Optimal Settlement Model of Energy and Reactive Power Market Using Stochastic Programming

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This study, addresses a novel optimization approach of energy and reactive power market settlement through Stochastic Programming (SP) and Artificial Fish Swarm Algorithm (AFSA). The study focused on enhancing energy efficiency and environmental sustainability, the study explores the integration of distributed energy resources, particularly distributed generation and energy storage systems. Emphasizing Demand Response (DR) and active distribution networks (ADN), the research introduces a virtual power plant concept to enable market participation and optimize network utilization. It combines stochastic programming, CAES, and the AFSA to address uncertainties, optimize financial gain, and enhance market efficiency. The two-settlement energy market model considers uncertainties in day-ahead energy prices, imbalance prices, and storage capacity. The study utilizes a two-stage stochastic planning strategy, presenting a mathematical model to maximize financial gain while adhering to constraints. The study evaluates the proposed approach on the IEEE 30 bus network, considering nine various scenarios with different weighting coefficients. It discusses the impact of weighting on indices such as the unit participation rate, market profitability rate, profitable player number rate, net surplus distribution rate, and generation sharing rate. Results showed that the effectiveness of the proposed settlement approach in decision-making amidst uncertainties, ultimately contributing to the advancement of energy market optimization strategies.

# Overview

The global community focused on enhancing energy efficiency and decreasing environmental pollutants through distributed energy resources (DER) such as distributed generation (DG) and energy storage system (ESS) programs has prioritized Demand Response (DR) as a key initiative to accomplish its goals (1–3). Protective laws have been enacted to support controllable distributed generation, distributed renewable generation, and combined electricity and heat production (4,5). The prevalence of distributed energy sources has led to the development of active distribution networks (ADN), which incorporate dispersive energy sources to meet operational, management, and control objectives (6,7). One of these objectives is to maximize the utilization of Distributed Energy Resources (DERs) to lower expenses, minimize losses, enhance voltage control, improve power quality, and defer investments (8). Unit participation planning is affected by uncertainties like energy price fluctuations, unit production capacity, water flow, and solar radiation levels.

The initial significant aspect is the procurement of a market-focused energy management system utilizing advanced communications and information technology (9). Another crucial aspect is that aggregating Distributed Energy Resources (DERs) can supply energy and ancillary services at the Point of Common Coupling (PCC) for the Distribution System Operator (DSO) and at the Grid Supply Point (GSP) for the Transmission Grid Operator or Independent System Operator (ISO) (10).

Reducing costs associated with reserving active and reactive power, minimizing unsupplied energy due to incorrect reactive power levels, minimizing market compensation costs for reactive power, minimizing final reactive power costs from Distributed Generators (DGs), and minimizing differences in active power trading contracts (11). The goal of determining the actual values of active power exchanged between the distribution system and DGs is to reduce active losses in grid lines while also lowering the voltage inconsistency index (12). Maximizing voltage safety margin and reactive power reserve while keeping final costs for reactive power compensation and energy transfer low (13). Furthermore, reducing network losses by increasing the load supply and voltage stability index (14). The active-reactive power market's ultimate cost aims to be as low as possible by factoring in expenses for procuring energy from distributed energy sources, distribution companies, and associated potential costs (15). Reducing CO2 emissions, improving reactive power compensation from distributed energy resources, lowering reactive power compensation costs, and increasing voltage safety margin (16). An independent and active power market that takes into account both the cost of environmental pollutants and regional market implementation (17).

This study introduces a novel approach to simultaneous planning of storage systems, with a specific focus on Compressed Air Energy Storage (CAES) for profit maximization using stochastic programming (SP) model. The optimization process is facilitated by the Artificial Fish Swarm Algorithm (AFSA), actively involving the producer company in the planning. The model incorporates the dynamics of day-ahead energy markets, revolving storage, and balance mechanisms. Notably, the planning accounts for uncertainties in day-ahead energy prices, positive and negative energy imbalance prices, revolving storage capacity, actual production energy prices, the amount of called storage, and the power production unit's. The overarching objective is to maximize profit by making informed decisions in the face of these uncertainties, leveraging the capabilities of CAES and other power plants.

**Methods**

The study delves into an energy market featuring shared rotating storage, examining a two-settlement energy market model encompassing the Balance Market (BM) and the Day-Ahead Market (DAM). The DAM, functioning as a pool market, is overseen by the market operator, responsible for executing settlement procedures, validating accepted offers, and distributing profits to producers based on the price multiplied by their actual output. The BM introduces dual-pricing, penalizing deviations from predetermined capacity – underperformance incurs penalties for power generation exceeding DAM prices, while overproduction below DAM prices results in penalties.

In the Revolving Reserve (RM) market, successful agents are compensated for their accepted reserve capacity at the RM settlement price, with additional compensation for actual stock production if needed. Notably, energy markets and rotating storage capacity are concurrently implemented and settled. The considered manufacturing company, presumably of small scale, ensures its negligible impact on market prices by setting its offer price at zero or slightly negative. This strategy guarantees acceptance, with subsequent payment aligned with the market's settled price.

*Description of Uncertainty*

Nondeterministic variables

Uncertain parameters refers to values that cannot be established with absolute certainty before they take place. Non-deterministic parameters include the price of capacity and energy in the Revolving Reserve (RM), the quantity of unit output, and the amount of rotational storage. These parameters are discussed in the context of the Day-Ahead Market (DAM) and the Balance Market (BM) prices for positive and negative imbalances, respectively. The fact that these variables are regarded as random processes makes it possible to achieve accurate modeling through the use of scenarios. After the DAM closes for the next twenty-four hours, it is presumed that the realization values of the DAM pricing and the revolving storage capacity will have been completely decided. The realization values of other non-deterministic parameters that are associated with each hour, on the other hand, will not be decided until the beginning of the hour that corresponds to that measurement (18).

Two-stage SP

SP employs a stochastic planning strategy that is anchored in scenario construction in order to achieve its goal of optimal decision-making in the face of uncertainty. With the purpose of selecting the most appropriate values for decision variables, this approach makes the assumption that there are a set number of different possible scenarios for uncertain parameters. The main objective is to minimize the average profit across all of the different situations while simultaneously establishing limits for each one. Typically, two-stage SP models involve two different sets of decisions, which are as follows: Decision variables in the first stage, also known as "Here-and-now variables," are made prior to the realization of random variables. On the other hand, decisions in the second stage, which are influenced by decisions made in the first stage and are dependent on the realization of the scenario, are referred to as "wait and see." Instead of referring to the phases that are involved in solving the optimization issue, the word "two-stage" is used in the context of two-stage stochastic planning to refer to the dependency or non-dependence of optimization variables on scenario realization. It is important to note that in this planning process, "here and now" choice variables include hourly energy offers and revolving storage capacity, but "wait and see" decision variables include other parameters that are contingent upon the execution of the scenario (19–21).

Generation and reduction of scenarios

The roulette wheel method is utilized for generating scenarios related to non-deterministic variables in the stochastic planning process. This method involves assigning probabilities to different scenarios based on their likelihood, and the selection of a scenario is analogous to spinning a roulette wheel, where each scenario's probability determines its share of the wheel. Additionally, the simultaneous backward reduction method is employed to streamline the scenario set by reducing its overall number. This reduction method is implemented in a simultaneous manner, allowing for the efficient elimination of scenarios, often based on criteria such as statistical significance or redundancy. Together, these methods contribute to the effective generation and reduction of scenarios, facilitating a more manageable and focused stochastic planning process (22,23).

*Assessing the realization of uncertain variables*

Following the completion of the planning process and the determination of optimal values for "here and now" variables, including offers in DAM and rotating storage capacity, the mathematical expectation of profit is calculated for the analyzed scenarios. Profits can be actualized by implementing any desired scenario. In such instances, the optimal values for "here and now" variables are held constant, and the programming is iteratively re-executed each hour, incorporating the realization of non-deterministic parameters specific to that hour. Subsequently, the values of "wait and see" variables are updated based on the realized parameters. This iterative procedure persists over a twenty-four-hour duration, culminating in the computation of profits generated from the execution of the intended scenario.

*Mathematical Model*

In the model, the bidding difficulty that the manufacturing company is facing is described as a mixed-integer linear programming problem. The random programming approaches are utilized in this model in order to incorporate the uncertainty that is associated with the parameters.

Objective function.

The proposed planning is intended to maximize financial gain. Consequently, the aim of the objective function is to optimize the mathematical expectation of profit (ExpProf), which represents expected value, across all possible scenarios (Equation 1).

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| --- | --- |
| , | (1) |

where, *sc* is the index of scenarios, *t* is the index of time periods, *prob(s)* is the probability of occurrence in scenario *s* and is profit in time period *t*. The profit obtained in scenario *sc* and time *t* is in the form of Equation 2.

|  |  |
| --- | --- |
| , | (2) |

where, offers energy production in the market the day before. offers for provision of rotating storage capacity. is positive imbalances sold in the market, balance negative imbalances purchased from the BM. is cost of CAES units and is cost of thermal units. is price of energy in the energy market day-ahead and is price of revolving storage, positive imbalance price, positive and negative imbalance price, the percentage of planned revolving storage capacity that is called for production, and *dt* is the length of each time period in an hour time step.

The right side of Equation 2 comprises six terms. The initial segment is associated with the revenue from energy sales or the cost incurred from purchasing energy in the Day-Ahead Market (DAM). The subsequent two terms encompass the revenue from selling surplus power in the positive balance market and the cost incurred from procuring power shortages from the negative Balance Market (BM). Ultimately, the last two terms represent the cost of thermal units and the cost of Compressed Air Energy Storage (CAES) units, calculated according to Equations 3 and 4 (24).

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| --- | --- |
| ; | (3) |
| , | (4) |

where:

* *cu*: CAES units index
* *tu*: Index of thermal units.
* : CAES power consumption in charging mode.
* CAES output power in discharge mode.
* : The variable cost of repair, maintenance and operation of the compressor.
* : The variable cost of maintaining and operating the expander.
* : CAES heat rate in discharge mode.
* : The price of natural gas.
* : Output power of the thermal unit
* : Actual generated energy for high rolling storage services.
* : Binary variable that indicates the participation status of the thermal unit is (1 if the unit is on)
* Binary variable that indicates the start-up status of the thermal unit at the beginning of the time period (1 if the unit is started)
* : Binary variable that indicates the shutdown status of the thermal unit at the beginning of the time period (1 if the unit is turned off).
* : Cost coefficients of thermal units.
* : The cost of turning on the thermal units.
* : The cost of turning off the heating units.

One of the most important distinctions in the cost modeling of CAES is highlighted by the explanation that has been provided. To be more specific, the cost of acquiring electrical energy for the compressor is already accounted for in Equation 2 when the CAES runs in the charging mode and produces electrical energy consumption. As a result, Equation 3 is meticulously designed to singularly address the costs pertaining to natural gas consumption, expander operation, and compressor maintenance, specifically during the discharge mode of CAES. This precision is essential to ensure an accurate representation of the comprehensive cost structure associated with CAES operations. It enables a nuanced understanding of the distinct components contributing to the overall operational expenses, thereby enhancing the model's fidelity in capturing the intricacies of CAES cost dynamics.

Constraints

Equations 5 to 11 represent the optimization constraints for day-ahead energy markets, rotating storage, and balance.

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| ; | (5) |
| ; | (6) |
| ; | (7) |
| ; | (8) |
| ; | (9) |
| ; | (10) |
| , | (11) |

where,

* *u* is the index of the manufacturing company's total units.
* *du* is the index of controllable units.
* *M* is a sufficiently large number.
* *va(sc,t)* is an auxiliary binary variable.

Equation 5 establishes the energy balance principle, ensuring that the summation of sold and purchased energies aligns with the sum of produced and consumed energies. Any disparities between these quantities are characterized as positive or negative energy imbalances. In Equation 6, it is specified that the rotating storage proposal, energy production for storage, and negative imbalances are all allowed to take non-negative values. Equation 7 mandates that control units must provide the called reserve amount. Additionally, Equations 8 to 11 articulate constraints preventing concurrent generators from simultaneously exhibiting both a positive imbalance and/or an energy supply for rotating storage, as well as a negative imbalance. These equations collectively govern the energy balance and operational behavior, ensuring consistency and adherence to specified constraints in the energy system.

The set of Equations 12 to 21 plays a crucial role in determining and characterizing the operational state of CAES. The series of equations presented delineate the operational characteristics and constraints governing the CAES system. The working mode Equations 12 and 13 ensure that CAES operates in a singular mode during each time interval, while Equations 14 and 15 determine permissible charge and discharge powers. Equation 16 specifies the power generation or consumption based on charge/discharge power, and Equation 17 defines the initial energy stored. Equations 18 and 19 model changes in stored energy due to charging and discharging, and Equations 20 and 21 establish constraints on stored energy, considering power and capacity limits. Collectively, these equations provide a comprehensive overview of CAES operational dynamics, encompassing working modes, power variations, initial storage, changes in stored energy, and limitations on stored energy (25).

These equations collectively provide a comprehensive representation of the CAES system, encompassing its working modes, power generation and consumption, alterations in stored energy, and constraints on its capacity and power capabilities.

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| ; | (12) |
| ; | (13) |
| ; | (14) |
| ; | (15) |
| ; | (16) |
| ; | (17) |
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| ; | (19) |
| ; | (20) |
| , | (21) |

where,

: Binary variable indicating the charging status of CAES (1 if the unit is charging)

: Binary variable indicating the discharge status of CAES (1 if the unit is being discharged.)

: The energy stored in the CAES tank at the beginning of time *t*

: The final energy stored in CAES

: Efficiency of energy injection to CAES,

: Energy production efficiency by CAES

: Minimum compression power of the compressor.

: Maximum compression power of the compressor.

: Minimum capacity of the expander.

: Maximum production capacity of the expander.

: Initial level of storage in the CAES

: Minimum equivalent energy stored in the CAES

: Maximum equivalent energy stored in the CAES

The provided information outlines the modeling and constraints related to the working mode and operational characteristics of a CAES system, as well as constraints associated with thermal units (Equations 22 to 29). These equations collectively define the operational behavior and constraints for both CAES and thermal units within the planning problem (26).

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| --- | --- |
|  | (22) |
|  | (23) |
|  | (24) |
|  | (25) |
|  | (26) |
|  | (27) |
|  | (28) |
|  | (29) |

where, is minimum production power of thermal units, maximum production power of thermal units, is low slope rate of thermal units, high slope rate of thermal units. The logic that governs the shutdown, startup, and operational status of thermal units is formulated by the equations 22 to 24. The maximum amount of power that can be produced by the thermal unit is described by Equation 25. The power output of the thermal power plant can be increased or decreased, but only within the parameters of Equations 26 and 13. In the model, the minimum on and off time limitations for thermal power plants are addressed by Equations 28 and 29, respectively. In conclusion, Equation 30 provides a thorough formulation of the planning problem that describes the problem in its entirety.

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|  | (30) |

*Reactive Power Market Settlement*

To illustrate the proposed approach to settlement, a number of quality measurement indicators for reactive power compensation have been implemented. In order to optimize the objective function of this project, the independent quality indicators for reactive power compensation are as follows: unit participation rate, market profit rate, profit distribution rate, production share rate, and production and payment rate for an opportunity area. They are used items. The aforementioned indicators are presented via the Equations 31 to 38 (27).

The participation of units (UPR) is the ratio of the total number of participating units in the reactive power compensation of the network to the total number of network units (Equation 31).

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| --- | --- |
| . | (31) |

The Market Profitability Rate (MPR) and the Profitable Player Number Rate (PPNR) are calculated according to Equations 32 and 33.

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| --- | --- |
| . | (32) |
| . | (33) |

The MPR is defined as the ratio of the total net surplus generated by participating units involved in compensating reactive power within the network to the overall final market costs. This ratio is referred to as the MPR. An indicator of the efficiency and effectiveness of units that contribute to reactive power compensation in relation to the total market costs, MPR serves as an indicator of the power compensation units. In contrast, the PPNR is computed by dividing the total number of units that are participating in reactive power compensation within the network by the number of units that are profitable in the context of reactive power compensation. This ratio is then used to determine the PPNR. A better understanding of the proportion of units that positively contribute to the network's reactive power compensation in terms of profitability can be gained through the consideration of PPNR. MPR and PPNR are both useful indices that can be used to evaluate the performance and profitability of units that are involved in reactive power compensation within the network. These indices provide a comprehensive understanding of the economic aspects and efficiency that are associated with such participation.

Net Surplus Distribution Rate (NSDR) according to Equation 34 is the standard deviation (SD) of the ratio of the profit of each unit to the total profit of reactive power compensators. The value of this index is the difference of the profit share of each unit from the average profit It also shows the profit of the units.

|  |  |
| --- | --- |
| . | (34) |

The Generation Sharing Rate (GSR) 14 is based on the ratio of 35 standard deviations of the reactive power compensation ratio of each unit to the total reactive power compensated by the units. The control of the GSR index causes the distribution of the reactive power compensation share It will be done.

|  |  |
| --- | --- |
| . | (35) |

The Risk of Work in Capacity Limits (RWCL) capacity is calculated according to Equation 36. The control of the index causes the management of additional costs caused by the technical and financial losses of reactive power generation at the maximum capacity limits.

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| --- | --- |
|  | (36) |

Equation 37 is the Cost Rate for Lost Opportunity (CRLO) and Equation 38 is the rate of the Number of Generating Units in Opportunity Zone Equalized Weighting (NPO).

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| --- | --- |
| ; | (37) |
| . | (38) |

The regulation of CRLO and NPO indices results in the regulation of costs associated with unit damages in the opportunity area; consequently, the reactive power market's cost management attains autonomy.

*Artificial Fish Swarm Algorithm*

The Artificial Fish Swarm Algorithm (AFSA) is a population-based metaheuristic optimization algorithm inspired by the collective behavior of fish shoals. It simulates the foraging behavior of fish in search of food and applies this concept to solve complex optimization problems. The AFSA offers several advantages in solving optimization problems. It is capable of handling complex search spaces, is robust against local optima, and has good global exploration and exploitation capabilities. By mimicking the collective behavior of fish, the algorithm effectively balances exploration and exploitation to find optimal solutions (28,29).

In the context of the energy and reactive power market settlement model, the AFSA can be used to optimize various parameters such as energy generation, reactive power compensation, and cost allocation. By iteratively adjusting the positions and velocities of artificial fish, the algorithm seeks to minimize costs, maximize efficiency, and improve the overall performance of the market.

The AFSA algorithm consists of the following steps:

* *Initialization*: A population of artificial fish is randomly generated within the search space. Each fish is assigned a position and a velocity.
* *Evaluation*: The fitness of each fish is evaluated based on the objective function of the optimization problem. In the case of the energy and reactive power market settlement model, the objective is to minimize costs and optimize the performance of the market.
* *Movement*: Each fish updates its position and velocity based on its current state and the information obtained from neighboring fish. This step simulates the movement and interaction of fish in a shoal.
* *Feeding*: The food attractiveness of each fish is determined based on its fitness value. Fish with higher fitness values are considered to have higher food attractiveness.
* Individual Behavior: Each fish adjusts its movement direction based on its own food attractiveness and the positions of neighboring fish. This helps the fish explore the search space more effectively and improves their individual performance.
* *Collective Behavior*: Each fish also adjusts its movement direction based on the average movement direction of the neighboring fish. This promotes information sharing and cooperation among the fish, leading to better global exploration and exploitation of the search space.
* *Updating the Best Solution*: The best solution found so far is updated and stored. This allows the algorithm to keep track of the most promising solution throughout the optimization process.
* *Termination*: The algorithm iteratively repeats steps 2-7 until a termination criterion is met. This criterion can be a maximum number of iterations, reaching a satisfactory solution, or a predefined convergence threshold.

# Results

The approach proposed in this study has been tested on IEEE 30 bus network. This network includes 35 production units and a synchronous condenser. The objective function of the proposal has been made by AFSA. The evaluations have been done in total in nine scenarios according to Table 1 for two cases of equal weighting and separation. The values of the weighting coefficients applied to the indices in each scenario are according to Table 1.

Table 1. Details of scenarios

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Scenario No. | *WNGO* | *WCRLO* | *WRWCL* | *WGSR* | *WNSDR* | *WPPNR* | *WNPR* | *WUPR* |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | 90 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3 | 1 | 90 | 1 | 1 | 1 | 1 | 1 | 1 |
| 4 | 1 | 1 | 90 | 1 | 1 | 1 | 1 | 1 |
| 5 | 1 | 1 | 1 | 90 | 1 | 1 | 1 | 1 |
| 6 | 1 | 1 | 1 | 1 | 90 | 1 | 1 | 1 |
| 7 | 1 | 1 | 1 | 1 | 1 | 90 | 1 | 1 |
| 8 | 1 | 1 | 1 | 1 | 1 | 1 | 90 | 1 |
| 9 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 90 |

Optimizing the UPR index directly through an objective function as defined results in a rise in the quantity of market participants. This issue discusses the distribution of production share, decrease in production within a specific area, and reduction of market power potential through an increase in the number of competitors. Reducing production in the opportunity area due to increased market competitors will lower additional costs resulting from high production prices in that area. Simply put, optimizing the participation index of units has enhanced the quality of reactive power compensation in various ways.

The UPR index values for each scenario are detailed in Table 2. The index exhibits its maximum value in scenario No. 9, which utilizes equal weighting, as well as in scenarios No. 2, 3, and 9, which employ separate weighting. The application of greater weight to this index in the scenario No. 9 has increased its significance in the market settlement, resulting in the index attaining its maximum value. Conversely, during the scenarios No. 2 and 3, greater emphasis is placed on production indicators in the opportunity area. As a result, an increase in the number of participants leads to a decrease in production in the opportunity area; thus, the value of this indicator is at its peak in these particular scenarios.

Table 2. Weighting index in different scenarios

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Scenario No | UPR | MPR | PPNR | NSDR | GSR | RWCL | CRLO | NGO |
| 1 | 100 | 25.11 | 100 | 3.21 | 3.12 | 0 | 0 | 0 |
| 2 | 100 | 26.08 | 100 | 3.32 | 3.09 | 0 | 0 | 0 |
| 3 | 100 | 27.19 | 100 | 3.07 | 3.3 | 0 | 0 | 0 |
| 4 | 100 | 24.07 | 100 | 2.72 | 3.31 | 0 | 0 | 0 |
| 5 | 94.17 | 26.09 | 100 | 2.98 | 2.79 | 0 | 0 | 0 |
| 6 | 94.29 | 21.15 | 100 | 2.72 | 2.99 | 0 | 0 | 0 |
| 7 | 100 | 25.17 | 100 | 3.13 | 2.18 | 0 | 0 | 0 |
| 8 | 84.89 | 29.81 | 100 | 3.71 | 3.06 | 0 | 0 | 0 |
| 9 | 100 | 25.13 | 100 | 3.08 | 3.02 | 0 | 0 | 0 |

As predicted based on the practical weight assigned to the MPR index for case two of separate weighting, the MPR index has a greater value in these situations. The correlation between the enhancement of the MPR index values and the WMPR values provides strong evidence that the application of weighting coefficients in the direction of market settlement results is effective. The historical profitability of the market is a significant incentive for production units to participate; therefore, providing historical data on the market's profitability indices is an effective way to inspire confidence in the market's profitability. The proposed approach places emphasis on market profitability indicators, enabling direct optimization of these indicators in accordance with the objective. This framework establishes the conditions for enhancing profitability and promoting market participation.

Table 2 indicates that the mean MPR for scenarios utilizing separate weighting mode for WMPR is 27.19%. This value provides confirmation that weighting has an effect on the MPR index, even when the weighting coefficients are small. As shown in Table 2, the average PPNR for all light weights is consistently 100%. This finding validates the subject matter and provides a positive market resume with the assurance of profit.

Equation 34 establishes the NSDR index as a metric for quantifying the equitable distribution of profits. When weighting coefficients were applied to the NSDR index, scenario 4 yielded the lowest value of this index (the ideal value) using the separate weighting mode with the largest WNSDR in comparison to the other weighting coefficients.

Increasing the value of the coefficient of Variation (CV) results from increasing the value of the NSDR index while ensuring a fair profit distribution. Utilizing statistical data, equations 39 through 40 represent, respectively, profit dispersion, reactive power generation unit dispersion, and reactive power compensation cost dispersion. Aiming directly at the NSDR index as a target minimizes the dispersion of profits. Figure 1 presents the CVNS values, with the lowest associated CVNS value, the objective function aims to achieve scenario 4 through the use of a separate weighting that exceeds the weight of the NSDR index. The implementation of greater weight coefficients on the NSDR index to reduce profit dispersion results in a decline in the competitiveness potential of the participants and a reduction in overall profitability.

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| --- | --- |
| ; | (39) |
| ; | (40) |
| , | (41) |

The GSR index serves as a metric to assess the degree of market competition and ensure that the participants receive equitable compensation for reactive power. The distribution of the reactive power compensation contribution is facilitated by the proposed settlement approach's capability to support the control of the reactive power compensation contribution through direct access to minimizing the GSR index; thus, scenario number five exhibited the lowest value of CVQ due to the separate weighting in which the coefficient of the GSR index is greater than that of the other indices. By controlling the dispersion of the reactive power compensation values of CVQ units and optimizing the GSR index directly, a payment is made to the producers; this represents the distribution of the producers' income. Because the compensation provided to the units is precisely equivalent in value to their compensatory reactive power. Figure 1 indicates that, relative to the other scenarios, the CVRPCC value in scenario 5 is lower than that of separate life. This demonstrates the impact of direct optimization of the GSR index on the equitable distribution of the units' income.



Figure 1. Dispersion of net surplus, income and contribution of reactive power compensation

The CRLO, NGO, and RWCL indices, which measure the payment for production and the quantity of production units in the opportunity area, serve as pertinent metrics for evaluating the effectiveness of the settlement approach based on the index of proposals. These indices provide valuable insights into the optimization of payment and production in the region. Notably, there are opportunities for optimizing both payment and production in the identified opportunity area. The correlation between the escalation of final market costs and increased production within the opportunity area, driven by producers' high prices for reactive power, highlights the consequential impact of optimizing production on effectively managing the market's final costs. Figure 2 illustrates the information on final cost values in the reactive power market and LOC, underscoring that the index-based settlement method adeptly optimizes production costs in the opportunity area. Notably, the consistently low values of CRLO, NGO, and RWCL indices (all at 0%) across various scenarios indicate the efficacy of the settlement method in achieving optimal results.



Figure 2. Income and profit of market players in different scenarios

**Conclusions**

The settlement approach outlined in this study is predicated on market quality indicators of reactive power compensation, such as the distribution of production and profit, the production and payment for the area of opportunity, and the market profitability index. Overall, in accordance with the tenets of the suggested settlement methodology, the quality measurement indices directly or, in certain instances, indirectly offset the reactive power; furthermore, they are susceptible to the influence of market factors and indices; and are subject to control. By incorporating weighting coefficients into the proposal design for the indicators, a dynamic approach to proposal settlement is achieved in accordance with the network's conditions and requirements. The outcomes derived from the simulations validate that the proposed settlement method yields the optimal values for the quality indicators of the independent reactive power market settlement. The control demonstrates the market's competitiveness potential. Given the significance of market participation in the reactive power industry for enhancing market competitiveness, the implementation of the suggested strategy has resulted in a surge in participant motivation, both directly and indirectly, thereby contributing to an overall improvement. The level of competition on the market for reactive power is independent.

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