Customer Load Strategies for Demand Response in Bilateral Contracting of Electricity

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Abstract. Electricity markets are systems for affecting the purchase and sale of electricity using supply and demand to set energy prices. Electricity can be traded in organized markets or by negotiating forward bilateral contracts. Demand response (DR) refers to participation by customers in electricity markets, seeing and responding to prices as they change over time. Customers may adopt several basic load response strategies, notably foregoing electricity usage at times of high prices without making it up later, and shifting or rescheduling usage away from times of high prices to other times. This article describes on-going work that uses the potential of agent-based technology to develop a computational tool for supporting bilateral contracting in electricity markets with demand response. From the perspective of end-use customers, it investigates how foregoing and shifting affect the energy and monetary outcomes of consumers applying DR during bilateral contracting.

Keywords: Energy markets, multi-agent systems, bilateral contracting, demand response, load response strategies, trading strategies.

1 Introduction

Electricity markets (EMs) are systems for effecting the purchase and sale of electricity using supply and demand to set energy prices. Two major market models are often considered: electricity pools and bilateral contracts. The system price in a typical day-ahead market is frequently determined by matching offers from suppliers to bids from consumers to develop a classic supply and demand equilibrium price, usually on an hourly interval. Market participants have a balance responsibility, meaning that they should deliver or consume in accordance with their bids. For instance, if utility companies produce less than declared they will probably have to buy more power (in external markets) at higher prices.

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Bilateral contracts are negotiable agreements on delivery and receipt of power between two traders—they involve mainly the sale of large amounts of power (hundreds or thousands of megawatts) over long periods of time (several months to years). Market participants set the terms and conditions of agreements independent of a market operator, i.e., the negotiating parties specify their own contract terms [1]. Typically, bilateral contracts have the advantage of price predictability in comparison to uncertain pool prices.

Demand response (DR), defined broadly, refers to participation by customers in electricity markets, seeing and responding to prices as they change over time. DR may be defined more definitively as changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized [2]. From the perspective of the electric system as a whole, the emphasis of DR is on reductions in usage at critical times.

Demand response programs enable customers to manage their consumption of electricity in response to supply conditions. Several basic categories of demand response programs (or options) have been considered, notably incentive-based and price-based programs. Incentive-based DR programs offer customers some monetary bonus to reduce load upon operators request. These programs represent contractual arrangements to elicit demand reductions from customers at critical times—incentives may be in the form of explicit bill credits or payments for pre-contracted or measured load reductions. Price-based DR programs allow customers to voluntarily adjust their demand based on electricity prices, to take advantage of lower-priced periods and/or avoid consuming when prices are higher. Customer response is typically driven by an internal economic decision-making process and any load modifications are entirely voluntary. This work is being developed in the context of price-based DR programs.

Customers participating in demand response programs may adopt one or more of the following three basic load response strategies:

1. *Foregoing*: reducing the electricity usage at times of high prices without changing the consumption pattern during other periods.
2. *Shifting*: rescheduling usage away from times of high prices to other times.
3. *Onsite Generation*: turning on onsite or backup emergency generators to supply some or all electricity needs.

We are developing this study in the context of both foregoing and shifting responses.

Agent-based modeling and simulation (ABMS) has generated lots of excitement in recent years because of its promise as a new paradigm for designing and implementing complex software systems (see, e.g., [3]). The major motivations for the increasing interest in ABMS research include the ability to solve problems that have multiple problem solving entities and multiple problem solving methods. Conceptually, a multi-agent approach in which autonomous agents are capable of flexible action in order to meet their design objectives is an ideal fit to the naturally distributed domain of a deregulated energy market.

This paper describes on-going work that uses the potential of agent-based technology to develop a computational tool to support bilateral contracting in electricity markets with demand response. From the perspective of end-use customers, it investigates how different load response strategies affect the energy and monetary outcomes of consumers applying DR during bilateral contracting. Specifically, it studies the influence of both foregoing and shifting on electricity prices and consumption using the ABMS approach.

The work presented here is a natural extension of our previous work in the area of automated negotiation [4–7, 11]. It also refines and extends our previous work in the area of multi-agent electricity markets with demand response [8–10]. In particular, Lopes et al. [8, 9] formalize two novel strategies: a "price management" strategy, for producers/retailers, and a "volume management" strategy, for end-use consumers, associated with the shifting load response, and thus enabling customers to promote demand response. The authors also present a case study on forward bilateral contracts: a retailer agent (seller) and a customer agent (buyer) negotiate a 6-rate tariff using the two novel strategies. Lopes et al. [10] pay special attention to the preferences of the negotiating agents, notably the additive and multiplicative models to rate and compare incoming offers and counter-offers. They also present a case study on forward bilateral contracting involving DR management and a 24h-rate tariff.

2 Bilateral Contracting in Multi-agent Energy Markets

This section describes the process of forward bilateral contracting involving a seller agent and a buyer agent. The agents exchange offers and counter-offers until they reach an agreement or one of the agents decides to opt out of the negotiation. Negotiation includes the determination of prices and quantities of energy, and is executed on a long term, usually six months or more. A brief description of the key features of a negotiation model that handles two-party and multi-issue negotiation follows (see [6] for an in-depth discussion).

Pre-Negotiation. Pre-negotiation is the process of preparing and planning for negotiation and involves mainly the creation of a well-laid plan specifying the activities that negotiators should attend to before actually starting to negotiate. Accordingly, we describe below various activities that negotiators make efforts to perform in order to carefully prepare and plan for negotiation. We consider a set $\mathcal{A}=\{a_s, a_b\}$ of autonomous agents (negotiating parties). The negotiation issues $\{x_1, \dots, x_n\}$ are quantitative in nature and defined over continuous domains $\{D_1, \dots, D_n\}$, respectively. The negotiating agenda is the set $\mathcal{I}=\{x_1, \dots, x_n\}$ of issues to be deliberated during negotiation. For each issue x_k, the range of acceptable values is represented by the interval $D_k=[min_k, max_k]$. In particular, let $\left[P^s_{k_{min}}, P^s_{k_{max}}\right]$, $k=1\dots n$, denote the range of values for price that are acceptable to the seller agent a_s. Also, let $\left[P^b_{k_{min}}, P^b_{k_{max}}\right]$ and $\left[V^b_{k_{min}}, V^b_{k_{max}}\right]$, $k=1\dots n$, denote the range of values for price and volumes that are acceptable to the buyer agent a_b.

Effective pre-negotiation requires that negotiators prioritize the issues and define the limits. Priorities are set by rank-ordering the issues, i.e., by defining the most important, the second most important, and so on. The priority prt_k^i of an agent $a_i \in \mathcal{A}$ for an issue $x_k \in \mathcal{I}$ is a number that represents the importance of x_k. The weight w_k^i is a number that represents the preference for x_k. The limit lim_k^i or resistance point is the ultimate fallback position for x_k, the point beyond which a_i is unwilling to concede on x_k.

Additionally, effective pre-negotiation requires that negotiators agree on an appropriate protocol that defines the rules governing the interaction. We consider an alternating offers negotiation protocol [12]. This protocol models the iterative exchange of offers and counter-offers. At any given period of negotiation, an agent may accept an offer, send a counter-offer, or end the negotiation. If a counter-offer is submitted, the process is repeated until one of the agents accept or abandon the negotiation. Thus, the agents a_s and a_b bargain over the division of the surplus of $n \geq 2$ issues by alternately proposing offers at times in $\mathcal{T} = \{1, 2, ...\}$. This means that one offer is made per time period $t \in T$, with an agent offering in odd periods and the other agent offering in even periods. A proposal $p_{i \to j}^t$ submitted by an agent $a_i \in \mathcal{A}$ to an agent $a_j \in \mathcal{A}$ in period $t \in \mathcal{T}$ is a vector of issue values: $p_{i \to j}^t = (v_1, \ldots, v_n)$, where v_k, $k = 1 \ldots n$, is a value of an issue $x_k \in \mathcal{I}$. As noted, the agents have the ability to unilaterally opt out of the negotiation when responding to a proposal.

Negotiators should also express their own preferences to rate and compare incoming offers and counter-offers. We consider that each agent $a_i \in \mathcal{A}$ has a continuous utility function, denoted as U_i. Accordingly, when the utility for a_i from one outcome is greater than from another outcome, we assume that a_i prefers the first outcome over the second. The additive model is probably the most widely used in multi-issue negotiation [13]: the agents determine weights for the issues at stake, assign scores to the different levels on each issue, and take a weighted sum of them to get an entire offer evaluation. The additive model is simple and intuitive, but assumes two types of independence, namely additive independence and utility independence. In particular, the additive independence assumption is usually not acceptable when there are specific interactions among issues. This seems to be the case of the present work, since agents negotiate prices and volumes of energy, variables that are interdependent. The multiplicative utility function is the most well-known function handling interactions among issues. It accommodates inter-dependencies by considering a specific interaction constant and interaction terms involving the multiplication of the weighted scores together (see, e.g., [14]). However, for it to be valid, every pair of issues must be utility independent of the remaining issues.

Actual Negotiation. The actual negotiation process involves basically an iterative exchange or offers and counter-offers. The negotiation protocol marks branching points at which agents have to make decisions according to their strategies. Accordingly, this subsection describes two groups of strategies that have attracted much attention in negotiation research, namely [15]:

1. *concession making or yielding*: negotiators reduce their demands or aspirations to accommodate the opponent;
2. *problem solving or integrating*: negotiators maintain their aspirations and try to find ways of reconciling them with the aspirations of their opponent.

Concession strategies are functions that model typical patterns of concessions throughout negotiation. The host of existing concession strategies includes the following:

1. *starting high and conceding slowly*: negotiators adopt an optimistic opening position and make small concessions throughout negotiation;
2. *starting reasonable and conceding moderately*: negotiators adopt a realistic opening position and make substantial concessions during the course of negotiation.

Problem solving behaviour aims at finding agreements that appeal to all sides, both individually and collectively. Two representative problem solving strategies are as follows:

1. *logrolling*: two parties agree to exchange concessions on different issues, with each party yielding on issues that are of low priority to itself and high priority to the other party;
2. *nonspecific compensation*: one party achieves its goals and pays off the other for accommodating its interests.

Lopes and Coelho [6] present a formal definition of relevant concession strategies and important logrolling strategies.

3 Bilateral Contracting with Demand Response

This section presents strategies for promoting demand response, namely two different types of load response strategies: foregoing (or curtailment) and shifting. Demand response refers to participation by customers in electricity markets in response to prices as they change over time, and typically involves customer behavioral changes. During the trading process (involving an iterative exchange or offers and counter-offers), we consider that customers may respond to changes in retailers' prices either by foregoing usage at times of high prices (proposed by retailers) without making it up later or by shifting their energy usage from periods of high prices (again, offered by retailers) to the remaining hours. Customers are equipped with strategic models allowing them to minimize cost, through DR actions. On the other hand, seller agents are equipped with strategic models allowing them to maximize benefit.

Customer Load Response Strategies. These strategies have the main goal of minimizing the energy cost of customers through DR actions. Thus, through this type of actions, customers can manage their energy consumption in response to high prices for different periods of the day.

Foregoing or Curtailment Response Strategy. This strategy involves reducing energy usage away from times of high prices without making it up later. It aims at minimizing the cost C^b of the customer agent a_b, by considering the prices P_k^s, $k=1\ldots n$, proposed by the seller agent a_s, and determining appropriate values for the volumes V_k^b of a_b. The mathematical formulation of the problem is as follows:

$$Minimize\ C^b = \sum_{k=1}^{n} P_k^s \times V_k^b \tag{1}$$

subject to:

$$V_{k_{min}}^b \leq V_k^b \tag{2}$$

$$\sum_{k=1}^{n} V_k^b = (1 - CR) \times V_{tot}^b \tag{3}$$

The constraint expressed by (2) assures that the volumes considered by a_b may only decrease to admissible values. Also, the constraint (3) guarantees that the total quantity of energy considered by a_b is reduced to a particular level defined by a curtailment response constant CR.

Shifting Response Strategy. This strategy involves involves rescheduling energy usage away from times of high prices to other times. Similarly to the foregoing strategy, it aims at minimizing the cost of a_b by considering the prices proposed by a_s and determining appropriate values for the volumes (see also [8–10]):

$$Minimize\ C^b = \sum_{k=1}^{n} P_k^s \times V_k^b$$

subject to:

$$V_{k_{min}}^b \leq V_k^b \leq V_{k_{max}}^b \tag{4}$$

$$\sum_{k=1}^{n} V_k^b = V_{tot}^b \tag{5}$$

The constraint expressed by (4) assures that the volume considered by a_b is in the range of its acceptable values. Also, the constraint (5) assures that the total quantity of energy V_{tot}^b either does not change or remains close to its initial value (for convenience).

At this stage, it is important to mention that a customer load response strategy considering both the foregoing and the shifting responses could be defined by considering the constraints (3) and (4) simultaneously. The problem for a_b is stated in a similar way and is therefore omitted (see, however, the case study on forward bilateral contracting with demand response described in the next section).

The optimization problem is resolved through a linear programming method called simplex using lp_solve, a Mixed Integer Linear Programming solver.[1] lp_solve is a free linear (integer) programming solver based on the revised simplex method and the Branch-and-bound method for integers. It solves pure linear, (mixed) integer/binary, semi-continuous and special ordered sets models.

Beyond the volumes of energy, the customer also negotiates prices. The prices offered in a new proposal are obtained by the following formula:

$$P^b_{k_{new}} = P^b_{k_{prev}} + Ct \times P^b_{k_{prev}},\ k = 1..n \tag{6}$$

where $P^b_{k_{new}}$ is the (new) price to send by a_b, $P^b_{k_{prev}}$ is the (previous) price sent by a_b and not accepted by a_s, and $Ct \in [0, 1]$ is a constant.

Price Management Strategy for Seller. This strategy aims at maximizing the benefit B^s of a_s, by considering the cost of production C_k, $k=1 \ldots n$, and the volumes V^b_k proposed by the buyer agent a_b, and determining appropriate valuers for the prices P^s_k of a_s. Thus, we consider that a_s accept the volumes proposed by a_b. The mathematical formulation of the problem is as follows:

$$Maximize\ B^s = \sum_{k=1}^{n} (P^s_k - C_k) \times V^b_k \tag{7}$$

subject to:

$$P^s_k \geq C_k \tag{8}$$

The constraint expressed by (8) assures that the cost of production does not exceed the price of energy considered by a_s.

4 A Case Study on Customer Response Strategies

David Owen, CEO of the SCO Bank, agrees to meet with Tom Britton and John Adams, representatives in Portugal and specialists in operational efficiency. In the meeting, David Owen requests a solution to reduce 5% of the electricity costs in the bank headquarter, located in Lisbon. The corresponding building is constituted by 4 floors, where 200 employees work a five-day week to cope with normal demands. The main sources of consumption are 200 computers, 8 printers, 200 electric lamps, 12 HVAC systems, 3 lifts, 4 kitchens and 4 televisions. Other sources of consumption, such as surveillance cameras, the alarm system and other critical equipment, are not considered. David Owen requests to both Tom Britton and John Adams to negotiate a more beneficial tariff and mainly to find a technical and efficient solution for reducing consumption without affecting the normal activity of the bank. The major objective is to determine the possible five-days workweek electricity cost savings.

[1] `lpsolve.sourceforge.net`

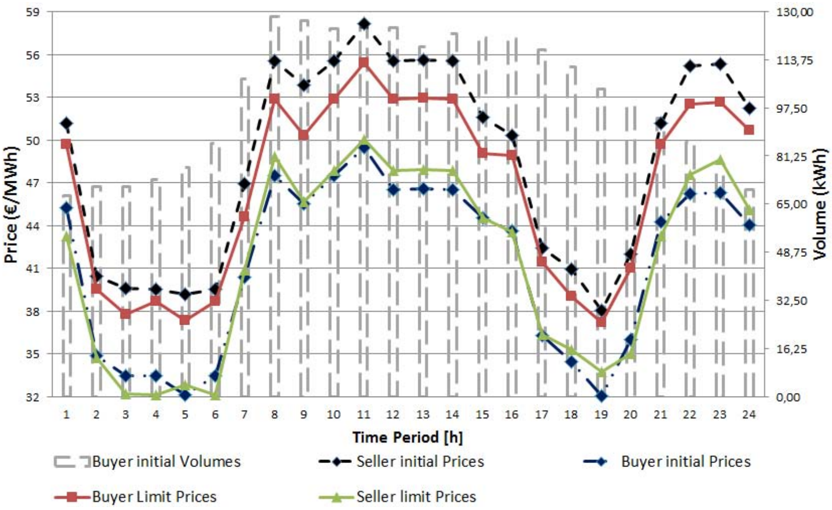

Fig. 1. Initial prices, initial volumes, and limits for price

At SCO Bank, it was previously agreed that there must not be any reduction in computer usage to keep normal bank operation. John Adams starts addressing the problem and notices that the peak consumption occurs normally between 8am and 4pm. The peak hour is usually at 8am, where 180 computers, 8 printers, 180 lamps, 8 HVAC systems, 3 lifts, 2 kitchens and 2 televisions are in use. Accordingly, John Adams suggests the following three response solutions:

- a shifting load response;
- a curtailment load response of 5%;
- a curtailment of 5% together with a shifting response.

In practice, the consumption curtailment will conduct roughly to the following energy usage: a reduction of around 20% of electric lamp usage, and a minimum of 4 printers, 4 HVAC systems, 2 lifts, 1 kitchen and 1 television in normal operation.

Next, Tom Britton (playing the role of a customer) contacts David Colburn, representing N2K Power (a retailer company), in order to negotiate a 24-rate tariff. Figure 1 shows the load profile of the customer agent, and the initial offers and price limits for the two agents. Some values were selected by looking up to real trading prices associated with pool markets in an attempt to approximate the case study to the real-world. In particular, market reference prices were obtained by analysing the Iberian Electricity Market.[2] The minimum seller prices (i.e., the limits) were then set to these reference prices. Also, some energy quantities were based on consumer load profiles provided by the New York State Electric & Gas.[3]

[2] `www.mibel.com`
[3] `www.nyseg.com`

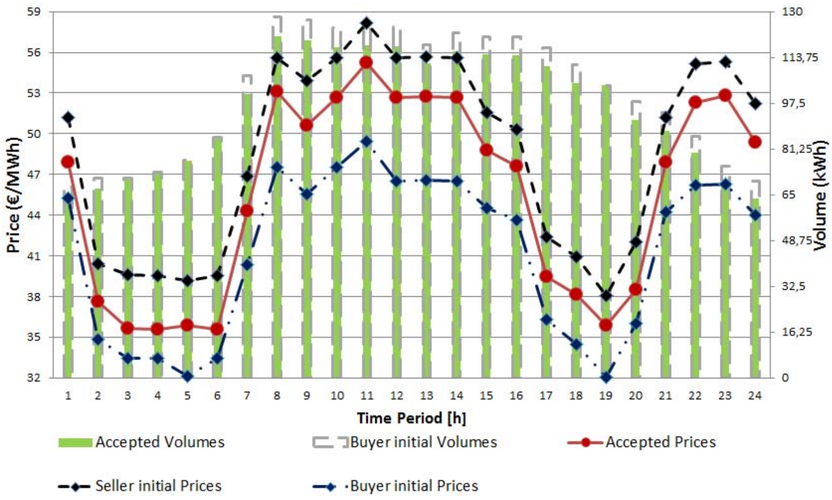

Fig. 2. Variation of customer volumes and energy prices

Negotiation involves an iterative exchange of offers and counter-offers. We consider the following:

- priorities are set indirectly for the prices and volumes of the energy (higher values mean greater importance);
- preferences are specified by using the multiplicative model;
- before starting the negotiation, the customer submits the initial load profile;
- after receiving the customer's load profile, the retailer submits the first proposal;
- the agents are allowed to propose only strictly monotonically—the customer's offers increase monotonically and the retailer's offers decrease monotonically;
- the acceptability of a proposal is determined by a negotiation threshold—an agent $a_i \in \mathcal{A}$ accepts a proposal $p^{t-1}_{j\to i}$, submitted by $a_j \in \mathcal{A}$ at $t-1$, when the difference between the benefit provided by the proposal $p^t_{i\to j}$ that a_i is ready to send in the next time period t is lower than or equal to the negotiation threshold;
- the agents are allowed to exchange only a maximum number of proposals, denoted by max_p.

Figures 2 and 3 and Table 1 summarize the results obtained. During the course of negotiation, the customer agent adjusts the load profile using the load response strategies formalized in section 3, in response to the prices submitted by the retailer agent. Also, the customer defines new values for the prices of the energy using (6). The retailer agent adjusts the prices of the energy by using the "Price Management" strategy formalized in section 3. As mentioned earlier, this agent accepts the load profile proposed by the customer.

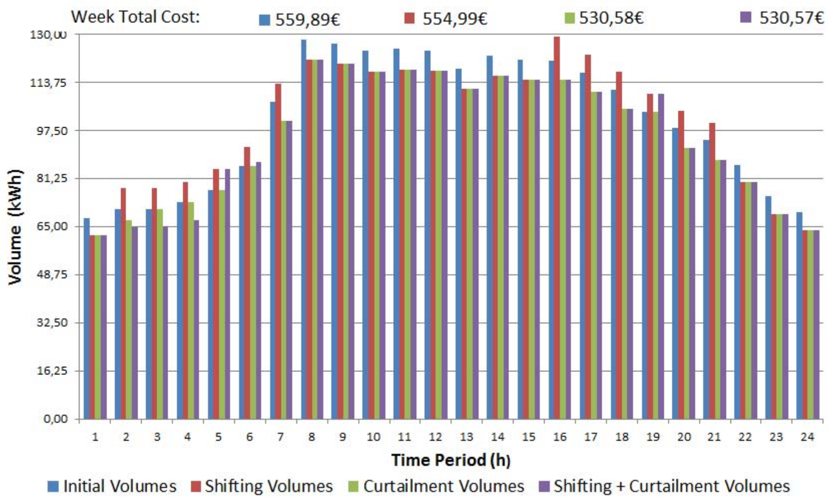

Fig. 3. Variation of volumes for the three proposed solutions

Figure 2 shows the variation of customer volumes and energy prices, considering the first proposal submitted and the final proposal accepted by both agents. Figure 3 summarizes the results of the three response solutions suggested by John Adams. Table 1 shows the cost values of the received and ready to send proposals of the customer agent. Taking into account the goal of reducing 5% of the electricity costs, defined initially by the CEO of the SCO Bank, John Adams dismisses the "shifting solution", since it does not fulfill this goal (see Fig. 3). Also, by analysing the results of the "curtailment+shifting solution" shown in Fig. 3, this agent concludes that it makes little or no sense to increase consumption in hours 5 and 19 (e.g., by turning on 1 HVAC system).

John Adams meet next with David Owen to carefully analyze the results and both agree that the "curtailment solution" seems to be the best one. In the worst case (peak hours), this solution results in turning off 4 printers, 40 lamps, 4 HVAC systems and 1 television. Technically speaking, turning off 40 lamps may be substituted by other actions, such as closing 1 lift or even 1 kitchen.

Table 1. Cost of received and ready to send proposals of the customer

Cost (€)	1^{st} Round	2^{nd} Round	3^{rd} Round
Received proposal	596,00	545,00	530,58
Ready to send proposal	480,00	526,00	540,00

From the analysis of the results, it is important to mention that the customer agent reduces energy usage at times of high prices, notably from 8am to 6pm, in strict accordance with a fully automated demand response. Also, the cost of the energy has proven to be minimal for the distribution of volumes in the final proposal. Negotiation ended when the customer agent accepted the third proposal sent by the retailer agent.

5 Conclusion

This paper has described research work that uses the potential of agent-based technology to develop a computational tool to support bilateral contracting in electricity markets with demand response. From the perspective of end-use customers, it has investigated how different load response strategies affect the energy and monetary outcomes of consumers applying demand response during bilateral contracting. Specifically, it has studied the influence of both the curtailment and the shifting load response strategies on electricity prices and consumption using agent-based modeling and simulation techniques. To this end, it has presented a case study on forward bilateral contracts and customer load response strategies: a customer agent and a retailer agent have negotiated a 24h-rate tariff.

Although preliminary, the simulation results support the belief that the simulation tool can help the parties to make decisions during the negotiation of bilateral contracts in competitive electricity markets with demand response. Furthermore, the results support the belief that commercial customers adopting a curtailment response strategy can gain considerable benefits. In the future, we intend to perform a number of inter-related experiments to empirically evaluate different key load response strategies.

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