.
- Integrate real-time grid balancing to handle deviations in renewable energy production.

Chapter 2

Background

2.1 Literature Survey

The concept of peer-to-peer (P2P) energy trading has gained significant traction in recent years as a viable solution for managing decentralized energy systems. With the rise of distributed energy resources (DERs) such as solar panels and wind turbines, there is a need for market structures that allow prosumers to directly trade surplus energy with each other, reducing dependence on centralized utilities. This section reviews the key literature surrounding P2P energy trading platforms, optimization frameworks, grid stability analysis, and their practical implementations.

2.1.1 P2P Energy Trading Models

Several studies have proposed different models and architectures for P2P energy trading. One approach widely discussed in the literature is the use of decentralized market mechanisms where prosumers actively engage in energy trading without intermediaries. Zhang et al. [2] introduced a blockchain-based energy trading platform, enabling transparent, secure, and decentralized transactions. The use of smart contracts ensures that energy transactions are executed automatically based on predefined conditions, eliminating the need for centralized control. Similarly, Tushar et al. [3] explored a cooperative game theory-based approach, where prosumers collaborate to maximize their collective benefits in energy trading. Their model demonstrates how prosumers can achieve better financial outcomes by forming energy trading coalitions. This work emphasizes the potential for cooperative P2P networks to increase the efficiency of energy allocation.

2.1.2 Multi-Objective Optimization in Energy Markets

Optimization plays a crucial role in P2P energy trading, particularly in balancing the interests of buyers and sellers while ensuring the stability of the power grid. Liu et al. [4] proposed a multi-objective optimization framework for energy trading that maximizes both social welfare and grid stability. They used a market-clearing mechanism where bids and offers are optimized to ensure that both parties achieve maximum satisfaction. Park et al. [5] further explored the integration of multi-objective optimization techniques into P2P platforms. Their work highlights the importance of welfare maximization, where the allocation of energy is done to ensure fairness in pricing and allocation among the prosumers. Their model sorts buyers and sellers based on price bids, similar to the welfare-maximization approach used in this project.

2.1.3 Grid Stability and Load Flow Analysis

One of the major challenges in integrating renewable energy resources into the grid is ensuring network stability. Several studies have addressed the risks posed by intermittent generation and fluctuations in power supply. Guerrero et al. [6] proposed the use of backward-forward sweep (BFS) flow analysis to ensure that grid stability is maintained throughout the energy trading process. Their research indicates that BFS is a computationally efficient method to update node voltages and current flows, providing real-time feedback on grid performance. Yang et al. [7] emphasized the need for continuous monitoring of grid stability in real-time P2P energy trading environments. They developed an optimization algorithm that integrates grid flow analysis at each iteration, ensuring that the grid remains within operational limits after every energy transaction. This approach is closely aligned with the BFS method integrated into the current project to ensure that network stability is maintained after each iteration of the optimization algorithm.

2.1.4 Summary

The reviewed literature highlights the evolving landscape of P2P energy trading systems, which leverage decentralized mechanisms, advanced optimization techniques, and robust grid stability frameworks. Decentralized platforms such as blockchain-based trading [2] and cooperative game theory models [3] have showcased the potential to enhance transparency and efficiency in energy transactions. Multi-objective optimization frameworks [4][5] play a critical role in balancing the needs of buyers and sellers while maintaining grid stability. Furthermore, grid stability analysis methods, particularly the backward-forward sweep approach [6][7], ensure that energy trading does not compromise the operational integrity of the power grid.

The insights from these studies provide a strong foundation for developing P2P energy trading platforms that optimize energy allocation, promote fairness, and ensure technical feasibility. These frameworks and methodologies are directly applicable to the current project, aiming to integrate welfare maximization with real-time grid stability checks for a reliable and efficient energy trading environment.

Chapter 3

Methodology

3.1 Time-Based Segmentation of Sellers and Buyers

Sellers and buyers are categorized into distinct time frames based on the **Time of Day (ToD) tariff structure** of KSEB:

- **Off-peak hours:** 10 PM to 6 AM
- **Normal hours:** 6 AM to 6 PM
- **Peak hours:** 6 PM to 10 PM

This segmentation ensures that energy transactions align with demand and pricing variations throughout the day.

3.2 Market Clearing Price (MCP) Calculation

For each time frame, the **Market Clearing Price (MCP)** is calculated based on the participating sellers and buyers.

The MCP is determined by matching the sellers' offers with the buyers' demands. The grid tariff structure is used to ensure that the MCP remains competitive with grid prices. The total energy demand of buyers is matched with the sellers' offers, and the MCP is set to either the sellers' offer price or slightly below the buyer's grid price, ensuring competitive pricing.

MCP Constraint: To ensure both sellers and buyers profit relative to the grid tariff, the market clearing price (MCP) is bounded as follows:

$$P_{\text{seller}} \leq \text{MCP} \leq P_{\text{grid}}$$

This ensures that prosumers benefit from the energy trading process, balancing the welfare of both sellers and buyers. By adhering to this constraint, the framework guarantees fair pricing while maintaining competitiveness with grid tariffs.

3.3 Optimization Algorithm and Network Feasibility Check

A **multi-objective optimization algorithm** (NSGA-II) is employed to optimize seller and buyer welfare for each time frame. After each iteration:

- A **network feasibility check** is performed using the **Backward-Forward Sweep (BFS)** method to assess voltage stability across the network.
- Nodes with voltage violations (deviating from the permissible range of 0.95–1.05 p.u.) are identified as **critical nodes**.

3.4 Adaptive Constraint Adjustment

If voltage violations are detected, the following adjustments are made:

- The maximum generation capacity of sellers at critical nodes is capped at 90% of the previous iteration's value.
- The optimization algorithm is rerun with these updated constraints until a feasible solution is obtained.

3.5 Solution Validation

The final solution is validated to ensure:

- Each buyer's load demand is fully satisfied.
- Network stability is maintained across all nodes.

This methodology ensures optimal and feasible energy trading, aligning with both economic objectives and network constraints.

3.6 Summary

This section outlines a comprehensive framework for time-based segmentation, market clearing, optimization, and feasibility validation in peer-to-peer energy trading. Sellers and buyers are categorized into three distinct time frames—off-peak, normal, and peak hours—based on the Time of Day (ToD) tariff structure, ensuring alignment with demand and pricing variations. The Market Clearing Price (MCP) is calculated for each time frame by matching sellers' offers with buyers' demands, constrained to be competitive with grid tariffs. This approach ensures fair pricing while balancing the welfare of both sellers and buyers. A multi-objective optimization algorithm (NSGA-II) is employed to maximize seller and buyer welfare, followed by a network feasibility check using the Backward-Forward Sweep (BFS) method. Critical nodes with voltage violations are identified, and adaptive constraints are applied by capping sellers' generation capacities at these nodes. The algorithm iteratively adjusts until a feasible solution is obtained. The final solution is validated to ensure buyer demands are met and network stability is maintained, achieving an optimal balance between economic benefits and technical feasibility.

Chapter 4

Choosing Optimization Approach

4.1 Objective

The primary objective is to design an energy trading model that maximizes both buyer and seller welfare in a balanced and feasible manner, with the flexibility to switch between solutions if network feasibility issues arise.

4.2 Problem Context and Requirements

In a P2P energy trading scenario, the objective is to fairly and efficiently match buyers and sellers in a way that maximizes welfare. Additionally, the system should allow for flexibility in selecting an optimal trade-off solution based on network feasibility checks.

Key Requirements:

- **Multi-Objective Nature**: Maximize both buyer and seller welfare independently.
- **Range of Solutions**: Multiple solutions are needed to check against network constraints and select feasible alternatives.
- **Feasibility**: Solutions must meet network feasibility requirements (e.g., node voltage constraints in power flow).

4.3 Candidate Optimization Approaches

Several optimization approaches were considered:

1. **Nash Bargaining Solution (NBS)**
2. **Weighted Sum Approach**
3. **Maximin Approach**
4. **Minimizing Welfare Disparity**
5. **Goal Programming**

6. **Pareto Optimization (Selected Approach)**

Each method was assessed based on its ability to:

- Generate multiple solutions for flexibility.
- Balance welfare between buyers and sellers.
- Adapt to network feasibility constraints.

4.4 Comparative Analysis of Approaches

4.4.1 Nash Bargaining Solution (NBS)

- **Description**: NBS finds a single balanced solution by maximizing the product of buyer and seller welfare.
- **Drawback**: Provides only one solution, lacking flexibility if network feasibility checks require alternative options.
- **Reason for Rejection**: Lack of multiple solutions is a limitation in a dynamic, feasibility-driven context.

4.4.2 Weighted Sum Approach

- **Description**: This approach combines buyer and seller welfare into a single objective by assigning weights.
- **Drawback**: It produces a single solution for each weight configuration and does not inherently generate a diverse set of Pareto-optimal solutions. Additionally, finding the right weights is complex.
- **Reason for Rejection**: The weighted sum lacks natural multi-objective balancing and flexibility to switch between solutions based on feasibility.

4.4.3 Maximin Approach

- **Description**: Maximin prioritizes the lowest welfare among participants, ensuring a baseline for all parties.
- **Drawback**: While it ensures that no participant is too disadvantaged, it overly emphasizes the minimum welfare, often at the expense of total welfare.
- **Reason for Rejection**: Maximin may sacrifice overall efficiency, and its single-solution focus does not meet the requirement for multiple feasible solutions.

4.4.4 Minimizing Welfare Disparity

- **Description**: This method minimizes the welfare difference between buyers and sellers.
- **Drawback**: By focusing on reducing welfare disparity, it might prevent efficient transactions and lead to lower overall welfare. It also typically results in a single outcome.
- **Reason for Rejection**: Although fair, it does not maximize welfare effectively and does not produce a set of solutions for flexibility.

4.4.5 Goal Programming

- **Description**: Goal programming seeks to meet specific welfare targets for buyers and sellers.
- **Drawback**: This method depends on rigid target-setting, limiting its adaptability if targets need frequent adjustment. It also doesn't generate a set of solutions.
- **Reason for Rejection**: Goal programming's focus on fixed targets is restrictive and unsuitable for scenarios needing solution diversity and adaptability.

4.4.6 Pareto Optimization (Selected Approach)

- **Description**: Produces a range of optimal trade-off solutions (Pareto front), balancing welfare for both buyers and sellers.
- **Advantages**:
  - **Multiple Solutions**: Provides a set of non-dominated solutions, allowing flexibility to choose alternatives based on network feasibility.
  - **Trade-off Insights**: The Pareto front offers insights into various trade-offs between buyer and seller welfare.
  - **Adaptability**: Allows quick switching between solutions based on network constraints or evolving welfare priorities.
- **Reason for Selection**: Meets all key requirements by offering flexibility, balanced welfare, and adaptability to network feasibility constraints.

Chapter 5

Optimization Formulation

In P2P energy trading, multiple participants (buyers and sellers) interact to transact energy at mutually beneficial prices. The primary challenge is to optimize the welfare of both buyers and sellers while considering network feasibility constraints.

5.1 Key Objectives

- **Maximize Buyer Welfare**: Ensure buyers derive maximum benefit from transactions.
- **Maximize Seller Welfare**: Enable sellers to achieve optimal returns from their energy trades.
- **Network Feasibility**: Solutions must satisfy network constraints, such as node voltage limits, to ensure stability.

5.2 Objective Functions

Buyer Welfare (f_1)

$$\boxed{\begin{aligned}\text{Maximize } f_1 = \sum_{\text{buyers}} & (\text{buyer\_price} \times \log(\text{transacted\_energy} + 1e - 6) \\ & -\text{MCP} \times \text{transacted\_energy})\end{aligned}}$$

Seller Welfare (f_2)

$$\boxed{\text{Maximize } f_2 = \sum_{\text{sellers}} (\text{transacted\_energy} \times \text{MCP})}$$

Definitions:

- buyer_price: Price buyers are willing to pay per unit of energy.
- transacted_energy: Amount of energy transacted in each buyer-seller pair.
- MCP: Market clearing price, representing the transaction price between buyers and sellers.

5.3 Constraints

Supply Constraints (Seller Limits):
Each seller's total transacted energy should not exceed their maximum generation capacity. For seller i with maximum generation G_i:

$$\sum_j E_{ij} \leq G_i$$

Demand Constraints (Buyer Limits):
Each buyer's total received energy should not exceed their load demand. For buyer j with load demand D_j:

$$\sum_i E_{ij} \leq D_j$$

5.4 Decision Variables

The decision variable matrix E_{ij} represents the energy transactions between sellers and buyers, where E_{ij} denotes the energy transacted from seller i to buyer j. The matrix can be represented as:

$$E = \begin{bmatrix} E_{11} & E_{12} & \cdots & E_{1n} \\ E_{21} & E_{22} & \cdots & E_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ E_{m1} & E_{m2} & \cdots & E_{mn} \end{bmatrix}$$

where m is the number of sellers and n is the number of buyers.

5.5 Pareto Optimization Technique

To identify Pareto-optimal solutions, **NSGA-II (Non-dominated Sorting Genetic Algorithm II)** is selected due to its effectiveness in handling multi-objective problems.

Key Features of NSGA-II:

- **Non-Dominated Sorting**: Organizes solutions based on dominance, allowing identification of non-dominated solutions that are not worse than any other solution in all objectives.
- **Diversity Preservation**: Uses crowding distance to maintain diversity in the solution set, ensuring a spread across the Pareto front.
- **Selection of Trade-Off Solutions**: Provides a set of Pareto-optimal solutions, giving flexibility to select a feasible solution that meets network constraints.

Chapter 6

Results

The optimization process for peer-to-peer energy trading was carried out across multiple time frames, each representing different periods of energy demand and generation availability. For each time frame, the sellers and buyers were filtered based on their respective time slots. The market clearing price (MCP) was calculated using the sellers' offers and buyers' demand, with grid tariffs playing a crucial role in determining the MCP. The optimization used the NSGA-II algorithm to generate a Pareto optimal potential solution, with the objective of maximizing seller welfare and buyer welfare while adhering to supply and demand constraints. During each iteration, the transactions were evaluated for feasibility through a backward-forward sweep (BFS) analysis, checking for voltage violations across nodes in the network. If voltage violations occurred, adjustments were made to the sellers' maximum generation capacities to reduce the risk of instability. The process was repeated until a feasible solution was found for each time frame. The final results indicated successful energy allocation that satisfied the welfare objectives for both sellers and buyers, while maintaining network stability within defined voltage limits. The optimization for each time frame concluded with an optimal set of transactions and an overall balanced market operation.

Initial Conditions

Time Frame	Seller ID	Max. Gen. Capacity (kWh)	Offering Price (INR/kWh)
Time Frame 1	Seller 1	30	2.8
	Seller 2	25	3.0
	Seller 3	35	4.0
	Seller 4	28	3.5
Time Frame 2	Seller 5	60	5.2
	Seller 6	55	6.0
	Seller 7	70	5.5
	Seller 8	80	5.3
	Seller 9	75	5.8
	Seller 10	65	5.4
Time Frame 3	Seller 11	80	6.8
	Seller 12	90	6.9
	Seller 13	95	7.0

Table 6.1: Sellers' data: generation capacity and offering price for each time frame.

Time Frame	Buyer ID	Load Demand (kWh)	Bid Price (INR/kWh)
Time Frame 1	Buyer 1	20	4.0
	Buyer 2	15	4.5
	Buyer 3	10	3.8
Time Frame 2	Buyer 4	50	6.5
	Buyer 5	40	6.0
	Buyer 6	35	7.0
	Buyer 7	45	6.2
Time Frame 3	Buyer 8	60	7.5
	Buyer 9	70	7.8
	Buyer 10	75	7.0

Table 6.2: Buyers' data: load demand and bid price for each time frame.

Time Frame 1: Off-Peak Hours (10 PM to 6 AM)

A feasible solution was obtained at iteration 7.

Market Clearing Price (MCP): The MCP for this time frame was determined to be **2.75** INR.

Transaction Matrix: The best transactions among sellers and buyers are represented as:

$$\begin{bmatrix} 4.26 & 11.14 & 1.10 \\ 13.14 & 2.11 & 2.01 \\ 0.71 & 0.57 & 1.62 \\ 1.87 & 1.13 & 5.13 \end{bmatrix}$$

Each row represents a seller, and each column represents a buyer. The values indicate the energy transacted (in kWh). The explanation of the formation of the matrix is provided in previous chapter (Subsection 5.4).

Time Frame 2: Normal Hours (6 AM to 6 PM)

A feasible solution was obtained at iteration 10.

Market Clearing Price (MCP): The MCP for this time frame was determined to be **5.5** INR.

Transaction Matrix:

$$\begin{bmatrix} 16.27 & 5.06 & 13.11 & 5.10 \\ 0.69 & 2.40 & 4.29 & 8.95 \\ 1.72 & 3.53 & 6.37 & 13.86 \\ 29.45 & 16.95 & 4.73 & 1.70 \\ 0.29 & 10.26 & 4.77 & 8.79 \\ 0.95 & 1.77 & 1.69 & 6.52 \end{bmatrix}$$

Time Frame 3: Peak Hours (6 PM to 10 PM)

A feasible solution was obtained at iteration 5.

Market Clearing Price (MCP): The MCP for this time frame was determined to be **7.0** INR.

Transaction Matrix:

$$\begin{bmatrix} 17.64 & 45.53 & 0.49 \\ 25.33 & 10.15 & 44.04 \\ 16.84 & 14.07 & 30.40 \end{bmatrix}$$

Summary

The proposed P2P energy trading framework successfully calculated the MCP and determined optimal energy transactions across all three time frames. In all cases, the buyer load demands were met, and the network feasibility constraints were satisfied. This demonstrates the efficacy and robustness of the implemented methodology.

References

1. Mohan, Vivek, et al. "Realistic energy commitments in peer-to-peer transactive market with risk adjusted prosumer welfare maximization." Electrical Power and Energy Systems (2021): 106377.

2. Zhang, C., Wu, J., Long, C., Cheng, M. (2018). A blockchain-based platform for peer-to-peer energy transactions in a community microgrid. IEEE Transactions on Industrial Informatics, 15(1), 69-77.

3. Tushar, W., Saha, T. K., Yuen, C., Smith, D. B. (2020). Peer-to-peer energy trading with cooperative game theory: Motivations, models, and future directions. IEEE Transactions on Smart Grid, 11(2), 1407-1416.

4. Liu, N., Yu, X., Wang, C., Li, C., Ma, L., Lei, J. (2019). Energy-sharing model with multi-objective optimization for P2P trading in the smart grid. IEEE Transactions on Industrial Informatics, 15(8), 4940-4951.

5. Park, J. H., Kim, K. H., Lee, J. W. (2021). Welfare maximization in peer-to-peer energy trading using a multi-objective optimization framework. International Journal of Electrical Power and Energy Systems, 124, 106358.

6. Guerrero, J. I., Monroy, A., Carretero, J., Giuliani, G. (2020). Efficient backward-forward sweep algorithm for radial distribution system load flow analysis in smart grids. Energies, 13(16), 4142.

7. Yang, S., Dong, Y., Liu, Z., Wu, Q. (2022). Grid stability and optimization in real-time peer-to-peer energy trading systems. IEEE Access, 10, 22560-22571.

8. Kou, Y., Zhang, H., Wang, Q., Xia, F. (2021). Blockchain-based security framework for peer-to-peer energy trading in smart grids. Journal of Cleaner Production, 295, 126420.