Decentralized Foresighted Energy Purchase and Procurement
With Renewable Generation and Energy Storage

Yuanzhang Xiao and Mihaela van der Schaar

Abstract—We study a power system with one independent system operator (ISO) who procures energy from energy generators, and decentralized aggregators who purchase energy from the ISO to serve their customers. With the penetration of renewable energy generation, the aggregators are adopting energy storage to deal with the high volatility in supply and prices. In the presence of energy storage, it is beneficial for all of renewable energy generation, the aggregators are adopting from the ISO to serve their customers. With the penetration of renewable energy generation, the aggregators are adopting energy storage to deal with the high volatility in supply and prices. In the presence of energy storage, it is beneficial for all of renewable energy generation, the aggregators are adopting from the ISO to serve their customers.

We propose a design framework in which the ISO provides each aggregator with a conjectured future price, and each aggregator distributively minimizes its own long-term cost based on its conjectured price as well as its local information. The proposed framework can achieve the social optimum despite the decentralized information among the entities. Simulation results demonstrate significant reduction in the total cost by the proposed foresighted energy purchase and procurement (EPP), compared to the optimal myopic EPP (up to 60% reduction), and the foresighted EPP based on the Lyapunov optimization framework (up to 30% reduction).

I. INTRODUCTION

We consider a power system with multiple energy generators, one independent system operator (ISO) that operates the system, and multiple aggregators that serve their customers. Each aggregator is located in a different geographical area and purchases energy from the ISO to serve its customers (e.g., households) in the neighborhood. The ISO receives energy purchase requests from the aggregators as well as reports of (parameterized) energy generation cost functions from the generators, and based on these, procures energy from generators. We call the aggregators’ energy purchase and the ISO’s energy procurement collectively as energy purchase and procurement (EPP) 1.

In the current power systems, the optimal EPP decisions are made roughly every hour (the frequency of the decisions may be slightly different in different power systems). Each aggregator’s energy purchase decisions are simple: just purchase an amount of energy that is enough to serve the demand of its customers. The ISO’s energy procurement decisions are more complicated and determined by solving the optimal power flow (OPF) problem, which minimizes the total energy generation cost in the current time slot (e.g., in one hour) subject to the constraints of the power network (e.g., Kirchhoff’s laws, line capacity constraints). We call such EPP strategies myopic, in the sense that the decision makers aim to optimize the short-term performance. As we will see, myopic EPP can be very suboptimal in future power systems with renewable generation and energy storage.

The adoption of renewable energy in the power systems introduces high fluctuation and uncertainty in energy generation and prices. To cope with this uncertainty, the demand side of the system is deploying various solutions, one of which is the use of energy storage [6]. The use of energy storage endows the system with “a buffer” that correlates the EPP decisions across time. Hence, the optimal EPP decisions should not only maximize the current system performance, but also consider the impact of the decisions on the future system performance. In other words, the optimal EPP decisions should be foresighted. For example, an aggregator can purchase from the ISO more energy than requested from its customers, and store the unused energy in the energy storage for future use, if it anticipates the shortfall of renewable generation and the rise of energy prices in the future.

In this paper, we design the optimal foresighted EPP strategy in the presence of energy storage, and show that the resulting strategy significantly outperforms the myopic EPP strategies. However, the optimal foresighted EPP decisions are difficult to make, because of the decentralized information in the system. Specifically, the total cost of the system depends on the generation cost functions (e.g., the speed of wind for wind energy generation, the amount of sunshine for solar energy generation), the status of the transmission lines (e.g., their capacity), the amount of electricity in the energy storage, and the demand from the customers, all of which may change due to supply and demand uncertainty. However, none of the entities knows all the above information: the ISO knows only the generation cost functions and the status of the transmission lines, and each aggregator knows only the status of its own energy storage and the demand from its own customers. Yet, each entity’s local information influences its decisions, and hence influences the others’ costs in the future. This is in sheer contrast with myopic EPP, in which the decentralized information does not affect the decision making very much: the aggregators purchase energy just enough to serve the demand without worrying about the future shortfalls and price fluctuations, and the ISO procures energy to minimize the current cost without worrying about

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1It should be noted that we focus on the interaction among the ISO and the aggregators, and study the aggregators’ energy purchase and the ISO’s energy procurement. This is very different from the works (see [1]–[3] for representative papers) that focus on the interaction among one aggregator and its customers, and study the customers’ energy consumption scheduling.
the future demand.

To overcome the difficulty resulting from information decentralization, we propose a decentralized EPP strategy based on conjectured prices. Specifically, each aggregator makes decisions based on its conjectured price and local information on the status of its energy storage and the demand from its customers. Since the energy price is usually determined based on the generation cost and the status of the transmission lines, the conjectured prices are determined by the ISO. We propose a simple online algorithm for the ISO to update the conjectured prices based on its local information, and prove that by using the algorithm, the ISO obtains the optimal conjectured prices under which the aggregators’ (foresighted) best responses minimize the total system cost.

In the rest of the paper, we will first discuss related works in Section II. Then we will present the system model and problem formulation in Section III. We present our design framework of foresighted EPP in Section IV, and demonstrate its performance gain by simulation in Section V. Finally, Section VI concludes the paper.

II. RELATED WORKS

The key feature that sets apart our paper from most works on EPP [4]–[8] is that in our work, all the decision makers in the system are foresighted. Each aggregator seeks to minimize its long-term cost, consisting of its operational cost of energy storage and its payment for energy purchase. In contrast, in most existing works [4]–[8], the aggregators are myopic and seek to minimizing their short-term (e.g. one-day or even hourly) cost.

Although some works [9]–[12] assume that the aggregator is foresighted, they study the decision problem of a single aggregator. When there are multiple aggregators in the system (which is the case in practice), this approach neglects the impact of aggregators’ decisions on each other, which leads to suboptimal solutions in terms of minimizing the total cost of the system.

In Table I, we summarize the above discussions on the related work by comparing with them in various aspects.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

We consider a power system with one ISO indexed by 0, G generators indexed by \( g = 1, 2, \ldots, G \), I aggregators indexed by \( i = 1, 2, \ldots, I \), and L transmission lines (see Fig. 1 for an illustration). In the following, we may refer to the ISO or an aggregator generally as entity \( i \in \{0, 1, \ldots, I\} \), with entity 0 being the ISO and entity \( i \in \{1, \ldots, I\} \) being aggregator \( i \).

The power system can be modeled as a stochastic dynamic system described as follows.

States: The ISO’s state is defined as \( s_0 = (\varepsilon, \xi) \in S_0 \), where \( \varepsilon = (\varepsilon_1, \ldots, \varepsilon_G) \) are the parameters of the energy generation cost functions reported by the generators, and \( \xi = (\xi_1, \ldots, \xi_L) \) are the status of the transmission lines such as the phases measured by the phasor measurement units (PMUs). Each aggregator \( i \)’s state is defined as \( s_i = (d_i, e_i) \in S_i \), where \( d_i \) is the aggregate demand from aggregator \( i \)’s customers and \( e_i \) is the amount of energy left in aggregator \( i \)’s storage. Each entity’s state is known to itself only.

Actions: The ISO’s action is how much energy each generator should produce, denoted by \( a_0 \in A_0 \subset \mathbb{R}_+^G \). Each aggregator \( i \)’s action is how much energy to purchase from the ISO, denoted by \( a_i \in A_i \subset \mathbb{R}_+ \).

Instantaneous Costs: Each entity’s instantaneous total cost consists of two parts: the operational cost and the payment. Each entity \( i \)’s operational cost \( c_i(s_i, a_i) = p \cdot \max\{d_i - (e_i + a_i), 0\} + m_i(e_i) \), where \( p > 0 \) is the penalty of failing to fulfill the demand (i.e., when \( e_i + a_i < d_i \)), and \( m_i(e_i) \) is the maintenance cost of the energy storage that is convex [6].

The ISO’s operational cost \( c_0(s_0, a_0) = \sum_{g=1}^G c_g(\varepsilon_g, a_{0,g}) \), where \( c_g(\varepsilon_g, a_{0,g}) \) is the convex increasing energy generation cost of generator \( g \). An example cost function can be \( c_g(\varepsilon_g, a_{0,g}) = (q_{0,g} + q_{1,g} \cdot a_{0,g} + q_{2,g} \cdot a_{0,g}^2) + q_{r,g} \cdot (\alpha_{0,g} - \alpha_{0,g}^-)^2 \), where \( \alpha_{0,g}^- \) is the production level in the previous time slot. In the cost function, \( a_{0,g} + q_{1,g} \cdot a_{0,g} + q_{2,g} \cdot a_{0,g}^2 \) is the quadratic cost of producing \( a_0 \) amount of energy [1][2], and \( q_{r,g} \cdot (\alpha_{0,g} - s_{a_0})^2 \) is the ramping cost of changing the energy production level.

Each aggregator \( i \)’s payment to the ISO is \( y_i(s_0, a_i, a_{-i}) \), where \( y_i(s_0, a_i, a_{-i}) \) is the unit energy price that depends on the ISO’s state \( s_0 \), its own purchase \( a_i \), and the other aggregators’ purchases \( a_{-i} \). Similarly, the ISO’s payment to the generators is \( y_0^T \cdot a_0 \), where \( y_0 \) is the vector of unit prices for each generator.

Each entity \( i \)’s total cost \( \tilde{c}_i \) is the sum of its operational cost and its payment.

State Transitions: We assume that each entity’s state transition is Markovian, namely its current state depends only on its previous state and its previous action [5][7][8][11][12]. Under the Markovian assumption, we denote the transition...
TABLE I
COMPARISONS WITH RELATED WORKS ON ENERGY PURCHASE AND PROCUREMENT.

<table>
<thead>
<tr>
<th>Interaction</th>
<th>Energy storage</th>
<th>Time horizon</th>
<th>Foresighted</th>
<th>Aggregators</th>
<th>Supply uncertainty</th>
<th>Demand Uncertainty</th>
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<td>No</td>
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<td>No</td>
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<td>[3]</td>
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<td>No</td>
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<tr>
<td>[4]</td>
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<td>No</td>
<td>Multiple</td>
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</tr>
<tr>
<td>[5]</td>
<td>ISO-Aggregator</td>
<td>No</td>
<td>1 day</td>
<td>No</td>
<td>Multiple</td>
<td>Yes</td>
</tr>
<tr>
<td>[6]</td>
<td>ISO-Aggregator</td>
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<td>1 day</td>
<td>No</td>
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<td>No</td>
</tr>
<tr>
<td>[7][8]</td>
<td>ISO-Aggregator</td>
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<td>Yes</td>
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<td>Yes</td>
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<td>Yes</td>
</tr>
</tbody>
</table>

Fig. 2. Illustration of the interaction between the ISO and aggregator i (i.e., their decision making and information exchange) in one period.

The probability of entity i’s state $s_i$ by $p_i(s_i'|s_i, a_i)$. We also assume that conditioned on the ISO’s action $a_0$ and the aggregators’ action profile $a$, each entity’s state transition is independent of each other.

We divide time into periods (e.g., hours) $t = 0, 1, 2, \ldots$. In each period $t$, the entities act according to the time line shown in Fig. 2. Each entity i’s strategy is a mapping from its set of states to its set of actions, denoted by $\pi_i : S_i \rightarrow A_i$. Each entity chooses its action based on its strategy in each period.

The joint strategy profile $\pi = (\pi_0, \ldots, \pi_T)$ and the initial state $(s_0^0, s_1^0, \ldots, s_T^0)$ induce a probability distribution over the sequences of states and prices, and hence a probability distribution over the sequences of total costs $c_0^t, c_1^t, \ldots$. Taking expectation with respect to the sequences of stage-game payoffs, we have entity i’s expected long-term total cost given the initial state as

$$C_i(\pi(s_0^0, s_1^0, \ldots, s_T^0)) = E \left\{ (1 - \delta) \sum_{t=0}^{\infty} \delta^t c_i^t \right\},$$

where $\delta \in [0, 1)$ is the discount factor. We define each entity i’s expected long-term operational cost $C_i(\pi(s_0^0, s_1^0, \ldots, s_T^0))$ given the initial state in a similar way.

B. Problem Formulation

The ISO aims to minimize the long-term total cost in the system. In addition, we need to satisfy the constraints due to the capacity of the transmission lines, the supply-demand requirements, and so on. We denote the constraints by $f(s_0, a_0, a) \leq 0$, where $f(s_0, a_0, a) \in \mathbb{R}^N$ with $N$ being the number of constraints. We assume that the electricity flow can be approximated by the direct current (DC) flow model, in which case the constraints $f(s_0, a_0, a) \leq 0$ are linear in each $a_i$. Hence, the design problem can be formulated as

$$\min_{\pi} \sum_{s_0^0, s_1^0, \ldots, s_T^0} \sum_{t=0}^{T} C_i(\pi(s_0^0, s_1^0, \ldots, s_T^0))$$

s.t. $f(s_0, a_0(s_0), \ldots, a_T(s_T)) \leq 0, \forall (s_0, \ldots, s_N)$. Note that in the above optimization problem, we use entity i’s operational cost $C_i$ instead of its total cost $C_i$, because all the payments are transferred with in the system and are thus canceled in the total system cost. Note also that we sum up the cost under all the initial states. This can be considered as the expected total system cost when the initial state is uniformly distributed. The optimal stationary strategy profile that minimizes this expected total system cost will also minimize the total system cost given any initial state.

We write the solution to the design problem as $\pi^*$ and the optimal value of the design problem as $C^*$.

IV. OPTIMAL FORESIGHTED EPP

A. The aggregator’s Decision Problem and Conjectured Price

Contrary to the ISO, each aggregator aims to minimize its own long-term cost $C_i(\pi(s_0^0, s_1^0, \ldots, s_T^0))$. In other words,
each aggregator $i$ solves the following problem:

$$\pi_i = \arg \min_{\pi_i} C_i(\pi_i, \pi_{-i}(s_0^i, s_1^i, \ldots, s_t^i)).$$

Assuming that the aggregator knows all the information, the optimal solution to the above problem should satisfy the following:

$$V_i(s_0, s_i, s_{-i}) = \min_{a_i \in A_i} \left\{ (1 - \delta) C_i(s_0, s_i, a_i, a_{-i}) + \delta \cdot \sum_{s'_i, s'_{-i}} \rho_i(s'_i | s_i) \prod_{j=1}^{t-1} \rho_j(s'_j | s_j, a_j) V_i(s'_0, s'_i, s'_{-i}) \right\}.$$

However, the information (such as the other aggregators’ strategies $\pi_{-i}$ and states $s_{-i}$, and the ISO’s state $s_0$) necessary to solve the above problem is never available to aggregator $i$.

One way to decouple the interaction among the aggregators is to endow each aggregator with a conjectured price. Denote the conjectured price as $\tilde{y}_i$, we can rewrite aggregator $i$’s decision problem as:

$$\tilde{V}_i^{\tilde{y}_i}(s_i) = \min_{a_i \in A_i} \left\{ (1 - \delta) \left[ c_i(s_i, a_i) + \tilde{y}_i \cdot a_i \right] + \delta \cdot \sum_{s'_i} \rho_i(s'_i | s_i) \tilde{V}_i^{\tilde{y}_i}(s'_i) \right\}.$$

Clearly, we can see from the above equations that given the conjectured price $\tilde{y}_i$, each aggregator can make decisions based only on its local information.

In Fig. 3, we illustrate the entities’ decision making and information exchange in the design framework based on conjectured prices. We can see that in the proposed design framework, the ISO sends the conjectured prices to the aggregators before the aggregators make decisions. This additional procedure of exchanging conjectured prices allows the ISO to lead the aggregators to the optimal EPP strategies. The remaining question is how to determine the optimal conjectured prices, such that when each aggregator reacts based on its conjectured price, the resulting strategy profile minimizes the system cost.

B. The Optimal Decentralized EPP Strategy

We propose a distributed algorithm used by the ISO to iteratively update the conjectured prices and by the aggregators to update their optimal strategies. The algorithm will converge to the optimal conjectured prices and the optimal strategy profile that achieves the minimum total system cost $C^*$.

At period $t$, given the conjectured price $\tilde{y}_i$, each aggregator $i$ solves

$$\tilde{V}_i^{\tilde{y}_i}(s_i) = \min_{a_i \in A_i} \left\{ (1 - \delta) \left[ c_i(s_i, a_i) + \tilde{y}_i \cdot a_i \right] + \delta \cdot \sum_{s'_i} \rho_i(s'_i | s_i) \tilde{V}_i^{\tilde{y}_i}(s'_i) \right\}.$$

and obtains the optimal value function $\tilde{V}_i^{\tilde{y}_i}$ as well as the corresponding optimal strategy $\pi_i^{\tilde{y}_i}$ under the current conjectured price $\tilde{y}_i$.

Similarly, given the conjectured prices $\tilde{y}_0^i \in \mathbb{R}^G$, the ISO solves

$$V_0^{\tilde{y}_0^i}(s_0) = \min_{a_i \in A_i} \left\{ (1 - \delta) \left[ \sum_g c_g(s_0, a_0) + (\tilde{y}_0^i)^T \cdot a_0 \right] + \delta \cdot \sum_{s'_i} \rho_i(s'_0 | s_0) \tilde{V}_0^{\tilde{y}_0^i}(s'_0) \right\},$$

and obtains the optimal value function $V_0^{\tilde{y}_0^i}$ as well as the corresponding optimal strategy $\pi_0^{\tilde{y}_0^i}$ under the current conjectured price $\tilde{y}_0^i$.

Then the ISO updates the conjectured prices using a stochastic subgradient method. The detail of this update, along with the complete description of the algorithm, is given in Table II.

**Theorem 1**: The algorithm in Table II converges to the optimal strategy profile, namely

$$\lim_{t \to \infty} \left| \sum_{s_0, s_1, \ldots, s_t} \sum_{i=0}^{t} C_i(\pi_i^{\tilde{y}_i}((s_0, s_1, \ldots, s_t))) - C^* \right| = 0.$$

**Proof**: See the appendix in [15].

From Fig. 3, we can see that the amount of information exchange at each period is small ($O(I)$), compared to the amount of information unavailable to each entity ($\prod_{j=1}^{|S_i|}$ states plus the strategies $\pi_{-i}$). In other words, the algorithm enables the entities to exchange a small amount ($O(I)$) of information and reach the optimal EPP strategy that achieves the same performance as when each entity knows the complete information about the system.

V. SIMULATION RESULTS

In this section, we validate our theoretical results and compare against existing EPP strategies through extensive simulations. We use the widely-used IEEE test power systems [13]. We describe the other system parameters as follows:

- One period is one hour. The discount factor $\delta = 0.99$.
- The demand of aggregator $i$ at period $t$ is uniformly distributed among the interval $[d_i(t \mod 24) - \Delta d_i(t \mod 24), d_i(t \mod 24) + \Delta d_i(t \mod 24)]$. We let the peak hours for all the aggregators to be from 17:00 to 22:00. The mean value of aggregator $i$’s demand $d_i(t$...
mod 24) = 50 + (i − 1) · 0.5 MW in peak hours and 
\[d_i(t \mod 24) = 25 + (i − 1) \cdot 0.5\] MW in off-peak
hours. The range \[\Delta d_i(t \mod 24) = 5\] MW in peak
hours and \[\Delta d_i(t \mod 24) = 2\] MW in off-peak.
These values are adapted from [14].
• All the aggregators have the same linear energy
storage cost function [6]: \[c_s(s_i, a_i) = 2 \cdot (a_i − d_i)^4\].
• All the renewable energy generators have linear energy
generation cost functions [14]: \[c_g(a_{0,g}) = g \cdot a_{0,g}\], where the
unit energy generation cost has the same value as
the index of the generator (these values are adapted
from [14], which cited that the unit energy generation
cost ranges from $0.19$/MWh to $10$/MWh). Although
the energy generation cost function is deterministic,
the maximum amount of energy production is stochastic
due to wind speed, the amount of sunshine, and so on.
The maximum amounts of energy production of all the
renewable energy generators follow the same uniform
distribution in the range of [90, 110] MW.
• The conventional energy generators have the same en-
ergy generation cost function [6]:
\[c_g(a_{0,g}) = \frac{0.5 \cdot (a_{0,g})^2 + 0.1 \cdot (a_{0,g} - a_{0,g}^-)^2}{\text{generation cost}} + \text{ramping cost}\].

We compare the proposed EPP strategies with the follow-
ing schemes.
• Centralized optimal strategies (“Centralized”): We as-
sume that there is a central controller who knows
everything about the system and solves the long-term
cost minimization problem as a single-user MDP. This
scheme serves as the benchmark optimum.
• Myopic strategies (“Myopic”) [4]–[8]: In each period
\(t\), the aggregators myopically minimizes their current
costs, and based on their actions, the ISO minimizes
the current total generation cost.
• Single-user Lyapunov optimization (“Lyapunov”) [9]–
[12]: We let each aggregator adopt the stochastic opti-
mization technique proposed in [9]–[12]. Based on the
aggregators’ purchases, the ISO minimizes the current
total generation cost.

1) Impact of the energy storage: First, we study the
impact of the energy storage on the performance of different
schemes. We assume that all the generators are conventional
energy generators using fossil fuel, in order to rule out the
impact of the uncertainty in renewable energy generation
(which will be examined next). The performance criterion
is the total cost per hour normalized by the number of buses
in the system. We compare the normalized total cost achieved
by different schemes when the capacity of the energy storage
increases from 5 MW to 45 MW.

Fig. 4 shows the normalized total cost achieved by dif-
f erent schemes under IEEE 30-bus system. We can see
that the proposed EPP strategy achieves almost the same
performance as the centralized optimal strategy. The slight
optimality gap comes from the performance loss experienced
during the convergence process of the conjectured prices.
Compared to the EPP strategy based on single-user Lyapunov
optimization, our proposed strategy can reduce the total cost
by around 30% in most cases. Compared to the myopic EPP
strategy, our reduction in the total cost is even larger and
increases with the capacity of the energy storage (up to 60%).
2) Impact of the uncertainty in renewable energy generation: Now we examine the impact of the uncertainty in renewable energy generation. We let half of the generators to be renewable energy generators. Recall that the maximum amounts of energy production of the renewable energy generators are stochastic and follow the same uniform distribution. We keep the mean value of the maximum amount of energy production to be 100 MW, and vary the range of the uniform distribution. A wider range indicates a higher uncertainty in renewable energy production. Hence, we define the uncertainty in renewable energy generation as the maximum deviation from the mean value in the uniform distribution.

Fig. 5 and Fig. 6 show the normalized total cost with different degrees of uncertainty in renewable energy generation, when the aggregators have 25 MV and 50 MV energy storage, respectively. Again, the proposed strategy achieves the performance of the centralized optimal strategy, and has lower total cost compared to the other schemes. We can also see that when the aggregators have larger capacity to store energy, the increase of the total cost with the uncertainty is smaller. This is because the energy storage can smooth the demand, in order to mitigate the impact of uncertainty in the renewable energy generation. This shows the value of energy storage to reduce the cost.

VI. CONCLUSION

In this paper, we proposed a methodology to perform optimal foresighted EPP strategies that minimize the long-term total cost of the power system. We overcame the hurdles of information decentralization in the system, by decoupling the entities’ decision problems using conjectured prices. We proposed an online algorithm for the ISO to update the conjectured prices, such that the conjectured prices can converge to the optimal ones, based on which the entities make optimal decisions that minimize the long-term total cost. We prove that the proposed method can achieve the social optimum, and demonstrate through simulations that the proposed foresighted EPP significantly reduces the total cost compared to the optimal myopic EPP (up to 60% reduction), and the foresighted EPP based on the Lyapunov optimization framework (up to 30% reduction).

REFERENCES