Autonomy-Oriented Mechanisms for Efficient Energy Distribution

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Abstract

Due to the uneven geographical availability of energy resources and the world imbalanced economic development, it is essential for the energy suppliers and consumers in different countries or regions to most efficiently, economically, as well as reliably distribute energy resources. The general problem of energy distribution is a complex one in that many factors can be involved either endogenously or exogenously such as human activities, energy transportation efficiency, geopolitics, and so on. Traditional statistical and/or centralized models are impractical to tackle energy distribution problems that are, by nature, non-centralized and/or dynamically evolving. Although some decentralized approaches (e.g., multi-agent systems) may be adopted to solve certain types of dynamic distribution problems in a small scale, they are, at the moment, still quite limited in methodology and applications to practically address various important issues as related to the problems. In this paper, starting from a specific energy distribution problem, we present a decentralized behavior-based paradigm that draws on the methodology of self-organized computing, i.e., autonomy-oriented computing. The goal of our work is twofold: (i) to characterize the underlying mechanism of the energy distribution system, and (ii) to provide scalable solutions for efficient energy distribution. We provide simulation-based experiments to show the performances of four local behavior-based algorithms, with gradually increased behavioral complexity. The simulation results show that global objectives can be approximately reached through autonomous entities with even simple exploration and regulation behaviors. We conjecture that efficient energy trading markets can emerge from appropriate behavior-based mechanisms, which can autonomously improve energy distribution efficiency.

1 Introduction

Nowadays, the daily life of human being on the earth becomes more and more heavily depending on different kinds of energy resources (It is reported by International Energy Agency (IEA) in [14] that the total primary energy supply of the world has doubled at the end of 2007 comparing with the year 1971.). British Petroleum in [2] reports that the reserves of fossil fuels on the earth will not afford the requirement of human economic development in the very nearly future, for example, the reserves-to-production ratio of world oil (respectively, natural gas, coal) is estimated at 42 years (respectively, 60 years, 122 years), at the end 2008. In addition to the scarcity of energy resources, we are also facing another serious problem, i.e., the uneven geographical availability of energy resources and the world imbalanced energy demand. On one hand, according to the *Oil and Gas Journal* [1] and IEA [13], 56 percent of the world's proved oil reserves are located in the Middle East, and almost three-quarters of the world's natural gas reserves are located in the Middle East and Eurasia. On the other hand, North America and Europe contribute almost half the the world primary energy consumptions in 2008 [2]. Furthermore, it is predicted by IEA in [13] that, energy demand may grow rapidly in less developed regions (e.g., China, India) for the rapid development of these regions in recent years. For all above reasons, it becomes essentially important for the energy suppliers and consumers in different regions to distribute energy resources to meet their different requirements.

1.1 The Energy Distribution Problems

Distributing energy resources among energy suppliers and consumers at different regions relates to various issues in different areas (e.g., economy, geopolitics, logistics, systems, market, etc.). For example, the energy price issues; the transportation infrastructure (e.g., railway, oil or natural gas pipelines, etc.) investment issues for industries and/or governments [33]; the inventory management issues to meet short-term needs when supply of energy resources are interrupted for any reason (e.g., terrorism, severe weather events, etc.); the cascading control or congestion management issues on power grid [26][21]; and the issues about energy trading markets such as the world oil markets and oil futures markets. All these issues interrelate to form a very complex energy distribution system, which may have its own reliability [32], vulnerability [3], and system security [33]. For the reason that most of the distribution challenges arise from the fact that energy suppliers and consumers are located in different geographic regions, in the context of this paper, we mainly focus on the logistics networks of energy resources, i.e., the energy distribution management problems.

The logistics network required to supply energy resources from energy supplier to energy consumers is an integration of different distribution infrastructures (e.g., pipelines, ships, railways, etc.). Most existing studies (e.g., [20][5][24][25][26], just list a few) focus on the distribution managements under the physical constraints of the existing logistics networks. In this paper, inspired by the dynamics-driven network optimization problems proposed in [22], and biologically-inspired adaptive network proposed in [31], we will focus the formation of robust and adaptive energy flow networks or trading relationship networks in terms of distribution efficiency (e.g., minimal transportation cost).

1.2 Challenges

The reality of the energy distribution problems are more complex in terms of (i) the energy supply and/or demand may dynamically change either endogenously or exogenously, (ii) the coupling relationships between energy suppliers and consumers may not be explicitly represented by simple (linear) functions, (iii) the information may only be partially available due to private issues or competitions among energy suppliers and consumers, and (iv) in real market, entities (either energy suppliers or consumers) make decisions (e.g., where to import/export energy, how many to import, etc.) based on their own benefits rather than the global goal (e.g., to minimize the total cost of energy flows in [24][25]) of the distribution systems. Therefore, an energy distribution system can be considered to be a complex one, which is, by nature, open, highly distributed, and dynamically evolving. In this case, it is difficult for statistical models (e.g., [15][29], just list a few) and/or centralized optimization approaches (e.g., [7][24][25][20], just list a few) to solve such open, dynamic energy distribution problems.

Although some decentralized approaches (e.g., multi-agent systems [17][9]), which have been proposed to solve resource management (e.g., resource allocation [8]) problems, may also be adopted to solve certain type of dynamic energy distribution problems in a small scale, they are, at the moment, still quite limited in methodology and applications to practically address various important issues as related to the energy distribution problems, e.g., the natural mechanisms underlying an open, unpredictable energy distribution system. Most of these approaches focus on strategy design (e.g., multi-agent negotiation systems [18][16]), which belong to the problem of dynamics optimization on static networks in [22]. As far as we know, very few studies have been done to characterize the underlying mechanism of the energy distribution systems in terms of dynamics-driven network optimization [22] and/or adaptive network formation [31].

1.3 Our Considerations

In order to efficiently, economically, as well as reliably distribute energy resources in the open, dynamic environments, it is necessary for us to understand the underlying mechanisms of the distribution systems. In this paper, we present a decentralized behavior-based paradigm that draws on the methodology of self-organized computing, i.e., autonomy-oriented computing (AOC) [19]. According to AOC, the entities can spontaneously interact with each other as well as their environments, and operate based on their behavioral rules. The relationships between entities can therefore be self-organized through entities' behavioral dynamics. Global objectives can be effectively and efficiently achieved by involving positive-feedback mechanisms and collective regulation. The goal of our work is twofold: (i) to characterizing the underlying mechanisms of the energy distribution system through local interactions between energy supplier and consumers with different kinds of behavioral rules, and (ii) to provide scalable solutions for efficient energy distribution.

Before we move to study the more complex energy distribution problems, in this paper, we mainly focus on evaluating the performances of the local behavior-based paradigm for a static energy distribution problem in the first instance. The basic goals of the static energy distribution problem in this paper are (i) to distribute all energy resources from energy suppliers to energy consumers, and (ii) to minimize the total energy distribution costs. By evaluating performances of different kinds of local behavior-based algorithms, we try to answer the following questions.

- How does an optimal (i.e., minimizing the total energy distribution cost) energy flow network can emerge through local dynamic of supplier/consumer entities?
- What kind of local behaviors of supplier/consumer entities are crucial for achieving final optimal energy flow network?

The main objectives of this paper are not only to solve the energy distribution problem, but to present a natural behavior-based paradigm with respect to the energy distribution problem so that more complex energy distribution problems (i.e., open and dynamically evolving) can be studied in the future. The behavior-based paradigm may help to answer the following systematic questions of a complex energy distribution system.

- How does the energy flow network evolve in an open, unpredictable energy distribution system?

- What kind of local dynamics between supplies and consumers can improve the robustness and stability of the energy distribution system?

- What kind of energy trading mechanism (market) can be formed? What are the critical factors for the stability of the market?

The rest of this paper is organized as follows. In Section 2, we summarize related energy system models, and show their limitations in terms of the energy distribution problems discussed in this paper. In Section 3, we formulate the energy distribution problem in details. In Section 4, we present a decentralized behavior-based paradigm for the energy distribution problem, and four local behavior-based algorithms with gradually increased behavior complexity to study and solve the problem. We simulate our approaches in Section 5. Finally, we conclude our work and present some future works in Section 6.

2 Related Work

We classify the existing studies on energy systems modeling into two categories: macro- and micro-modeling. Macro-modeling aims to perform predictions (e.g., energy supply/consumption in the future) or scenarios analysis at a macroscopic level, while micro-modeling focuses on solving energy problems at specific energy domains (e.g., power grid, natural gas pipeline system). In this section, we will highlight some of the representative studies of the two categories.

2.1 Macro-modeling of Energy Systems

Traditional energy models (e.g., WORLD [12], COAL [23], FOSSIL [4], etc.) commonly use system dynamics approach, which deals with internal feedback loops and time delays that affect the behavior of an entire system through various interrelated components. System dynamics modeling has been used for strategic energy planning and policy analysis for more than three decades. The main issues the system dynamics energy models try to address include (i) understanding relationships among different components in an energy system [12][23] (e.g., the relationship between proven reserves and cumulative production in an energy discovery system), (ii) capturing the roles that an energy system plays in social, economic, and environmental systems [4][30][11], and (iii) integrating each related systems together to simulate the real world [15][29]. Most of these models are based on statistical data of population, economic growth rate, elasticity of energy substitution, and so on. Therefore, they are well suited for performing predictions or scenarios analysis at a macroscopic level.

Many in-depth work has been done to try to simulate the real world more precisely in recent years (e.g., the world energy model [15] proposed by IEA, the MIT Integrated Global System Model (IGSM) [29])). However, we are still facing the following challenges:

- To precisely simulate the real world requires significant advances in economics, the social science, and environmental science, each of which is quite complicated discipline. It is quite challenging to represent their relationships based only on statistical data.

- In reality, the energy systems are dynamically evolving (e.g., energy technology innovation). It is difficult to represent or predict this kind of dynamics.

- For such integrated systems, as reported in [28], the predictions at a global scale are considered reasonably reliable, while more work should be done to improve predictive capability at regional (i.e., microscopic) scale.

- Such simulations need exascale computing [28].

Limited by above mentioned difficulties, it is difficult for the system dynamics models to provide global/regional energy distribution solutions at specific energy domains, such as natural gas dispatch problem [20], congestion or bottlenecks management in power grid [26][6][7], cascade control [21] in power grid, etc. In the next section, we will introduce micro-modeling of energy systems which can be adopted to solve specific energy distribution problems.

2.2 Micro-modeling of Energy Systems

Micro-modeling of energy systems focuses on developing technological solutions to some specific energy problems of interest. For the energy distribution problems, most existing work are based on optimization approaches, which often combine with other techniques such as network flows models [24][25][20].

The network optimization models, which take into account the effect of spatial constraints (i.e., uneven geographical availability of energy resources), try to find optimal energy flows in a specific network [20][5][24][25]. The networks can represent either the physical energy distribution networks (i.e., the natural gas pipeline network, power grid, etc.) or the trading relationships between energy suppliers and consumers. For example, in [24][25], the authors describe U.S. integrated energy system as a network with collection of nodes and links, where energy resources may flow from one node to another under the constraints of transportation capacity and per unit energy distribution cost on each link. A constrained mathematical optimization approach is proposed to minimize the total cost of energy flows of the network. Different from the work of A. Quelhas et. al. [24][25], where energy flow in each link is independent with flows in other links, authors in [20] presents the economic dispatch in natural gas networks, where the gas flow from a node (i.e., inlet node) to another node (i.e., outlet node) in the networks is determined by the pressure at the inlet node and pressure at the outlet node. In this case, the potential flow in each pipeline is also dependent on the actual flows in other pipelines of the system (i.e., system effects in [20]). However, most existing network flow models, which are designed for optimization purposes, are still centralized approaches.

The idea of abstracting energy components into networks provides a more extensive research potential on energy system modeling. Although some decentralized approaches (e.g., [27][10]) as well as multi-agent systems (e.g., [9][8] [17]), which have been proposed to solve resource allocation problems, may also be adopted to certain dynamic energy distribution problems in a small scale. Most of these approaches focusing on strategy design (e.g., multi-agent negotiation systems [18][16]), belong to the problem of dynamics optimization on static networks in [22]. Except for the problem of dynamics optimization on static networks, the authors in [22] have also proposed the dynamics-driven network optimization problems, which include two types of dynamics. On one hand, the network structure may evolve over time to fit the dynamics (e.g., energy distribution) on the network. On the other hand, the dynamics on the network may inversely be affected by the network structure. Additionally, Tero et al. in [31] have proposed biologically-inspired approach to form adaptive networks with comparable efficiency, fault tolerance, and cost to real-world infrastructure networks (i.e., the Tokyo rail system in [31]). However, as far as we know, very few studies have been done to characterize the underlying mechanism of the energy distribution systems in terms of dynamics-driven network optimization [22] and/or adaptive network formation [31].

3 Problem Statements

As presented in Section 1, energy distribution networks (e.g., railway networks, natural gas pipeline networks) are essential for allocating energy resources under an open, dynamically evolving energy distribution system. A robust and adaptive energy distribution network plays important roles in distribution efficiency (e.g., minimizing transportation cost), and fault tolerance (e.g., transportation dysfunction during abnormal weather). In this case, designing mechanisms without centralized control [31] to form adaptive energy distribution network becomes quite significant for energy distribution management. In this paper, we first evaluate the performances of the local behavior-based paradigm (described in Section 4) for a static energy distribution problem so that the paradigm can be extended to more more complex energy distribution problems in the future.

Consider a set of n energy suppliers/consumers, we want to distribute energy resources from energy suppliers to energy consumers. As described in Section 1.1, distributing energy resources from one region to another may take various costs (e.g., capital cost associated with constructing pipelines, energy resources consumed or wasted during distribution, etc.). We abstract distribution costs among energy suppliers and consumers to be a a predefined cost matrix $CMatrix_{n\times n} = \{c_{ij}|1 \leq i,j \leq n\}$, where c_{ij} represents the per unit energy distribution cost from one supplier/consumer i to another supplier/consumer j. In this paper, we suppose $CMatrix_{n\times n}$ is symmetric, which means that $c_{ij} = c_{ji}$, for $1 \leq i,j \leq n$. However, triangle inequality may not be correct, i.e., $c_{ij} + c_{jk}$ may not definitely greater than or equal to c_{ik}.

Definition 1. ***Energy Distribution Network*** *The predefined cost matrix $CMatrix_{n\times n}$ forms a fully-connected energy distribution network, where each node represents an energy supplier/consumer, and each link is associated with the per unit energy distribution cost.*

Suppose that initially the total energy supply of suppliers equal to the total demand of consumers, in this paper, we will study how an efficient energy flow network can emerge from the energy distribution network through local dynamics of energy suppliers/consumers.

Definition 2. ***Energy Flow Network*** *The energy flows among energy suppliers/consumers can be represented by an undirect network $G =< V, L, Q >$. The node set $V = \{v_i|1 \leq i \leq n\}$ denotes the set of n suppliers/consumers. The link set $L = \{l_{ij}|1 \leq i,j \leq n\}$ represents all existing energy flows (if there are energy flows between node v_i and v_j, then $l_{ij} = l_{ji} = 1$; otherwise, $l_{ij} = l_{ji} = 0$). The quantity set $Q = \{q_{ij}|1 \leq i,j \leq n\}$ represents the volume of energy flows on each link l_{ij}.*

To evaluate the performances of different local behavior-based strategies proposed in this paper, we have two kinds of measurements for the final energy flow networks, i.e., the global cost and per unit cost of final energy flow networks.

Definition 3. ***Global Cost of Energy Flow Network*** *The global cost of energy flow network represents total distribution cost of allocating all energy supply to corresponding consumers based on the energy flow network. In this case, the total costs of all energy flows can be calculated by*

$$TC = \sum_{l_{ij}\in L} q_{ij} \cdot c_{ij} \cdot l_{ij} \quad (1)$$

Definition 4. ***Per Unit Cost of Energy Flow Network*** *The per unit cost of energy flow network represents average distribution cost of certain quantity of energy resources allocating from energy suppliers to corresponding consumers based on the energy flow network. By this definition, the per unit cost of energy flows can be calculated by*

$$PC = \frac{TC}{\sum_{l_{ij} \in L} q_{ij}} \quad (2)$$

Specific research issues to be studied include (i) *distribution rate* (i.e., can the local behavior-based strategies distribute all energy supply to consumers?), (ii) *distribution cost* (i.e., can the global cost or per unit cost of energy flow network generated by the local behavior-based strategies approach to that of the optimal solution?), and (iii) *scalability*(i.e., when the number of entities increases, can the performance of local behavior-based strategies remain efficient, i.e., higher distribution rate and lower distribution cost?). In order to answer the above questions, we will, first of all, present some detailed formulation of the local behavior-based strategies in the next section.

4 Formulations for the Behavior-based Paradigm

In this section, we will present in details the local behavior-based paradigm that draws on the methodology of autonomy-oriented computing (AOC) [19]. According to AOC, entities spontaneously interact with each other as well as their environments based on their behavioral rules to reach certain global objectives. In the context of the energy distribution problem in this paper, the global objectives are (i) to distribute all energy resources from energy suppliers to energy consumers, and (ii) to minimize the global energy distribution costs.

4.1 Entities Profile

In this paper, we have n entities $E = \{e_i | 1 \leq i \leq n\}$, each of which represents either an energy supplier or consumer. A supplier entity aims to sell its energy surplus to appropriate consumers, while a consumer entity aims to buy energy resources from appropriate suppliers to make up its energy deficit. Because the energy distribution costs are finally undertaken by both energy suppliers and consumers, in this paper, we assume that each entity prefers to energy resources with lower distribution costs.

The profile of an entity is represented as a tuple, $< id, type, volume, memory, rules >$, where id denotes the identifier of an entity. $type = \{supplier, consumer\}$ means that an entity may either be an energy supplier or consumer. $volume$ represents the amount of surplus/deficit an energy supplier/consumer has. $memory$ records information that the entity has. Since in real world no supplier/demander has complete information of the energy distribution systems, in this paper, we assume that initially, an entity only has information about its per unit distribution costs to all other suppliers/consumers on the distribution network (i.e., entity e_i only has cost information $\{c_{ij} | 1 \leq j \leq n\}$). The entity does not know other entities' $type$ and $volume$. Therefore, entities need to move on the distribution network and interact with other entities to collect more information. $rules$ determines how an entity move on the contact network and interact with other entities. In this paper, we represent two kinds of rules, i.e., behavioral rules and decision-making rules.

4.2 Behavioral Rules

The behavioral rule of an entity determines how the entity move on the distribution network to collect distribution cost information and find trading partners. In this paper, we assume that once an entity moves to a node on the distribution network, it will get the distribution cost information, as well as the energy surplus/deficit of the supplier/consumer on the node. Then the entity will determine whether or not to trade with the node based on its decision-making rules. The information of visited suppliers/consumers will be saved at the entity's $memory$. For the static energy distribution problem in this paper, entities move on the distribution network based on self-avoiding random walks, which play a central role in the modeling of the topological behavior of thread- and loop-like molecules.

Definition 5. ***Self-avoiding Random Walk*** *A self-avoiding random walk is a sequence of moves on a network that does not visit the same node more than once.*

In this paper, we will present two kinds of self-avoiding random walks to study the effects of entities $memory$ on the global performance of the mechanism. For the first kind of random walk (adopted by Algorithms 1 and 2), each entity only uses cost information of the current visited node to determine where to move for the next step, i.e., the entity does not memorize information. For the second kind of random walk (adopted by Algorithms 3 and 4), each entity will memorize all cost information of nodes that it has already visited, and integrate this information to determine its next step. The hypothesis is that by utilizing $memory$, it is much easier for an entity to find a path with small distribution cost on the static distribution network. The details of the random walks will be introduced in Section 4.4.

Remark: The self-avoiding random walk is adopted in this paper for the static energy distribution problem because the supply/demand of each entity will stay constant during the dynamic process. However, it is obviously unsuitable for the dynamic distribution problems. Here, it is necessary to emphasize that our focus is mainly on the impacts of entities $memory$ (i.e., with limited memory or with unlimited memory) on the performances of the mechanism.

4.3 Decision-making Rules

An entity makes decisions about whether or not to trade with other suppliers/consumers based on its decision-making rule. In this paper, we present three kinds of decision-making rules, i.e., first-come-first-serve, competition, and request-passing, to study the effects of different trading strategies on the global performances. Entities with first-come-first-serve decision-making rule will *passively* trade with entities by their visiting order without considering the distribution cost of energy resources; entities with competition rules prefers to trading with entities with lower distribution cost; entities with the third decision-making rule *proactively* send trading requests to a list of entities who it would like to trade with based on cost information in its memory. In other words, an entity will refuse to trade with entities who are not in its list. The hypothesis is that by proactively regulating trading partners and sending requests based on cost information in $memory$, it is more likely for an entity to find appropriate trading partners than passively trading with visitors. The details of the decision-making rules will be introduced in corresponding algorithms in Section 4.4.

4.4 Behavior-based Algorithms

To evaluate the two behavioral hypotheses, we present four behavior-based algorithms with gradually increased behavioral complexity in this section. Entities in Algorithms 1 and 2 have limited memory and adopt first-come-first-serve decision-making rule. Entities in Algorithms 3 and 4 can memorize all cost information of nodes that they have already visited. Especially, entities in Algorithm 4 can proactively send requests to potential trading partners based on information in $memory$.

Algorithm 1: *Self-avoiding Random Walk with First-come-first-serve*: At each round of this algorithm, each entity with $e_i.volume \neq 0, 1 \leq i \leq n$ (i.e., supply are not distributed or demand are not satisfied) behaves in a random order to find trading partners based on self-avoiding random walk on the distribution network. Denote $e_i.Path(t)$ as the set of entities that entity e_i has already visited up to round t, hence, the potential entities for e_i to visit at round $t+1$ is $PE = E \setminus e_i.Path(t)$. The selection probabilities are inversely proportional to the per unit energy distribution cost from current node to all other possible nodes, i.e., the probability of entity e_i selecting $e_j \in PE$ as trade partner at round $t+1$ is calculated by

Input: Cost matrix $CMatrix_{n\times n}$; Volume of each entity $\{e_i.volume | e_i \in E\}$;
Output: Energy flow network $RMatrix_{n\times n}$
1 Initialize $e_i.Path(1) \leftarrow e_i$ for all $1 \leq i \leq n$;
2 **foreach** *Round* $t = 1 : (n-1)$ **do**
3   Generate a random operation order $O(t)$ with $e_i.volume \neq 0$ for all $1 \leq i \leq n$;
4   **foreach** $e_j \in O(t)$ **do**
5         $PE = E \setminus e_j.Path(t)$;
6   Select $e_k \in PE$ based on Eq. 3;
7   **if** $e_k.volume \neq 0$ **then**
8   Update $e_j.volume$ and $e_k.volume$;
9   Update $RMatrix$ based on $e_j.Path(t+1)$;
10   **end**
11         $e_i.Path(t+1) \leftarrow e_i.Path(t) \cup e_k$;
12   **end**
13 **end**

Algorithm 1: Self-avoiding Random Walk with First-come-first-serve. In the algorithm, steps 5 and 6 are for the self-avoiding random walk; steps 7-10 are for the first-come-first-serve trading. We use $e_i.Path(t)$ to record the nodes that entity e_i has visited up to round t.

$$p_{ij}(t+1) = \frac{\frac{1}{CMatrix(e_i,e_j)}}{\sum_{e_k \in PE} \frac{1}{CMatrix(e_i,e_k)}} \tag{3}$$

The trading agreement will be reached based on a first-come-first-serve rule without considering the costs of energy distribution.

Algorithm 2: *Self-avoiding Random Walk with Competition*: The entities' behavioral rule in this algorithm is the same with the self-avoiding random walk in Algorithm 1. The only difference is that at each round, each entity with non-zero $volume$ will first move to the node it selected. Then, entities who selected the same node will compete for trading with the supplier/consumer at that node.

Algorithm 3: *Self-avoiding Random Walk with Information Sharing*: This algorithm is different with Algorithm 2 in terms of random walk process. In this algorithm, once an entity e_i visited a node j on the distribution network, it will memorize all cost information (i.e., $\{c_{jk} | 1 \leq k \leq n\}$) of the visited node j. Then, use information in its memory to determine next step of the random walk: the entity e_i will first calculate the minimum costs $ShortestPathCost(e_i, e_k)$ to all other potential entities $e_k, k \in PE$ based on $e_i.memory$, then generate random walk probabilities based on the calculated minimum costs. The probability of entity e_i visiting $e_j \in PE$ at round $t+1$ is calculated by

$$p_{ij}(t+1) = \frac{\frac{1}{ShortestPathCost(e_i,e_j)}}{\sum_{e_k \in PE} \frac{1}{ShortestPathCost(e_i,e_k)}} \tag{4}$$

Input: Cost matrix $CMatrix_{n \times n}$; Volume of each entity $\{e_i.volume | e_i \in E\}$;
Output: Energy flow network $RMatrix_{n \times n}$
1 Initialize $e_i.Path(1) \leftarrow e_i$ for all $1 \leq i \leq n$;
2 **foreach** *Round* $t = 1 : (n-1)$ **do**
3   **foreach** $e_j.volume \neq 0$ **do**
4     $PE = E \setminus e_j.Path(t)$;
5   Select $e_k \in PE$ based on Eq. 3;
6     $e_i.Path(t+1) \leftarrow e_i.Path(t) \cup e_k$;
7   **end**
8   Generate a random operation order $O(t)$ with $e_i.volume \neq 0$ for all $1 \leq i \leq n$;
9   **foreach** $e_l \in O(t)$ **do**
10     $V(e_l) = \{e_j | e_j.Path(t+1) = e_l\}$;
11     $S(e_l) = sort(V(e_l))$;
12   **foreach** $e_m \in S(e_l)$ **do**
13   **if** $e_l.volume \neq 0$ **then**
14   Update $e_l.volume$ and $e_m.volume$;
15   Update $RMatrix$ based on $e_m.Path(t+1)$;
16   **end**
17   **end**
18   **end**
19 **end**

Algorithm 2: Self-avoiding Random Walk with Competition. In the algorithm, steps 4-5 are for the self-avoiding random walk; steps 8-18 are for the competition trading. We use $e_i.Path(t)$ to record the nodes that entity e_i has visited up to round t.

Algorithm 4 *Self-avoiding Random Walk with Information Passing*: In this algorithm, at each round (i) each entity memorizes cost information of visited nodes to determine the next step of random walk, and (ii) entities pass trading requests to potential partners in its request list. The random walk is the same as that in Algorithm 3. For the trading part, at each round, each entity e_i will calculate the minimum costs $ShortestPathCost(e_i, :)$ to other nodes that it has not visited, and sort the entities by cost in increasing order. The request list $e_i.RL$ of e_i with size s contains entities who are top s in the sorted list of e_i. In this paper, the size of request list increases as the round t increases. Each entity will only agree to trade with another entity who is in its request list.

5 Simulations

In this section, we will describe several simulations to evaluate the performances of the local behavior-based algorithms. The four behavior-based algorithms presented in Section 4.4 are compared with the optimal solutions in terms of (i) distribution rate of energy resources, (ii) the global cost of final energy flow network, and (iii) the per unit cost of final energy flow network. The optimal solutions are calculated by a static and centralized method.

Input: Cost matrix $CMatrix_{n \times n}$; Volume of each entity $\{e_i.volume | e_i \in E\}$
Output: Energy flow network $RMatrix_{n \times n}$
1 **foreach** $e_i, e_j \in E$ **do**
2   $e_i.Path(1) \leftarrow e_i$;
3   $ShortestPath(e_i, e_j, :) \leftarrow e_i$;
4 **end**
5 **foreach** *Round* $t = 1 : (n-1)$ **do**
6   **foreach** $e_j.volume \neq 0$ **do**
7     $PE = E \setminus e_j.Path(t)$;
8   **foreach** $e_k \in PE$ **do**
9   Calculate $ShortestPathCost(e_j, e_k)$ based on $e_j.memory$;
10   **end**
11   Select $e_k \in PE$ based on Eq. 4;
12     $e_j.Path(t+1) \leftarrow e_j.Path(t) \cup e_k$;
13   Update $e_j.memory$ based on $e_j.Path(t+1)$;
14   Update $ShortestPath(e_j, e_k, :)$;
15   **end**
16   Generate a random operation order $O(t)$ with $e_i.volume \neq 0$ for all $1 \leq i \leq n$;
17   **foreach** $e_l \in O(t)$ **do**
18     $V(e_l) = \{e_j | e_j.Path(t+1) = e_l\}$;
19     $S(e_l) = sort(V(e_l))$;
20   **foreach** $e_m \in S(e_l)$ **do**
21   **if** $e_l.volume \neq 0$ **then**
22   Update $e_l.volume$ and $e_m.volume$; Update $RMatrix$ based on $ShortestPath(e_m, e_l, :)$;
23   **end**
24   **end**
25   **end**
26 **end**

Algorithm 3: Self-avoiding Random Walk with Information Sharing. In the algorithm, steps 7-11 are for the self-avoiding random walk; steps 16-25 are for the competition trading. We use $e_i.Path(t)$ to record the nodes that entity e_i has visited up to round t, and $ShortestPath(e_i, e_j, :)$ to record the dynamically changing lowest cost path from e_i to e_j.

5.1 Settings

There are three inputs for the simulations: the number of entities, the per unit distribution cost matrix, and entities' $volume$.

- **The number of entities:** In reality, the energy distribution problems may have different scales, for example, the distribution network may have scale about 100 (i.e., the number of transmission transformer) at a city level, but about 1000 at a country level [25]. Hence, it

Input: Cost matrix $CMatrix_{n\times n}$; Volume of each entity $\{e_i.volume | e_i \in E\}$
Output: Energy flow network $RMatrix_{n\times n}$
1 **foreach** $e_i, e_j \in E$ **do**
2 $\quad e_i.Path(1) \leftarrow e_i$;
3 $\quad ShortestPath(e_i, e_j, :) \leftarrow e_i$;
4 **end**
5 **foreach** *Round* $t = 1 : (n-1)$ **do**
6 $\quad$ **foreach** $e_i.volume \neq 0$ **do**
7 $\quad\quad PE = E \setminus e_i.Path(t)$;
8 $\quad\quad$ **foreach** $e_k \in PE$ **do**
9 $\quad\quad\quad$ Calculate $ShortestPathCost(e_i, e_k)$ based on $e_i.memory$;
10 $\quad\quad$ **end**
11 $\quad\quad$ Generate request list $e_i.RL$ with size t;
12 $\quad$ **end**
13 $\quad$ Generate a random operation order $O(t)$ with $e_i.volume \neq 0$ for all $1 \leq i \leq n$;
14 $\quad$ **foreach** $e_l \in O(t)$ **do**
15 $\quad\quad$ **foreach** $e_m \in e_l.RL$ **do**
16 $\quad\quad\quad$ **if** $e_l \in e_m.RL$ **then**
17 $\quad\quad\quad\quad$ Update $e_l.volume$ and $e_m.volume$;
18 $\quad\quad\quad\quad$ Update $RMatrix$ based on $ShortestPath(e_l, e_m, :)$;
19 $\quad\quad\quad$ **end**
20 $\quad\quad$ **end**
21 $\quad$ **end**
22 $\quad$ **foreach** $e_j.volume \neq 0$ **do**
23 $\quad\quad PE = E \setminus e_j.Path(t)$;
24 $\quad\quad$ **foreach** $e_k \in PE$ **do**
25 $\quad\quad\quad$ Calculate $ShortestPathCost(e_j, e_k)$ based on $e_j.memory$;
26 $\quad\quad$ **end**
27 $\quad\quad$ Select $e_k \in PE$ based on Eq. 4;
28 $\quad\quad e_j.Path(t+1) \leftarrow e_j.Path(t) \cup e_k$;
29 $\quad\quad$ Update $e_j.memory$ based on $e_j.Path(t+1)$;
30 $\quad\quad$ Update $ShortestPath(e_j, e_k, :)$;
31 $\quad$ **end**
32 **end**

Algorithm 4: Self-avoiding Random Walk with Information Passing. In the algorithm, steps 6-12 are for each entity to generate request list RL based on its $memory$; steps 13-20 are for the energy trading; steps 23-27 are for the self-avoiding random walk. We use $e_i.Path(t)$ to record the nodes that entity e_i has visited up to round t, and $ShortestPath(e_i, e_j, :)$ to record the dynamically changing lowest cost path from e_i to e_j.

is necessary to evaluate the performances of different behavior-based algorithms in different scales. In this paper, we preform the simulations for the distribution problem with $n = 10, 50, 100, 500, 1000$.

- **Per unit distribution cost matrix:** The values in the per unit distribution cost matrix are randomly generated from region $[10, 1000]$ to reflect the high cost heterogeneity between each pair of suppliers/demanders. Because we focus on the relative comparison of the behavior-based algorithms, the absolute value of the per unit distribution cost does not affect the final analysis of the algorithms.

- **Entities' *volume*:** The $volume$ of each entity is randomly generated from region $[-100, 100]$, where the global supply and demand are balanced. Similarly, the absolute value of entities $volume$ will also not affect the relative comparisons of the behavior-based algorithms.

5.2 Simulation Results and Observations

Distribution rate: The distribution rate is measured by the percentage of energy supply that has been distributed to consumers. Simulation results show that all the four behavior-based algorithms can successfully distribute all energy supply to consumers. This is because for the static energy distribution problem, the $volume$ of each entity remains constant during the dynamic process. According the the self-avoiding random walk, each entity will visit all other entities within $n-1$ rounds. Because of the simple decision-making rules each entity adopts, all supply will be distributed within $n-1$ rounds.

Distribution costs: The distribution costs are measured by global and per unit costs of final energy flow networks proposed in Section 3. Figure 1 shows the global cost comparisons of the four algorithms we proposed in Section 4.4 and the optimal solution. We can find that comparing with optimal solution, Algorithms 1 and 2 have quite worse performances. However, this is not surprising because entities in Algorithm 1 have limited memory and behave without considering cost at all. Though in Algorithm 2, entities may compete for trading when they visit the same node, this kind of competition is proved to be helpless for the minimization of global energy flow cost as shown in Figure 1. In Algorithm 3, by adopting information of visited nodes to calculate path with minimum cost and select trade partners, the entity can find appropriate walk path with much smaller energy flow cost. However, it is obvious that Algorithm 3 is still far away from optimal solution because (i) entities in this algorithm behave based only on cost information in its memory while the optimal solution is calculated by centralized algorithm based on complete information, and (ii) Algorithm 3 only uses cost information, however, there is another information, i.e., the availability of resources, which may help an entity to quickly find appropriate trade partners. We can observe from Figure 1 that Algorithm 4 achieves better performance than Algorithm 3 in terms of global cost of energy flow network. This is because in Algorithm 4, each entity calculates request list based on cost information in its memory before making decisions to trade.

The similar performance results can be observed for the per unit cost of energy flow network in Figure 2.

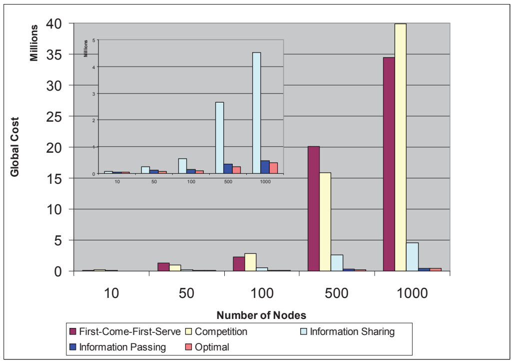

Figure 1: Global cost comparisons among four algorithms for different number of entities. The costs are calculated by Equation 1. The results show that Algorithm 4 preform better than other three Algorithms, where the global costs of Algorithm 4 are very close to the optimal solution.

Scalability: It can be observed that the per unit cost of energy flow network of Algorithm 4 approaches to optimal solution (see inset of Figure 2) as the number of nodes increases from 10 to 1000. This is because in Algorithm 4, entities collect cost information by exploring on the distribution network through more efficient random walks, and further determine potential trading partners (i.e., request list) by collected cost information. The larger the network scale, the more effective and efficient the behaviors of entities will become. Scalability is a very important characteristic for the local behavior-based paradigm to tackle huge distribution systems, where static and/or centralized algorithms cannot perform well. This evidence also shows that it is feasible and advantageous to study huge and complex systems from a bottom-up point of view.

Remark: The main purpose of this simple simulation is (i) to show the possibility that global objectives can be approximately reached through local behavior-based autonomous entities with even simple behavioral rules and decision-making rules, and (ii) to study the effects of different behavioral rules and decision-making rules on the global performances of the behavior-based paradigm. Evidences show that appropriate exploration behavior (i.e., the self-avoiding random walk in this paper) and regulation behavior (i.e., the request list generated in Algorithm 4) play important roles for the local behavior-based paradigm to achieving better global performances.

6 Conclusion and Future Work

In this paper, we present a local behavior-based paradigm that draws on the methodology of autonomy-oriented computing (AOC) for energy distribution problems, which are by nature, open, and dynamically changing over time. According to AOC, the entities in the behavior-based paradigm can spontaneously interact with each other, and operate based on their behavioral rules and decision-making rules. Simulation results on four algorithms with gradually increased behavioral complexity reveal that global objectives can be effectively and efficiently approached by involving explorations (i.e., self-avoiding random walk on the distribution network) and collective regulation (i.e., the request lists calculated by cost information in entities' memory). Furthermore, behavior-based paradigm with appropriately designed entity profiles and behavioral rules may also have scalable performance, i.e., the per unit cost of energy flow network of Algorithm 4 gradually approaches to optimal solution (see inset of Figure 2) as the number of nodes increases from 10 to 1000.

The main objectives of this paper are not only to solve the energy distribution problem, but to present a natural behavior-based paradigm with respect to the energy distribution problem so that dynamic energy distribution problems can be studied. As describe in Section 1.1, many systematic properties (i.e., vulnerability, criticality, and stability) can be involved in an open, dynamic energy distribution problem. For example, the energy supply vulnerability may relate to whether the distribution system can make sure sufficient energy supply for each energy consumer when supply of energy resources are interrupted for any reasons; the energy distribution criticality analysis may help to find out the critical suppliers/consumers in the distribution network. Understanding systematic properties of an energy distribution problem is essential for us to design robust mechanisms in the future to improve energy distribution efficiency, to study the formation of energy trading markets, to control the cascading failure of distribution networks (e.g., power

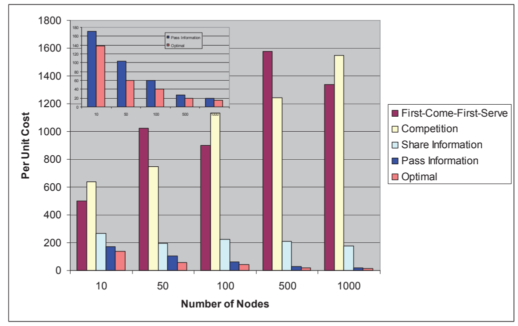

Figure 2: Per unit energy flow cost comparisons among four algorithms for different number of entities. Inset: Compare Algorithm 4 with optimal solution. The per unit energy flow costs are calculated by Equation 2. The results show that the per unit cost of energy flow network of Algorithm 4 approaches to optimal solution as the number of nodes increases from 10 to 1000.

grid), and so on. Since the energy distribution activities are by nature, performed by highly distributed energy suppliers and consumers, we conjecture that the local behavior-based paradigm (focusing on the local interactions of supplier/consumer entities) in this paper are more feasible than traditional centralized approaches to study the essences of the dynamic energy distribution problems.

References

[1] Worldwide look at reserves and production. *Oil and Gas Journal*, 106(48):23–24, December 2008.

[2] BP statistical review of world energy 2009. Technical report, British Petroleum, London, UK, 2009.

[3] R. Albert, I. Albert, and G. L. Nakarado. Structural vulnerability of the north american power grid. *Physical Review E*, 69(2):025103, Feb 2004.

[4] G. A. Backus. Fossil1: Documentation. Technical report, Resource Policy Center, Dartmouth College., 1977.

[5] M. Barthélemy and A. Flammini. Optimal traffic networks. *Journal of Statistical Mechanics*, (L07002), 2006.

[6] M. Bjørdal. *Topics on Electricity Transmission Pricing*. PhD thesis, Norwegian School of Economics and Business Administration, Bergen, 2000.

[7] H. Chao and S. Peck. A market mechanism for electric power transmission. *Journal of Regulatory Economics*, 10(1):25–59, 1996.

[8] Y. Chevaleyre, P. E. Dunne, U. Endriss, J. Lang, M. Lemaître, N. Maudet, J. Padget, S. Phelps, J. A. Rodríguez-Aguilar, and P. Sousa. Issues in multiagent resource allocation. *Informatica*, 30:3–31, 2006.

[9] P. S. Dutta, N. R. Jennings, and L. Moreau. Adaptive distributed resource allocation and diagnostics using cooperative information-sharing strategies. In *AAMAS '06: Proceedings of the fifth international joint conference on Autonomous agents and multiagent systems*, pages 826–833, 2006.

[10] M. Elkashlan, Z. Chen, I. B. Collings, and W. A. Krzymien. Selection based resource allocation for decentralized multi-user communications. *Physical Communication*, 1(3):194–208, 2008.

[11] T. S. Fiddaman. *Feeedback Complexity in Integrated Climate-Economy Models*. PhD thesis, the Alfred P. Sloan School of Management. Massachusetts Institute of Technology. Cambridge, MA 02139., 1997.

[12] J. Forrester. *World Dynamics*. Wright-Allen Press, 1971.

[13] IEA. International energy outlook 2009. Technical report, International Energy Agency, 2009.

[14] IEA. Key world energy statistics 2009. Technical report, International Energy Agency, 2009.

[15] IEA. World energy model - methodology and assumptions. Technical report, International Energy Agency, 2009.

[16] K. Iyer and M. N. Huhns. Negotiation criteria for multiagent resource allocation. *Knowledge Engineering Review*, 24(2):111–135, 2009.

[17] M. Jacyno, S. Bullock, M. Luck, and T. Payne. Understanding decentralised control of resource allocation in a minimal multi-agent system. In *AAMAS '07: Proceedings of the sixth international joint conference on Autonomous agents and multiagent systems*, pages 1–3, 2007.

[18] X. Li and L.-K. Soh. Hybrid negotiation for resource coordination in multiagent systems. *Web Intelligence and Agent Systems*, 3(4):231–259, 2005.

[19] J. Liu. Autonomy-oriented computing: The nature and implications of a paradigm for self-organized computing. *Keynote Talk at The* 4^{th} *International Conference on Natural Computation, and the* 5^{th} *International Conference on Fuzzy Systems and Knowledge Discovery*, pages 3–11, 2008.

[20] K. T. Midthun, M. Bjorndal, and A. Tomasgard. Modeling optimal economic dispatch and system effects in natural gas networks. *The Energy Journal*, 30(4), 2009.

[21] A. E. Motter. Cascade control and defense in complex networks. *Physical Review Letters*, 93(9):098701, 2004.

[22] A. E. Motter and Z. Toroczkai. Introduction: Optimization in networks. *Chaos*, 17(026101), 2007.

[23] R. F. Naill. *COAL1: A Dynamic Model for the Analysis of United States Energy Policy*. PhD thesis, the Thayer School of Engineering, Dartmouth College, 1976.

[24] A. Quelhas, E. Gil, J. D. McCalley, and S. M. Ryan. A multiperiod generalized network flow model of the U.S. integrated energy system: Part I - model description. *IEEE Transaction on Power Systems*, 22(2):829–836, May 2007.

[25] A. Quelhas and J. D. McCalley. A multiperiod generalized network flow model of the U.S. integrated energy system: Part II - simulation results. *IEEE Transaction on Power Systems*, 22(2):837–844, May 2007.

[26] F. Schweppe, M. Caramanis, R. Tabors, and R. Bohn. *Spot Pricing of Electricity*. Kluwer Academic Publishers, Norwell, Massachusetts, 1988.

[27] S. Shakkottai and R. Srikant. Network optimization and control. *Foundations and Trends in Networking*, 2(3):271–379, 2007.

[28] H. Simon, T. Zacharia, and R. Stevens. Modeling and simulation at the exascale for energy and the environment. Technical report, Report on the Advanced Scientific Computing Research Town Hall Meetings on Simulation and Modeling at the Exascale for Energy, Ecological Sustainability and Global Security (E3), 2007.

[29] A. P. Sokolov, C. A. Schlosser, S. Dutkiewicz, S. Paltsev, D. W. Kicklighter, H. D. Jacoby, R. G. Prinn, C. E. Forest, J. Reilly, C. Wang, B. Felzer, M. C. Sarofim, J. Scott, P. H. Stone, J. M. Melillo, and J. Cohen. The mit integrated global system model (IGSM) version 2: Model description and baseline evaluation. Technical report, MIT, 2005.

[30] J. D. Sterman. *The Energy Transition and the Economy: A System Dynamics Approach.* PhD thesis, the Alfred P. Sloan School of Management. Massachusetts Institute of Technology. Cambridge, MA 02139., 1981.

[31] A. Tero, S. Takagi, T. Saigusa, K. Ito, D. P. Bebber, M. D. Fricker, K. Yumiki, R. Kobayashi, and T. Nakagaki. Rules for biologically inspired adaptive network design. *Science*, 327(5964):439–442, 2010.

[32] National Energy Board. A compendium of electric reliability frameworks across canada. Technical report, The National Energy Board, Canada, 2004.

[33] Oil Division. A compendium of electric reliability frameworks across canada. Technical report, Petroleum Resources Branch, Canada, 2008.