Incentive-based Peer-to-Peer Distributed Energy Trading in Smart Grid Systems

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***Abstract*—This paper studies incentive-based peer-to-peer (P2P) energy trading between sellers and buyers in a smart grid distributed system. When designing an energy trading model the main goal is to maximize the social welfare of the involved parties. Peer-to-peer energy trading is a novel mechanism of power system operation which allows users to generate and trade renewable energy. Buyers are considered to be consumers and sellers are considered to be prosumers (producers and consumers of energy) with respect to time. Buyers are more motivated to purchase energy from the seller since the energy was generated from a green source and is typically cheaper than the main grid. Furthermore, by producing clean energy and distributing within small networks, the transmission line stress is mitigated since the overall demand required from the main grid is reduced. In this paper, we model the interaction as single-sided auction taking into consideration the grid infrastructure constraints (e.g capacity) and cost while maximizing the profit of the players. We assess through theoretical analysis and simulations the bidding properties including individually rational, truthful, computationally efficient, and fairness.**

***Index Terms*—Peer-to-Peer, Local Energy Trading, Bidding Mechanisms, Smart Grid.**

I. Introduction

Peer-to-peer energy trading is possible with emerging smart grid infrastructure since it utilizes two-communication and two-way energy transfer, necessary for traders to send and receive energy between each other [1]. Fig. 1 shows a simplified energy trading model which consists of a single prosumer and a single consumer connected to the smart grid. Depicting that the prosumer and consumer have the resources to transmit and receive energy. The main advantage of the smart grid is that the user can send back their surplus energy to the consumer in need or to the main electric grid, which is currently not possible using the traditional grid.

Energy trading models and optimization techniques have been previously demonstrated and have been become an active research topic. One specific example is a model for smart factories designed in [2], to perform intelligent energy trading. The work, however, proposes a model to trade energy between

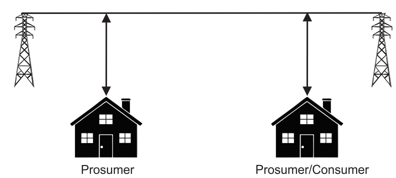

Figure 1. Simple energy trading infrastructure

the consumer and supplier in smart factories and utilizes a time limit for bidding. Meaning, the players in the network are allocated time slots to purchase energy. Once the bidding time is over, the market server decides and notifies the winner. The energy is then distributed to the winner. This is one of the many techniques in which energy trading can be performed. There are various basic variables and properties of energy trading models. For example, the auction-based mechanism is adopted in multiple areas and fields including cloud resource allocation, baseball free-agent draft, procurement, and search advertisement [3] [4] [5] [6] [7]. Auction mechanisms are used everywhere for a fair buying and selling of any product [8]. The different types of auctions are English auction, Dutch auction, sealed bid auction, Vickrey auction and reverse auction, etc. Overall, auctions are classified into sealed bid auction and iterative auction. These auctions have demonstrated powerful use in P2P energy trading for buyers and sellers to effectively purchase and sell energy [9] [10] [11]. In this paper, we focus on sealed bid auctions for P2P eneryg trading.

A sealed bid is a type of auction process in which all the players bid for the same product available in the market, and no player knows the bid of other players. All players must submit their complete bid [12]. Usually, the player with the highest bid wins the auction. For example, assume that there is a product available in the market for sale and three buyers $\{B_1, B_2, B_3\}$ need that product. Each buyer will have their own valuation $\{V_1, V_2, V_3\}$ on the product. The valuation is an intrinsic relationship with the product and the buyer. Furthermore, the buyer will submit a sealed bid $\{b_1, b_2, b_3\}$ for that product according to their valuation. No other buyer has any information of the bid of other buyers within the network.

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The bids are sealed and only the seller and the corresponding buyer have the information regarding the bid. Suppose that buyer B_3 submitted the highest bid b_3 and assume that buyer B_2 has the next highest bid b_2. The bids are then sorted in descending order according to their value, i.e. $\{b_3, b_2, b_1\}$. If the type of seal bid mechanism used is first price bid (FPB), the buyer j with the highest bid will win the auction and pay the submitted bid (b_j) as the payment to the seller for the market product. In this case, b_3 is paid to the seller. Alternative, in a second price bid (SPB) mechanism, the buyer with the highest bid wins and pays the second highest bid. Therefore, B_3 still wins the auction but pays the bid b_2 as the payment for the seller. Thus, a seal bid mechanism is a practical approach when implementing an auction for P2P energy trading.

The most commonly used auctions for product selling and buying are the single sided auction and the double-sided auction. Our focus in this paper is on single-sided auctions, where all buyers/sellers bid on the same product [13] [14] [15] [16]. Mainly, the seller/buyer does not ask for any specific price for the selling product and all the buyers/sellers play against each other by bidding on the product [17]. The main point is that the auction only receives variables from a single side. The privacy of the bidding is protected using some mechanisms such as those presented in [18] [19].

II. System Model

In this section, the model describing the P2P energy trading process for multiple sellers and a single buyer is presented. This is a typical case of peer-to-peer energy trading of single auction where multiple sellers are present in the market [20]. In this specific scenario, the sellers play among each other by trying to sell energy to a buyer who is in need of a specific amount of energy. Fig. 2 illustrates the communication flow and energy transfer between the sellers and the buyer. Sellers

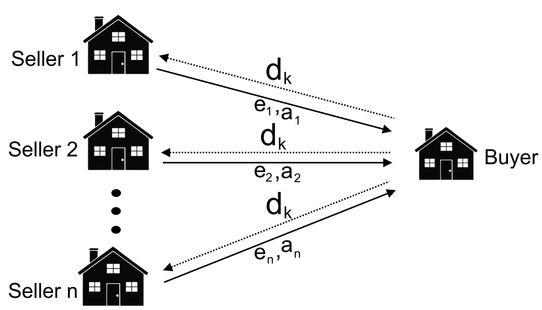

Figure 2. MSSB energy trading model

submit the ask and the amount of energy to the buyer, and no seller knows about the other sellers' valuation or ask price. The seller communicates only with the buyer regarding the amount of product and the ask for the product. All the sellers submit their ask to the buyers in a sealed bid fashion such that no other sellers know the asks submitted by other sellers. The buyer selects the seller with the cheapest ask and selects the clean green energy with a lesser cost. Thus the seller with the least ask wins the auction.

A. Parameters

The set of sellers in the network is represented as $S = \{1, 2, 3.., n\}$ where $i \in S$ and contains a surplus energy $E = \{e_1, e_2..., e_n\}$, where $e_i \in E$. There might be a case where the sellers will sell only apart from the surplus energy e_i since the profit may result as negative. In that case, the seller may store the remaining energy. The selling energy is denoted as e_k and the storing energy is e_y, thus $e_i = e_k + e_y$. The surplus energy is the summation of the selling energy and storing energy. When the seller sells the whole surplus energy e_i then, $e_y = 0$. Each seller has a ask price which is denoted as $A = \{a_1, a_2..., a_n\}$ where $a_i \in A$. The ask of the seller depends on the line cost c_l and the seller's cost c_i which includes generating and operating cost. Buyers are represented as $B = \{1, 2, 3.., m\}$ where $j \in B$. However, in this model, there is only one buyer $j = 1$. The demand of the buyer is represented as d_j with a valuation of V_j. The paths between the sellers and buyers are denoted as $p_{(i,j)} = \{p^1_{(i,j)}, p^2_{(i,j)}, p^3_{(i,j)}.., p^z_{(i,j)}\}$. Each path has its own line cost c_l, and transmission capacity x^p_{cap}. Additionally, the energy that is currently flowing through the path is denoted as $y^p_{g_{(i,j)}}$. In the proposed model, the seller pays the line cost c_l for transporting the energy to the buyer. The line cost c_l depends on the the profit of the seller, which is calculated by the difference in the bid b_j from the buyer and the loses. The total loss of the seller is the summation of the operating cost c_i and the line cost c_l for transporting the energy to the buyer. Moreover, the seller calculates the profit for each buyer and selects the buyer with the highest profit as the winner and if the profit from all the buyer resulted in zero, then the seller stores the energy.

B. Problem Description

The buyer's objective is to minimize the cost based on the sellers ask a_i offerings. Here, the seller is only paying the line cost when selling the surplus energy e_i to the buyer. The buyer's goal is to find the cheapest cost compared to all the sellers in the network. The purchasing cost $\mathrm{C_{ost}}$ of the buyer is expressed in equation (1) subject to constraints (2) and (3) .

$$\mathrm{C_{ost}(j)} = \sum_{i=1}^{n} a_i \tag{1}$$

$$\textbf{s.t.} \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{p=1}^{z} d^p_{j_{(i,j)}} < (x^p_{Cap} - y^p_{g_{(j,i)}}) \tag{2}$$

$$\sum_{j=1}^{m}\sum_{p=1}^{z} d^p_{j_{(i,j)}} \leq D_j, \forall j \in B \tag{3}$$

Equation (1) represents the total cost of the buyer which is given as the summation of all the winning sellers ask a_i. The constraint given in equation (2), ensures that the demand energy, $d^p_{j_{(i,j)}}$, never exceeds the transmission line capacity, x^p_{Cap}. This is needed to ensure the safety of the transmission grid in which the demand energy $d^p_{j_{(i,j)}}$, should always be less than the difference between the total amount of transmission line capacity x^{p}_{Cap}, and the current amount of electricity flowing in the line, $y^{p}_{g_{(i,j)}}$. The constraint given in equation (3), ensures that the buyer cannot purchase energy from a seller more than the total demand D_j. In the following part, the proposed CMA is presented showing the working procedure of the mechanism.

C. Cost Minimization Algorithm

Algorithm 1 Cost Minimization Algorithm(CMA)

Input: Surplus energy e_i, Sellers ask a_i, Transmission line capacity x^{p}_{Cap}, Grid flow y^{p}_{g}, Seller cost c_i and total demand Td_j.
Output: Selling energy e_k, Instant demand d_j and Buyer's cost $\mathrm{C_{ost}}$(j).

```
Stage:1 Determining the instant demand d_j
Sort e_i in ascending order foreach e_i ∈ E do
    if (min(e_i) < Td_j) then
        min(e_i) = d_j
    else
        Td_j = d_j
    end
end
Stage:2 Determining the selling energy
if e_i > d_j then
    e_k = d_j
else
    e_i = d_j
end
Stage:3 Determining the winning seller
foreach a_i ∈ A do
    Sort i in ascending order w.r.t a_i
    if (C_ost(j) ≤ V_j) then
        Check constraints for i
        if (d_j^p < (x_Cap^p + y_g^p)) then
            Buy it from the seller, i
        else
            eliminate that seller i
            Repeat for i+1
        end
        repeat till Td_j = 0
    else
        Buy energy from the grid
    end
end
end
```

The CMA initializes after the buyer indicates to the sellers that it is in need of energy demand. In the first stage, the buyer receives responses from the sellers indicating their current surplus energy e_i. The buyer will then sort this information in ascending order and select the minimum demand denoted as instant energy d_j. This process is critical to ensure fairness within the network. Alternatively, if the buyer receives demands above or equal to the total demand, they will set their total demand as d_j. This stage is an essential part for the buyer to determine the instant demand d_j. The second stage initializes with the buyer lets the sellers aware of the instant demand d_j. The sellers determine the amount of selling energy e_k by comparing it with the instant demand d_j. If the surplus energy e_i is greater than the received d_j, then the seller will set their selling energy e_k as d_j. Alternatively, the seller will set their surplus e_i as d_j. The sellers will respond back to buyer with the selling energy e_k or e_i depending on the previous condition. Additionally, the seller will respond with the ask a_i which depends on their line cost c_l to reach the buyer and the seller cost c_i for generating and operating purposes. This is the essential stage for the sellers to determine their selling energy. In the next stage, the buyer determines the winning seller. This is accomplished by sorting the ask a_i in ascending order according to the sellers. Then, the buyer will select the seller with the minimum ask and check the constraints given in equations (1) and (2). If the constraints are met, then the seller wins the auction and the agreed upon energy is transmitted to the buyer. If the winning seller has their surplus energy completed depleted in this process, they are removed from the list. If however, the constraint was not met, the seller is removed from the set S. This process is repeated until the total demand of the buyer is zero. Alternatively, if the calculated cost is greater than the buyer's valuation, the buyer will purchase its energy directly from the grid. The payment of the buyer is equal to the bid b_j.

D. Numerical Evaluations

In this section, we perform simulations using a toy example with one buyer and four sellers to test the performance of CMA. We assume that the sellers are small factories able to generate their energy requirements. For the remaining case studies, the number of sellers is significantly increased and the changes are observed in the simulation results. We also consider various ideal scenarios for a randomly chosen case study to observe the end effects. In addition, the CMA is compared with the first and the second price bid mechanisms to evaluate the performance of the proposed mechanism.

1) Simulation Setting: The CMA algorithm was tested and simulated using MATLAB to obtain a solution for the case studies. In the toy example the buyer has an energy demand of 60 kWh and the surplus energy from the sellers ranges from [20-80] kWh. The operating cost of the seller is 1.2 cents per kWh and the line cost ranges from [0.9 - 1.6] cents per kWh. The assumed transmission capacity is 1000 kWh for all possible paths within the network. The average grid flow throughout all possible paths is assumed to be 200 kWh. The sellers' offer ranges from [7-14] cents/kWh in each iteration. We further consider the main electric grid as a seller with a higher selling cost. We initialize the simulation with a set of seller's surplus energy. For latter case studies the number of sellers is increased from 20, 40, 60, 80, 100, and 300. In all cases, the seller has 5000 kWh of surplus energy and the demand from the buyers ranges from [40-1500] kWh.

2) Simulation Result: The simulation results from the toy example depicting the surplus and sold energy with respect to each seller is shown in Fig. 3. From here, we observe that both seller 1 and seller 2 were able to completely distribute and sell their energy to the buyer. Most importantly, we observe that the seller with lowest amount of surplus was also still able and win the auction. Furthermore, we make a comparison using the CMA with the first and second price bid mechanism. As shown from Fig. 4 we observe that the buyer's cost is significantly more using the second price bid mechanism. We also observe that the buyer achieves reduced energy costs when utilizing the proposed CMA.

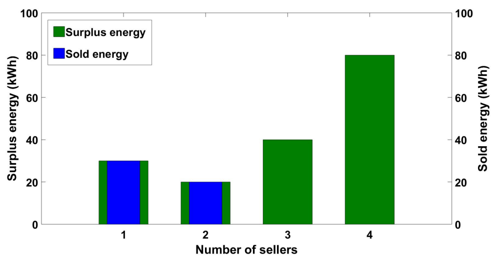

Figure 3. Toy Example: Surplus and sold energy for each seller when using the proposed mechanism

Next, we increase the number of sellers from 4 to 20. Fig. 5 displays the sold and surplus energy of all 20 sellers when employing the FPB mechanism. Observing that only four of the twenty sellers were able to sell their energy to the buyer. Fig. 6 depicts the sold and surplus energy of the sellers when using the CMA mechanism. We observe that an increase in amount of sellers were able to obtain a profit and distribute energy to the buyer. Here, a total of seven sellers were able to obtain profit as compared to four in the previous case. From these results, it is expected that the buyer's cost are significantly reduced since the CMA optimizes the P2P energy trading process in a more effective manner. This observation is clearly presented in Fig. 7. Observing that the CMA outperforms the first and second price bid mechanisms by reducing the buyer's cost significantly.

We continue the process of increasing the number of sellers form 20 to 100 in steps of 20 and compare the simulation results of the various mechanisms. Fig. 8. displays the buyer's cost when the network contains 20 to 100 sellers and the CMA, first and second price mechanisms are employed. The results display that no matter the number of sellers in the network,

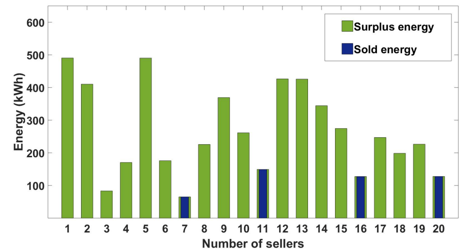

Figure 5. Surplus and sold energy for each seller using the first price bid method

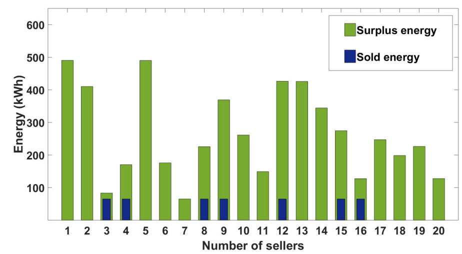

Figure 6. Surplus and sold energy for each seller using the proposed mechanism

the buyer obtains an optimized and reduced energy cost when the CMA is utilized. Demonstrating effective performance for a practical P2P energy trading process.

In the following simulation, we consider 300 sellers with various cost distribution such as normal, uniform, and exponential functions. Fig. 9 depicts the buyer's energy cost for each mechanism and distribution function. Observing that when using the CMA for a normal distribution, the buyer's energy costs are minimal. Additionally, using a uniform distribution and the second price bid mechanism, the buyer obtains the highest energy costs. Nonetheless, the CMA outperforms the alternative mechanisms when the sellers are distributed using various functions.

Fig. 10 illustrates the comparison with the total ask and the winning ask while using the proposed mechanism. It is noted that the exponential distribution attains the highest winning ask in comparison with the normal and uniform distributions. Lastly, the time complexity curve is analyzed by determining the computation time for all simulated case studies. The results

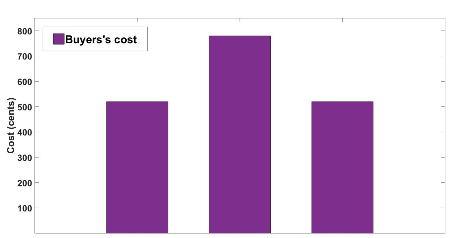

Figure 4. Comparing buyer's energy cost from 4 sellers using first price bid, second price bid and proposed mechanism

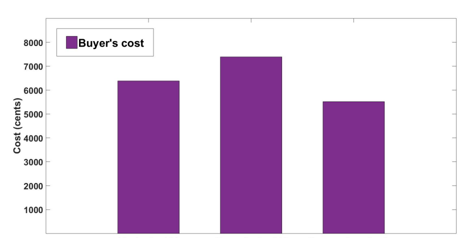

Figure 7. Comparing buyer's energy cost from 20 sellers using first price bid, second price bid and proposed mechanism

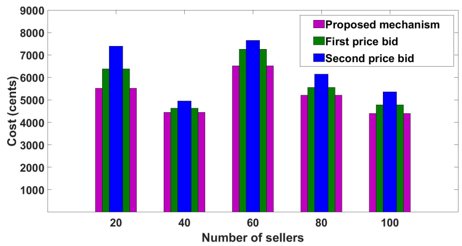

Figure 8. Comparing buyer's energy cost from various number of sellers using first price bid, second price bid and proposed auction mechanism

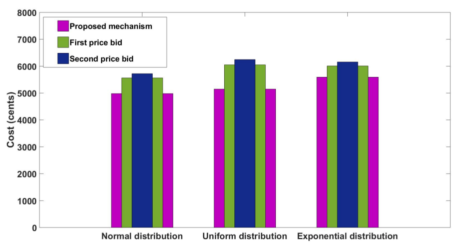

Figure 9. Comparing the cost of the buyer with 300 sellers using first price bid, second price bid and proposed mechanism at normal, uniform and exponential distribution

are presented in Table 1. Observing that the time does not increase when there is an increase in the sellers count, thus, the curve is bounded.

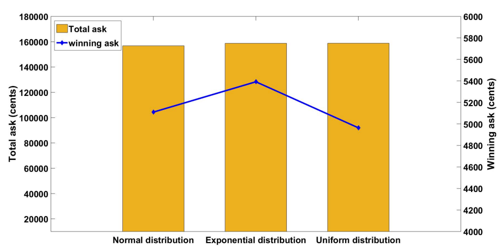

Figure 10. Comparing the total ask with the winning ask for 300 sellers using the proposed mechanism for normal, uniform and exponential distribution

Table1 shows the time complexity of the MSSB simulations. As the sellers increase from 20 to 300, the time increases from 1.26 - 2.8 ms. As a result, the time complexity is bounded and the optimal solution is computed in limited time.

III. Proof of Desirable Properties

This section presents the mathematical and descriptive proofs for the desirable properties of the CMA mechanism.

Property 1. Individually rational: All the participating users in the auction should have a non-negative payoff.

Proof that CMA is individually rational: In the CMA there are three conditions required for the seller to win the auction.

- $\forall \ a_i \in A$ the ask submitted to the buyer should be the minimum cost from all sellers.
- The foremost condition is the ask should be greater or equal to the buyer's valuation $(a_i \geq V_j)$
- The transferring energy should always follows the constraints in equation (1).

If any seller cleared these three stages then that particular seller i will be winning the auction and sells the energy to the buyer. In return, the buyer pays the ask a_i as the payment to the seller. The rest of the sellers $-i$ lose the auction and do not sell anything to the buyer. Furthermore, the losing sellers $-i$ do not generate any positive or negative profit. If the $\mathrm{C_{ost}} > V_j$ then the buyer will not purchase the energy from the seller. This ensures that the buyer is not paying more than the valuation and the seller is not receiving anything less than the ask. Moreover, this algorithm makes sure that the payoff of all the users remains zero or positive and no one loses anything by participating in the auction. This proves the designed algorithms, PMA and CMA, which use a single-sided auction mechanism are individually rational and no users lose anything by participating in the proposed auction mechanism.

Property 2. computational efficiency: The auction outcome should be intractable with polynomial time complexity.

Proof that CMA is computationally efficient: The CMA algorithm initiates with sorting the surplus energies e_i from the seller in ascending order. Finding the minimum demand takes $O(n \ log \ n)$ of time complexity. Next, a FOR loop is used to check all the demands d_j, which have a time complexity of $O(m)$. Lastly, assigning the minimum surplus energy as the demand $(min(e_i) = d_j)$ can be obtained in $O(1)$ time. The total time complexity of stage 1 is $O(nm \ log \ n)$. In stage 2 we are checking the condition using an IF statement which requires time $O(1)$. Stage 3 Checking the constraints can be obtained in $O(1)$ time. The total time complexity of stage 2 is $O(m \ log \ m)$. Therefore, the computational complexity of CMA is bounded by $O(m \ log \ m+nm \ log \ n)$. Table 4.5 shows that the computational efficiency of CMA which is bounded by a limited time.

Property 3. Truthfulness: The players in the auction do not cheat and are truthful with their values and cost when buying and selling products.

Proof that the CMA is truthful:

- The only possibility of the seller with the high ask to win the auction is only when the cost of the seller c_i is greater than or equal to the valuation of the buyer V_j. If any seller i submits a high ask to the buyer, and if the seller's i ask a_i is the lowest ask compared to all the sellers $-i$, then the seller i will win the auction unless the ask is greater than the valuation which will not increase the buyer's cost since it is less than the sellers cost.
- In this mechanism the buyer does not have any bid price, therefore there is no possible ways for the buyer to cheat in this mechanism.

Concluding that the buyer and seller cannot cheat using the algorithm. This shows that truthfulness exists in the proposed mechanism.

Property 4. Fairness: The mechanism should be designed to so that all the users have equal opportunities to participate in the auction.

Time Requirement						
Number of sellers	20	40	60	80	100	300
Time (ms)	2.334	2.876	3.003	3.12	3.63	3.47

Table I
MSSB TIME COMPLEXITY

Proof that CMA is fair: All sellers can send the ask price for their surplus energy according to their generating and line cost. Even the seller with lowest surplus energy can participate in this auction. When the buyer selects the highest ask by following the first price bid mechanism, the seller is more likely of losing the buyer with a lower bid, however this algorithm ensures the possibility of the winning of the buyer with the lower bid.

IV. CONCLUSION

This paper demonstrates a study of P2P energy trading following a single-sided auction mechanism. This timely work represents a trend of research towards local energy markets where consumers and prosumers involve in energy trading apart from the main grid but uses its infrastructure to transfer energy. The main benefit of such paradigm is that it alleviates the stress on the distribution system where most of the power demand is located. This paper shows a case study of one buyer and multiple sellers competing to satisfy the buyer's request for energy. We presented the theoretical model and analyzed the properties of the auction. Our work is different from existing auction system because it considers the factors of the underlying infrastructure. Our result shows that the mechanism is individually rational, computationally efficient, truthful for the buyer and the sellers, and fair. For future work, we intend to extend the model for double-sided auctions where multiple buyers and sellers compete among each other in the market. This is an interesting case as the number of peer-to-peer participants increase.

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