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A multi-objective market-driven framework for power matching in the smart grid

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ABSTRACT

Smart grids, to facilitate the electricity production, distribution, and consumption, employ information and communication technologies simultaneously. Electricity markets, through stabilizing the electricity prices, attempt to alleviate the challenges of power exchange. On one hand, buyers, by considering their full demand satisfaction, endeavor to purchase the electricity cost-effectively. On the other hand, sellers, by taking their limited electricity generation capacity into account, are interested in increasing their financial benefits. To address this challenge, this paper introduces a highly-functional semi-decentralized power matching framework based on multi-objective optimization techniques executing in a day-ahead electricity market. A two-stage price updating mechanism to continuously balance the electricity prices is also provided. At each time interval, buyers and sellers submit their individual electricity price offers to the market operator. The market operator tunes them and then, announces the electricity market price. A robust multi-objective power matching algorithm is developed to make the matching contracts considering buyers' and sellers' objectives along with grid stability constraints imposed by distribution system operators. It also considers the minimization of electricity distribution loss in the matching procedure. Simulation results indicate that the framework successfully reaches a reasonable balance of aforementioned conflicting objectives while conducing negotiating electricity price offers to an equilibrium. It is shown that the proposed algorithm behaves better compared to well-known multi-objective evolutionary algorithms in terms of both optimizing the social welfare and computational complexity (scalability). Finally, effects of the two-stage price updating mechanism on the stability of the proposed evolutionary algorithm is discussed. Performance comparisons show that the proposed framework outperforms the similar approaches available in the literature.

1. Introduction

The current structure of the electrical grid is inefficient in responding to the growing demand for electricity. The smart grid, by, for instance, demand response programs and distributed power matching, aims at revolutionizing the current electrical grid to reveal its concerns. Nevertheless, a solid introduction of the smart grid confronts numerous challenges in designing, controlling, and implementation. The smart grid employs bilateral electricity and information streams to establish a reliable energy management infrastructure (Farhangi, 2010). This is done by dividing it into: 1) smart infrastructure system for electric power transmission, 2) smart management system for controlling and managing grid services, and 3) smart protection system for protecting the smart grid (Fang et al., 2012). To integrate these systems while identifying main stakeholders and feasible communication paths in the smart grid, National Institute of Standards and Technology (NIST) has developed an inter-operable smart grid conceptual model (National Institute of Standards and Technology, 2014).

This paper concentrates on the interconnectivity of *customers* and *markets* domains in the smart grid. The first domain supports three customer types named industrial, commercial, and residential. For the sake of simplicity, this paper considers residential customers, in which they are characterized by *buyer* and *seller* agents. Each agent is an individual entity providing the markets domain with its preferences, requirements, and constraints. Hereinafter, customer and agent are interchangeably used as contextual synonyms. Markets domain, particularly electricity markets, intends to effectively manage the customers' information (Bichler et al., 2010).

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Nomenclature

Constants

$\mathbb{P}$	Pareto-front
$\delta_{s_{j,g}}$	Malleability rate of seller $s_{j,g}$
$\gamma_{b_{i,k}}$	Malleability rate of buyer $b_{i,k}$
$L_{b_{i,k}}$	Location of buyer $b_{i,k}$
$L_{s_{j,g}}$	Location of seller $s_{j,g}$
L_{ξ}	Location of the power plant ξ
p_l	Minimum offerable electricity price ($/kWh)
p_u	Maximum offerable electricity price ($/kWh)
$loss_{b_{i,k}\xi}$	Electricity distribution loss between buyer $b_{i,k}$ and the power plant ξ
$loss_{b_{i,k}s_{j,g}}$	Electricity distribution loss between buyer $b_{i,k}$ and seller $s_{j,g}$
$\mathrm{SEF}_{\mathbb{P}}$	Solution efficiency factor of solutions on Pareto-front $\mathbb{P}$
φ_a	Feasible power matching solution a
ξ	Power plant
$b_{i,k}$	Buyer i connected to feeder k
E	Euclidean distance parameter
f_k	Feeder k
K	Number of feeders
M_g	Number of sellers connected to feeder f_g
N_k	Number of buyers connected to feeder f_k
$p\xi$	Fixed electricity price offered by the power plant ξ ($/kWh)
p_c	Crossover probability
p_m	Mutation probability
Q	Population size of the evolutionary algorithm
$s_{j,g}$	Seller j connected to feeder g
T	Number of time intervals
W	Number of generations of the evolutionary algorithm
ELF_f	Electricity loss factor in the Customer–Customer trading method
ELF_{ξ}	Electricity loss factor in the Customer-to-PowerPlant trading method

Indices

a	Index of power matching solutions
i	Index of buyers
j	Index of sellers
k, g	Index of feeders
t	Index of time intervals

Sets

$\mathbb{B}$	Collection of sets of buyers
$\mathbb{Q}$	Parent population in the evolutionary algorithm
$\mathbb{S}$	Collection of sets of sellers
$D_{b_{i,k}}$	Load demand set of buyer $b_{i,k}$
f_g^S	Set of sellers connected to feeder f_g
f_k^B	Set of buyers connected to feeder f_k
$Q_{s_{j,g}}$	Surplus energy set of seller $s_{j,g}$
F	Set of all feeders

Variables

$\mathbb{C}_{\varphi_a}^t$	Matrix of contracts of solution φ_a at time interval t
$d_{b_{i,k}}^t$	Load demand of buyer $b_{i,k}$ at time interval t (kWh)
$q_{s_{j,g}}^t$	Surplus energy of seller $s_{j,g}$ at time interval t
$\overline{pb}^t$	Weighted average of electricity prices offered by all buyers at time interval t
$\overline{ps}^t$	Weighted average of electricity prices offered by all sellers at time interval t
$pb_{i,k}^t$	Electricity price offered by buyer $b_{i,k}$ at time interval t
pd^t	Electricity market price at time interval t
$ps_{j,g}^t$	Electricity price offered by seller $s_{j,g}$ at time interval t
$x_{b_{i,k}\xi}^t$	Total electric energy units transferred from the power plant ξ to buyer $b_{i,k}$ at time interval t
$x_{b_{i,k}s_{j,g}}^t$	Total electric energy units transferred from seller $s_{j,g}$ to buyer $b_{i,k}$ at time interval t
EDT_k^t	Electricity demand threshold imposed by feeder f_k at time interval t (kWh)
PAC_k^t	Peak aggregate consumption of customers at time interval t (kWh)

This is done by the market operator, who typically applies the *pricing scheme* and *demand and supply balancing strategies* to the electrical grid. Thus, having a reliable interface between these two domains is critical since it directly affects "matching production with consumption." Recent developments in electricity markets require the employment of a reliable power matching framework. In this regard, the market operator, to clearly specify the power exchange contracts over time, is responsible for matching buyer agents with seller agents. Nevertheless, far too little attention has been paid to build an effective framework considering the conflicting objectives and constraints that the customers and Distribution System Operators (DSOs) include.

This paper puts efforts into proposing a novel semi-decentralized power matching framework to the smart grid. Fig. 1 pictures the conceptual view of this framework. According to the current structure of the grid, the electricity is distributed to customers in a hierarchical manner. Since controlling all customers by a single system is not practically scalable, we propose to semi-decentralize such controlling system into a number of sub-systems. We consider *feeders* as the last points of delivering the electricity to households. Each feeder serves a non-overlapping set of customers. This will help the framework host a large number of customers in the grid. The framework runs the matching procedure in each feeder. In each feeder, on one hand, buyer agents have to satisfy their demands over time. They intend to minimize their power purchase cost considering their full demand satisfaction at each interval. On the other hand, seller agents are interested in maximizing their selling benefit considering their limited surplus electrical power production. It is becoming increasingly difficult to ignore the impact of grid stability constraints on market-driven power matching frameworks. We use the concept of "electricity demand thresholds" to respect the grid's capacity (Azar et al., 2015). The framework is physically distinguishable and completely compatible with the existing electrical grid. This also ties in well with future smart grids that are based on Distributed Energy Resources (DERs) and flexibly interconnected energy supply grids (Jacobsen et al., 2015).

Owing to the conflictive nature of discussed objectives, this paper frames the power matching problem as a multi-objective optimization framework. Multi-objective optimization is an area of multiple criteria decision-making structure, which has extensively been used in smart grids particularly in the electricity consumption scheduling (Lu et al., 2015) and demand side management (Ramachandran and Ramanathan, 2015). We activate such framework by proposing a multi-objective power matching algorithm to match the total demand with the total surplus production. This algorithm is a *revised* version of well-known Non-Dominated Sorting Genetic Algorithm-II (NSGA-II). It consecutively provides the market operator with admissible power matching solutions. Performing this algorithm helps balance the grid operations and equilibrate the electricity market better. To reach this point, the market operator has to conduct power exchange contracts with quite reasonable electricity prices. The algorithm, to enable customers to update their electricity price offers periodically, also employs a two-stage price updating mechanism. At each time interval, in the first stage, buyers/sellers provide the market operator with their updated

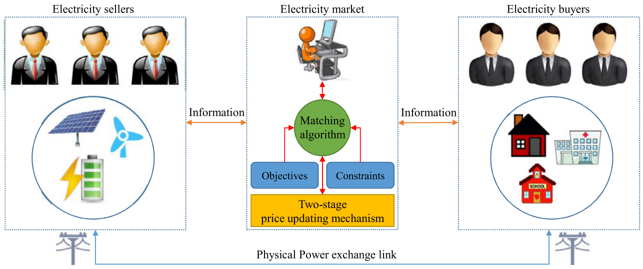


Fig. 1. Conceptual view of the power matching framework.

electricity price offers to based on their total demand/production and previous price offers. In the second stage, the market operator tunes these price offers and then, announces the electricity market price to make the contracts. This mechanism encourages customers to balance their electricity price offers to rapidly reach their purposes. Note that each offer refers to the price that customers aim at basing each electric energy unit on it.

The remainder of this paper is organized as follows: Section 2 overviews the related work. Section 3 describes the multi-objective power matching framework. Section 4 clarifies the power matching algorithm. Section 5 demonstrates the simulation setup and analyses. Finally, Section 6 concludes the paper.

2. Related work

In recent years, there has been an increasing interest in investigating the challenges of interactions among customers and electricity markets (Kirschen, 2003; Ventosa et al., 2005). Kirschen (2003) argued that the electricity market's development was undeniably based on the quantitative commodity because of its easily-measurable nature. He claimed that to orchestrate a competitive electricity market, it might be useful to propose some decision support frameworks. Ventosa et al. (2005) investigated such frameworks and discussed that these frameworks should possess three crucial features: 1) optimization to apply to a set of objectives and constraints, 2) equilibrium to provide customers and markets with, and 3) simulation to coordinate complex mathematical methods of first two features.

Evolutionary multi-objective optimization techniques have recently gained popularity and have been successfully applied to several research areas in the smart grid. For instance, Azar and Jacobsen (2016) proposed a multi-objective load scheduling framework concentrating on reducing the total electricity bills and CO_2 emissions as well as flattening the aggregated peak demand at the same time. Chai et al. (2016) developed a similar framework, which utilized an iterative learning method to keep a proper trade-off between the consumption expense and the satisfaction index. The framework was modeled by a hybrid mixed-integer multi-objective quadratic optimization technique. Furthermore, Jornada and Leon (2016) dealt with the electricity generation capacity expansion problem to minimize cost and water withdrawal. They introduced a robust methodology to aid the multi-objective decision making process.

To the best of our knowledge, this work is among the first attempts that investigates the usability and applicability of the multi-objective optimization techniques in the power matching problem with a focus on encouraging customers to participate in a hourly-basis market to match demand with supply. This paper follows the critical features discussed above by "outlining a reliable and novel multi-objective power matching framework attempting to match demands with supplies (optimization) under a competitive power exchange contract (equilibrium) proposed by an effective negotiation procedure (simulation)." It advances the state of the art in considering electricity prices as an incentive function of negotiations and contracts in the power matching framework.

In the markets, market clearing is a process to match demand with supply. The new classical economics assume that, in any given market, prices are always adjusted up or down to ensure market clearing. Ashkaboosi et al. (2016), to address the market clearing problem, proposed a bi-level optimization technique, where the upper-level was the profit of the investment in wind power and the lower-level was market clearing. Dourbois and Biskas (2016) addressed the similar problem from the transmission security's point of view. They formulated the market clearing problem as a mixed integer linear programming model in an European-type day-ahead market with multi-period products. The discussed papers fail to consider grid stability constraints. Sardou and Ameli (2016) determined this gap and framed the problem as a multi-objective mathematical programming model considering social welfare maximization and minimization of lines overload and voltage deviation as well as loadability limit maximization simultaneously. To do so, they developed a revised version of NSGA-II basing on fuzzy models. Müller et al. (2016) considered the concept of "future contract combinations" using game theory approaches, which included pairs of buy/sell-orders for swapping two items in equal quantity, for instance electricity. They presented a minimum cost flow formulation of the futures opening auction problem that guaranteed consistent prices in the market clearing problem.

Advancing power matching frameworks with respect to their potentiality has gained popularity in the recent years (Chen et al., 2010; Nygard et al., 2011; HomChaudhuri and Kumar, 2011; HomChaudhuri et al., 2011, 2012). Chen et al. (2010) proposed two market models, in which the former was trying to match the demand with production while the latter was aiming to schedule the demand by encouraging customers to shift or curtail their load consumption. Although the models were successful in competitively equilibrating the market, however, they were forcing customers to adapt their consumption behavior with the electricity market prices, which caused them not to get the expected benefit from their power matching contracts. Both models disregarded any grid stability constraint, which might have jeopardized the electrical grid in some unforeseen circumstances. Nygard et al. (2011) discovered a model proposing an optimal cooperation of customers together to minimize their electricity cost subject to the power flow balance and capacity restriction. Not only was the model required the total demand be equal to total supply, but also, the authors did not prove how and by which approach they solved the model since the discussing problem was NP-complete.

Market clearing, particularly in such matching frameworks, brings new challenges to the smart grid. HomChaudhuri and Kumar (2011) and HomChaudhuri et al. (2011, 2012) proposed a market-based power matching framework. Due to the uncertainty in the electricity generation, they offered a market-based linear optimization approach to minimize the electricity distribution loss (HomChaudhuri and Kumar, 2011). They executed an auction based on bids for the resource cost, which was iteratively updated by a simple price updating mechanism. Then, the authors extended the same single-objective model into a distributed optimization model assuming each customer as a discrete agent decomposing the complex power matching problem into small-scale agent-based sub-optimization problems (HomChaudhuri et al., 2011). Finally, the authors engaged the extended model with the optimal power flow problem to ensure the grid stability (HomChaudhuri et al., 2012). To this end, a linear programming mechanism has been used to route the produced electricity optimally through minimizing the overall electricity generation cost.

Even though the achievements discussed in the aforementioned papers demonstrate the overall cost reduction, however,: 1) proposed models force customers to only have one-to-one power exchanges, 2) the market operator makes the contracts utilizing a simple price updating mechanism, 3) the total production is more than the total demand, which leads the analysis not to confront any critical circumstance, and 4) the remaining demand of unsatisfied buyers at each interval are transferred to the future, which decreases the customers' comfort level. To overcome these weaknesses, Azar et al. (2014) provided an agent-based power matching framework to optimize the customers' purchasing cost considering their matching interest tables in smart electricity markets (Bichler et al., 2010). Each customer, with respect to electricity prices offered by producers and their pairwise Euclidean distance, creates an interest table based on his/her demand or production. Since the general power matching problem is NP-complete, they employed evolutionary computations and proposed a greedy power matching algorithm based on the interest tables. The analysis clearly indicated the significant cost reduction whilst equilibrating electricity prices.

Most recently, Razzaq et al. (2016) studied a similar problem and proposed an energy management framework for cooperation between customers. It attempted to minimize demand–supply mismatch, where sellers were equipped with renewable energy sources willing to sell their surplus energy to the grid. However, the formulation was only in the favor of buyers, in which maximum possible surplus energy was allocated to those with the maximum shortage and minimum associated price. Similarly, AlSkaif et al. (2016) addressed the same renewable power sharing challenge based on a repeated game among customers. Although they claimed that formulating the problem as a game led to a decentralized power sharing framework, however, they failed to: 1) consider electricity distribution loss, 2) respect grid stability constraints, and 3) use a dynamic electricity pricing scheme to calculate the payoffs and costs. Hong and Kim (2016) challenged the multi-objective energy routing problem with a similar game theory approach. Desired transaction price was set centrally to maximize profits while maximizing the cost. Minimization of the electricity distribution loss was mapped to the known traditional transportation problem. The simulations did not analyze how optimizing the conflictive objectives influenced the demand and supply prices over time.

As a recent challenging problem in this context, Malik and Lehtonen (2016) investigated the potentiality of matching high penetration of electric vehicles with intermittent renewable energy sources in the form of short-term power imbalances using a simple bidding–asking algorithm. They proposed an agent-based electricity market model for grid-to-vehicle and vehicle-to-grid power transactions while studying the optimal battery price for a better electric vehicle participation in the grid's operation. Finally, Endo et al. (2016) claimed that a real-time centralized multi-seller/multi-buyer power trading system would yield a truly competitive market, where anyone could become a power seller or buyer. They proposed a distributed power cooperation algorithm that maximized each customer's welfare based on local information. The authors considered that peer-to-peer information exchange and demand/supply balancing in a neighborhood were performed automatically using an energy consumption controller embedded in the home gateway. Nevertheless, the results assumed that buyers and sellers were equal. Also, no Pareto-front was given to show the diversity of solutions due to the conflictive nature of objectives.

This paper is an extended version of work published in Azar et al. (2014) and to account for the gaps identified in Kirschen (2003), Ventosa et al. (2005), Chai et al. (2016), Jornada and Leon (2016), Ashkaboosi et al. (2016), Dourbois and Biskas (2016), Sardou and Ameli (2016), Müller et al. (2016), Chen et al. (2010), Nygard et al. (2011), HomChaudhuri and Kumar (2011), HomChaudhuri et al. (2011, 2012), Bichler et al. (2010), Razzaq et al. (2016), AlSkaif et al. (2016), Hong and Kim (2016), Malik and Lehtonen (2016), and Endo et al. (2016), makes the following contributions:

- Proposing a highly-functional power matching framework running in a day-ahead electricity market;
- Engaging multi-objective optimization techniques with the framework considering the minimization of buyers' power purchasing cost and the maximization of sellers' power selling benefit at the same time;
- Providing a robust multi-objective power matching algorithm based on the minimization of electricity distribution loss;
- Proposing a new two-stage iterative price updating mechanism to update the electricity price offers over time;
- Adapting the framework to the electrical grid topology considering grid stability constraints.

3. Power matching framework: A multi-objective approach

Fig. 2 illustrates the conceptual view of the framework adapted to the current structure of the electrical grid. The electric power is transmitted through high-voltage transmission lines, terminates in several feeders, and finally, reaches customers (Machowski et al., 2011). Let $F = \{f_1, f_2, \dots, f_K\}$ be a set of electricity distribution feeders. Each feeder f_k, where $k \in \{1, 2, \dots, K\}$, hosts two non-empty sets of buyer agents f_k^B and seller agents f_k^S. Then, let $\mathbb{B} = \bigcup_{k=1}^{K} f_k^B$ and $\mathbb{S} = \bigcup_{k=1}^{K} f_k^S$ be collections of sets of buyers and sellers, respectively. This paper assumes there is an power plant ξ, which is always capable of undertaking the buyers' electricity demand satisfaction in critical and unpredictable circumstances, for instance, when there is no seller with any adequate surplus energy. This power plant has two specific characteristics: being far from the main electricity distribution grid and offering a high electricity price. The framework, by applying two power trading methods named `Customer-Customer` and `Customer-to-PowerPlant`, strives to keep the power exchanges more distributed. For the former, we define two power trading sub-methods named `Inside-Feeder` and `Feeder-to-Feeder`. These methods will be described in more detail later.

Next, we define how buyers and sellers using these layers are formulated.

3.1. Customers domain

As information is basically distributed over customer agents in the smart grid, we use three layers of agent's strategy design, i.e., the information, knowledge, and behavior (Lamparter et al., 2010). For each customer agent:

- **Information**: Providing demand/surplus, electricity price offer, and location.
- **Knowledge**: Obtaining other agents' information.
- **Behavior**: Behaving rationally with respect to the available information and knowledge.

3.1.1. Buyer agents

Let $f_k^B = \left\{b_{1,k}, b_{2,k}, \dots, b_{N_k,k}\right\}$ be a set of $N_k \in \mathbb{N}$ buyers connected to feeder f_k. Each buyer $b_{i,k}$, where $i \in \left\{1, 2, \dots, N_k\right\}$, holds a set of appliances. Let

$$D_{b_{i,k}} = \left\{d^1_{b_{i,k}}, d^2_{b_{i,k}}, \dots, d^T_{b_{i,k}}\right\}, \quad (1)$$

where $D_{b_{i,k}}$ denote the set of load demands of buyer $b_{i,k}$. $d^t_{b_{i,k}} \in \mathbb{Z}^*$ (kWh) is the aggregated load demand at time interval t, where $t \in \{1, 2, \dots, T\}$. Let

$$d^t_{b_{i,k}} = \left\lfloor \sum_{g=1}^{K} \sum_{j=1}^{M_g} x^t_{b_{i,k}s_{j,g}} \times \left(1 - loss_{b_{i,k}s_{j,g}}\right) \right\rfloor + \left\lfloor x^t_{b_{i,k}\xi} \times \left(1 - loss_{b_{i,k}\xi}\right) \right\rfloor, \quad (2)$$

where $f_g^S = \left\{s_{1,g}, s_{2,g}, \dots, s_{M_g,g}\right\}$ is a set of $M_g \in \mathbb{N}$ sellers connected to feeder f_g. $x^t_{b_{i,k}s_{j,g}}, x^t_{b_{i,k}\xi} \in \mathbb{Z}^*$ (kWh) are the decision variables of the optimization problem (will be described later). They represent the total electric energy transferred from "seller $s_{j,g}$" and "power plant ξ" to buyer $b_{i,k}$ at each time interval t, respectively. Buyer $b_{i,k}$ is able to negotiate with sellers connected to the same feeder, i.e., $k = g$ (using inside-feeder trading method, or even other feeders, i.e., $k \neq g$ (feeder-to-feeder trading method). This also ensures buyers from completely satisfying their demands over time. The electricity produced does not match with the electricity reached customers. Technical loss of electric power in the distribution grid is due to the distribution network

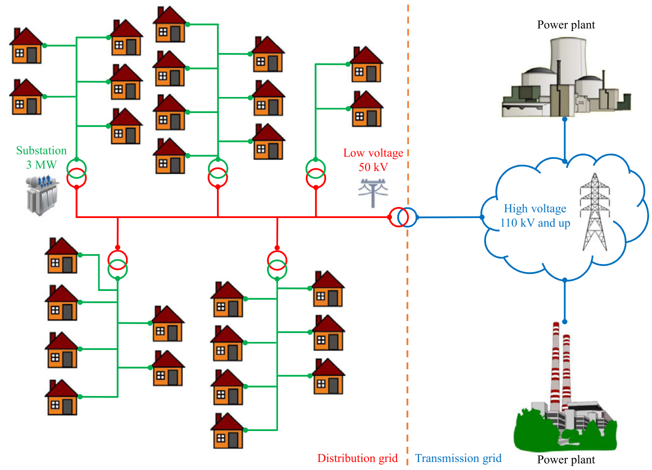


Fig. 2. Conceptual view of the framework adapted to the current structure of the electrical grid.

transformers and cables (International Electrotechnical Commission et al., 2007). We define an Electricity Loss Factor, $ELF \in (0,1)$, where ELF_f, ELF_ξ correspond to the `Customer-Customer` and `Customer-to-PowerPlant` methods, respectively. ELF is proportional to the square of current, resistance, and the total electric power being transported in a cable. Let

$$loss_{b_{i,k}s_{j,g}} = ELF_f \times E\left(L_{b_{i,k}}, L_{s_{j,g}}\right), \quad loss_{b_{i,k}\xi} = ELF_\xi \times E\left(L_{b_{i,k}}, L_\xi\right), \tag{3}$$

where E is the Euclidean distance functions. $L_{b_{i,k}}$, $L_{s_{j,g}}$, and L_ξ are the locations of buyer $b_{i,k}$, seller $s_{j,g}$, and power plant ξ respectively (Chiradeja, 2005). Although the buyer should purchase more electric energy at each time interval t, however, equality in Eq. (2) shows that the buyer must exactly receive $d^t_{b_{i,k}}$ electric energy (after loss), since no storage option is considered.

3.1.2. Sellers agents

Let us assume each seller agent $s_{j,g}$ possesses a set of DERs, e.g., Photovoltaic solar panels, as a small power plant (Lasseter, 2002). Each DER first satisfies the load demands of the seller's appliances and then, the remaining is provided to buyers. Therefore, let

$$Q_{s_{j,g}} = \left\{q^1_{s_{j,g}}, q^2_{s_{j,g}}, \dots, q^T_{s_{j,g}}\right\}, \tag{4}$$

where $Q_{s_{j,g}}$ is the set of surplus energy over time. $q^t_{s_{j,g}} \in \mathbb{Z}^*$ (kWh) is the amount of surplus energy of seller $s_{j,g}$ at time interval t. For the sake of simplicity, we do not consider the electricity production and energy storage costs, however, the framework is completely expandable. Let

$$\sum_{k=1}^{K}\sum_{i=1}^{N_k} x^t_{b_{i,k}s_{j,g}} \le q_{s_{j,g}}, \tag{5}$$

where it clearly shows that seller agents can sell their surplus energy to buyers connected to any feeder. The remaining is not transferred to future time intervals (storing capability will be studied in the future). Thus, seller agents are interested in increasing the total electricity sold at each time interval. Nevertheless, due to the potential electricity production cost, it is likely for them not to sell electricity in some periods, e.g., when the market price is low. This challenge can be relieved by considering the agents' decision as a strategic game (Saad et al., 2011). In that situation, they can modify their production volume effectively considering the following items: 1) total "electricity sold" and the "electricity production cost" at current time interval, 2) future load consumption behavior of all customer agents, and 3) electricity prices. It is worthwhile noting that the current structure of the framework is able to easily cope with these fundamental updates in the future.

3.2. Markets domain

In the smart grid, the power trading is definitely based on market-driven principles. From the economic point of view, the electricity is bought and sold as a commodity. We envision an electricity market, which intelligently balances the supply with demand while providing reasonable electricity market prices. This paper proposes the power matching framework for a retail electricity market. In fact, the electric energy is traded through bids to buy and offers to sell, which finally, terminates in short-term contracts in the form of financial or obligation swaps. The market operator intends to match parties to these contracts based on a competitive market model.

3.2.1. Market operator

We assume the market operator runs the power matching framework on a day-ahead basis. Its main responsibility includes clarifying: 1) which pair of customers should make a contract with each other, 2) how much electric power transfer should be specified in each contract, and 3) what the energy price should be. To this end, let

$$\min G(x) = \sum_{t=1}^{T}\sum_{k=1}^{K}\left(\sum_{g=1}^{K}\sum_{i=1}^{N_k}\sum_{j=1}^{M_g}\left(x^t_{b_{i,k}s_{j,g}} \times pd^t\right) + \sum_{i=1}^{N_k}\left(x^t_{b_{i,k}\xi} \times p\xi\right)\right),$$
$$\max H(x) = \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{g=1}^{K}\sum_{i=1}^{N_k}\sum_{j=1}^{M_g}\left(x^t_{b_{i,k}s_{j,g}} \times pd^t \times \left(1 - loss_{b_{i,k}s_{j,g}}\right)\right), \tag{6}$$

where $G(x)$ shows buyers' interest in paying for the electricity at the lowest possible cost. This can be done by decreasing the total purchased electric energy considering the full demand satisfaction (see Eq. (2)). $G(x)$ is split to two `Customer-Customer` and `Customer-to-PowerPlant` contracts. $p\xi \in \mathbb{R}^*$ stands for the fixed electricity price offered by the power plant ξ. In contrast, $H(x)$ shows sellers are eager to increase their selling benefit. This can also be done by increasing the total electricity sold considering the remaining surplus energy (see Eq. (5)). To equalize the penalty of electricity distribution loss among customers, each seller benefits less than the real expected benefit. Evidently, these objective functions are in conflict with each other, since increasing or decreasing $x^t_{b_{i,k}s_{j,g}}$ and $x^t_{b_{i,k}\xi}$ causes each objective to behave differently. This multi-objective optimization model demonstrates how the market operator is able to change the market's behavior in miscellaneous circumstances with respect to "distinguishable solutions" obtained from this framework. It would also be possible to consider both objectives linearly as one single function. To make contracts, the market operator announces $pd^t \in \mathbb{Z}^*$ (\$/kWh) as the electricity price at time interval t. Next, we describe how the market operator, by using a two-stage price updating mechanism, calculates pd^t over time.

3.3. Two-stage price updating mechanism

This paper designs a novel day-ahead electricity pricing scheme, in which customers are its most important players. Its main advantage is twofold: 1) meeting the demand response goal, i.e., matching demand with supply, and 2) helping the customers increase their social welfare (optimization objectives). This mechanism is used at each time interval. In the first stage, each customer agent offers a price to trade each electric energy unit in the market. In the second stage, the market operator updates the electricity price considering the electricity price offers received from the first stage. This mechanism does not consider `Customer-to-PowerPlant` contracts. Here, no offer is broadcast erroneously, since this mechanism assumes customers are trustworthy and their privacy is ensured.

3.3.1. First stage

Let

$$pb^1_{i,k} \in \left[p_l, p_u\right],$$
$$ps^1_{j,g} \in \left[p_l, p_u\right],$$
$$pb^{t+1}_{i,k} = pb^t_{i,k} - \left(\gamma_{b_{i,k}} \times \left(pb^t_{i,k} - \overline{pb}^t\right)\right),$$
$$ps^{t+1}_{j,g} = ps^t_{j,g} - \left(\gamma_{s_{j,g}} \times \left(ps^t_{j,g} - \overline{ps}^t\right)\right), \tag{7}$$

where $p_l, p_u \in \mathbb{Z}^*$ (\$/kWh) are the minimum and maximum offerable electricity prices in the market, respectively. This range ensures the market not to confront any abnormal electricity price. $pb^t_{i,k}, ps^t_{j,g} \in \mathbb{Z}^*$ (\$/kWh) are the electricity prices offered by buyer $b_{i,k}$ and seller $s_{j,g}$ at time interval t, respectively. Let

$$\overline{pb}^t = \left\lfloor \frac{\sum_{k=1}^{K}\sum_{i=1}^{N_k}\left(d^t_{b_{i,k}} \times pb^t_{i,k} \times \gamma_{b_{i,k}}\right)}{\sum_{k=1}^{K}\sum_{g=1}^{K}\sum_{i=1}^{N_k}\sum_{j=1}^{M_g}\left(x^t_{b_{i,k}s_{j,g}} \times pd^t\right)} \right\rfloor,$$
$$\overline{ps}^t = \left\lfloor \frac{\sum_{g=1}^{K}\sum_{j=1}^{M_g}\left(\left(\sum_{k=1}^{K}\sum_{i=1}^{N_k} x^t_{b_{i,k}s_{j,g}}\right) \times ps^t_{j,g} \times \delta_{s_{j,g}}\right)}{\sum_{k=1}^{K}\sum_{g=1}^{K}\sum_{i=1}^{N_k}\sum_{j=1}^{M_g}\left(x^t_{b_{i,k}s_{j,g}} \times pd^t\right)} \right\rfloor, \tag{8}$$

where $\overline{pb}^t, \overline{ps}^t \in \mathbb{Z}^*$ are the weighted average of electricity prices offered by buyers and sellers at time interval t, respectively. The rationale behind using $\left(pb^t_{i,k} - \overline{pb}^t\right)$ and $\left(ps^t_{j,g} - \overline{ps}^t\right)$ in Eq. (7) is the need for having a quick balance in the electricity market. The market operator encourages each customer to update the electricity price offer to make it as close to the corresponding weighted average of electricity price offers as possible. The difference in the numerators in Eq. (8) comes from the buyers' full demand satisfaction constraint (see Eq. (2)). Buyers have to satisfy their demands anyway while sellers benefit from the amount they sell, not their surplus energy.

From the economic point of view, customers have some characteristics, such as the financial situation, risk-taking threshold, level of confidence, etc. These characteristics measure their financial ability considering the available funding support (Bichler et al., 2010). Moving over time, these characteristics get influenced by the fluctuation of some market parameters, e.g., attractiveness, competitiveness, etc. Thus, to engage customers with the two-stage price updating mechanism, we propose new parameters named *malleability rates* $\gamma, \delta \in [0, 1)$ for buyers and sellers, respectively. We assume the malleability rate of the power plant is zero (lowest possible). Market parameters have a direct influence on these rates. The value of the malleability rate affects the performance of the following actions: 1) offering an appropriate initial electricity price, 2) updating electricity price offers, and 3) updating the weighted average of electricity prices offered by customers.

The weighted average of electricity price offers is a reliable target for customers. For instance, let us assume a seller, who: 1) offers the highest possible amount of energy, and 2) expects to sell all or, at least, a big portion of his/her surplus energy. With respect to the buyers' objective, probably no buyer is found to purchase any unit of electricity from that seller agent. On one hand, the seller has to decrease the value of the electricity price offer consecutively at a rate to get as close to the weighted average of electricity prices as possible. On the other hand, the malleability rate should be relatively high since it permits the agent to update electricity price offers rapidly. This would definitely help the agent increase the total electric energy being sold in the short term. As a result, the malleability rate effectively helps customers and market operator make more profitable contracts while dealing with fluctuating electricity price offers. In the interest of simplicity, the calculation method of this parameter is eliminated (Bichler et al., 2010).

3.3.2. Second stage

Let

$$pd^t = \frac{\left(|\mathbb{B}| \times \overline{pb}^t\right) + \left(|\mathbb{S}| \times \overline{ps}^t\right)}{|\mathbb{B} \cup \mathbb{S}|}, \tag{9}$$

Table 1
Customers' status in various critical situations in the grid.

	$\lvert\mathbb{B}\rvert \ll \lvert\mathbb{S}\rvert$	$\lvert\mathbb{B}\rvert \gg \lvert\mathbb{S}\rvert$
$\sum_{k=1}^{K}\sum_{i=1}^{N_k} d^t_{b_{i,k}} \ll \sum_{g=1}^{K}\sum_{j=1}^{M_g} q^t_{s_{j,g}}$	Buyers dominate sellers and pd^t is close to $\overline{pb}^t$.	
$\sum_{k=1}^{K}\sum_{i=1}^{N_k} d^t_{b_{i,k}} \gg \sum_{g=1}^{K}\sum_{j=1}^{M_g} q^t_{s_{j,g}}$		Sellers dominate buyers and pd^t is close to $\overline{ps}^t$.

where it defines the electricity market price pd^t at each time interval t. Table 1 lists situations discussing how market's competitiveness and attractiveness can influence the market's fixed price at each time interval. For situations listed in the first row, there are many sellers available to negotiate with few buyers. Thus, their market share tends to be very small and therefore, their price offers should be low. For other situations, buyers should compete to have more `Customer--Customer` power exchanges rather than `Customer-to-PowerPlant` contracts. Here, sellers will offer high prices for their surplus electric energy, since all will definitely be sold. Therefore, it is very important to have a balance between "customer participation percentage" and "amount of demand and supply."

3.4. Grid stability constraints

The Council of European Energy Regulators (CEER) splits the quality of electricity supply into three components: continuity of supply, voltage quality, and commercial quality (Council of European Energy Regulators (CEER), 2018). The first two components fall outside the scope of this paper. The third component is crucial for markets since market-based grid stability refers to the grid's ability in maintaining the continuity of supply and demand balance in case of perturbations. DSOs, as maintainers of the electricity distribution grid, impose some capacity constraints. The main motivation for engaging the multi-objective power matching framework with grid stability constraints is to improve the stability of the power system in the face of the growing penetration of intermittent DERs. It is important that such frameworks do not compromise the quality of supply. The main grid stability challenge arises from the mismatch between production and demand on the markets' premises. Since there is a little prior experience on the impact of power matching frameworks on the quality of supply, its investigation has been included at an early stage in this paper. With respect to the physical dynamics of the electrical grid system, this paper considers the electricity demand threshold as the hard grid constraint (Jacobsen et al., 2015). Let

$$A_1 = \sum_{i=1}^{N_k}\sum_{j=1}^{M_k} x^t_{b_{i,k}s_{j,k}}, \tag{10}$$

where $A_1 \in \mathbb{Z}^*$ (kWh) is the total energy transferred among customers at time interval t using the `Inside-Feeder` trading method. Let

$$A_2 = \sum_{g=1\backslash g\neq k}^{K}\sum_{i=1}^{N_k}\sum_{j=1}^{M_g} x^t_{b_{i,k}s_{j,g}}, \tag{11}$$

where $A_2 \in \mathbb{Z}^*$ (kWh) is the total energy that buyers, using `Feeder-to-Feeder` method, buy at time interval t. Following this, let

$$A_3 = \sum_{k=1\backslash k\neq g}^{K}\sum_{j=1}^{M_g}\sum_{i=1}^{N_k} x^t_{b_{i,g}s_{j,k}}, \tag{12}$$

where $A_3 \in \mathbb{Z}^*$ (kWh) is the total energy that sellers, using `Feeder-to-Feeder` method, sell at time interval t. Finally, let

$$A_4 = \sum_{i=1}^{N_k} x^t_{b_{i,g}\xi}, \tag{13}$$

where $A_4 \in \mathbb{Z}^*$ (kWh) is the total energy transferred from the power plant ξ to buyers at time interval t. Then, let

$$A_1 + A_2 + A_3 + A_4 \le EDT^t_k, \tag{14}$$

where $EDT_k^t \in \mathbb{Z}^*$ (kWh) is the electricity demand threshold imposed by feeder f_k at time interval t. We call EDT_k^t a hard threshold meaning that violating it will jeopardize electrical grid services (Azar et al., 2015). It should be mentioned that the grid stability cannot be guaranteed by considering only electricity demand threshold and disregarding other technical issues such as capacity limits, network congestions, and inappropriate voltage profiles. A comprehensive stability analysis should be invested on the physical dynamics of the electrical grid and their behavior, when a new pricing scheme is introduced. Although it falls out of the scope of this paper, however, the multi-objective power matching framework is completely compatible with adding other grid constraints. Next, we propose the multi-objective power matching algorithm.

4. Multi-objective power matching algorithm: An evolutionary approach

The multi-objective power matching problem is NP-complete by a reduction from the general quadratic assignment problem (Lawler, 1963). In the assignment problem, there are two sets of $v \in \mathbb{N}$ facilities and $w \in \mathbb{N}$ locations. For each pair of facilities a weight and for each pair of locations a Euclidean distance are specified. The purpose is to assign all facilities to different locations with the goal of minimizing the sum of distances multiplied by the corresponding flows.

To operate the multi-objective power matching framework necessitates the market operator computing all or a representative set of solutions. Each solution is represented as an admissible collection of customers' contracts on the daily basis specifying "how much electric energy" each buyer agent should purchase from each seller agent and the power plant at each time interval. The reason for producing this set is the conflicting nature of objectives (see Eq. (6)). A solution refers to the state where it is impossible to make any solution better off without making at least one solution worse. The market operator aims at finding a Pareto-front in the objective space including a set of non-dominated solutions as diverse as possible. In this space, one solution can dominate another one, when it is better with values of some objectives and perhaps is equivalent to values of other objectives. Evolutionary algorithms are one of the most well-known meta-heuristic search mechanisms utilized to generate these solutions to a multi-objective optimization problem. An important advantage of evolutionary algorithms is that they are free of the difficulties and properties of the objective function (e.g., discreteness or continuity, convexity, differentiability, etc.) (Deb, 2001).

This paper proposes a *Revised* version of Non-dominated Sorting Genetic Algorithm-II (RNSGA-II) (Deb et al., 2000). NSGA-II is among the most popular multi-objective evolutionary algorithms due to its fast non-dominated sorting approach and ability to find a much better spread and convergence of solutions near the true Pareto-front. Fig. 3 demonstrates the flowchart of RNSGA-II.

Preprocessing is done to initiate the simulation structure and analyze the input data. The algorithm starts randomly generating an initial parent population $\mathbb{Q} = \{\varphi_1, \varphi_2, \ldots, \varphi_Q\}$ including $Q \in \mathbb{N}$ feasible solutions φ_a, where $a \in \{1, 2, \ldots, Q\}$. The fitness value of each solution is evaluated through the objective functions (see Eq. (6)). Then, RNSGA-II creates possible Pareto-fronts using the dominance rule, as Fig. 4 pictures.

To distinguish among solutions in each Pareto-front, a niching strategy, named crowding distance, is used to assign a value to each solution in the Pareto-front. Fig. 5 shows its schematic view. The crowding distance is a measure of how close a solution is to its neighbors in the objective space. A larger crowding distance indicates the solution is far away from others. To this end, RNSGA-II sums the Euclidean distances among each solution and its nearest left and right neighbors in the objective space, as the largest hypercube around it. The first and the last solutions in each Pareto-front, to preserve the diversity, are assigned a crowding distance of infinity.

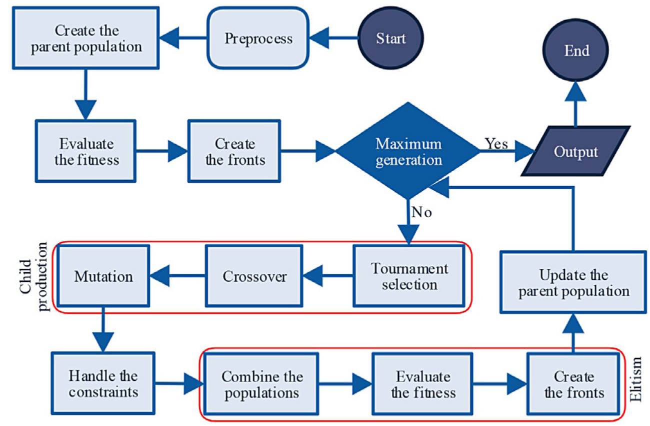


Fig. 3. Flowchart of the RNSGA-II.

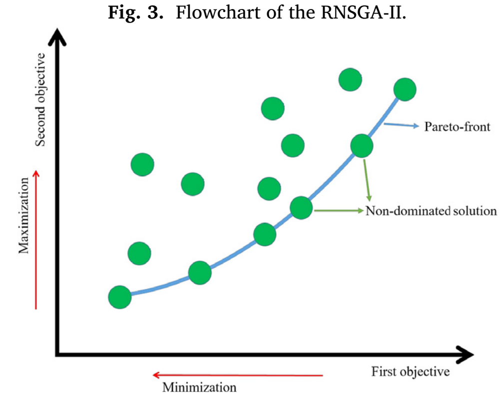


Fig. 4. A Pareto-front in the RNSGA-II.

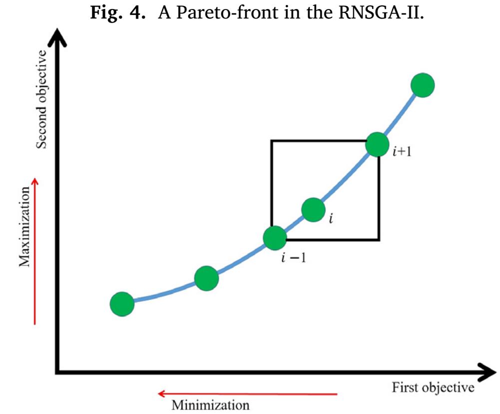


Fig. 5. Crowding distance.

RNSGA-II continues until the maximum number of generations $W \in \mathbb{N}$ is reached. In each generation, it produces new solutions (children), handles their constraints, applies the elitism to them, and finally, updates the parent population. The output of RNSGA-II is the set of solutions lying on the first Pareto-front. Next, we precisely clarify each part of RNSGA-II.

4.1. Initial parent population

Fig. 6 displays how a single power matching solution is produced. Let

$$\varphi_a = \bigcup_{t=1}^{T} \mathbb{C}_{\varphi}a^t, \qquad \mathbb{C}_{\varphi a}^t = \begin{bmatrix} x^t_{b_{1,1}s_{1,1}} & \cdots & x^t_{b_{N_k,k}s_{1,1}} \\ \vdots & \ddots & \vdots \\ x^t_{b_{1,1}s_{M_k,k}} & \cdots & x^t_{b_{N_k,k}s_{M_k,k}} \end{bmatrix}, \tag{15}$$

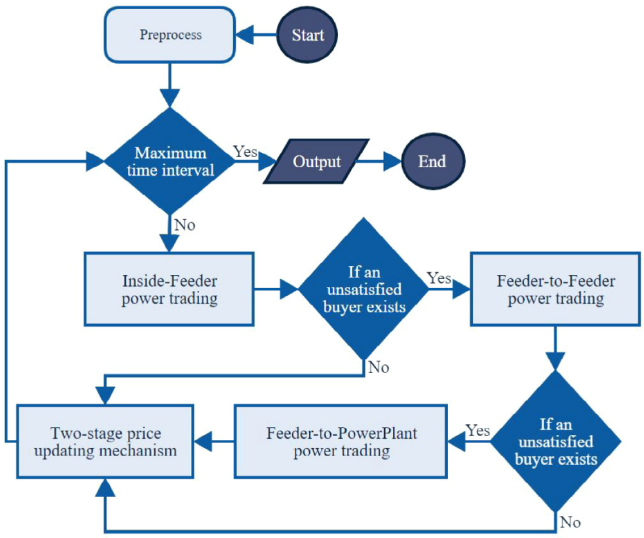


Fig. 6. Flowchart of producing a single power matching solution.

where φ_a is a single matching solution encoded as T matrices. Each matrix $\mathbb{C}^t_{\varphi a}$ is $|\mathbb{B}| \times |\mathbb{S}|$ contracts at time interval t comprising the total units transferred among customers. Contracts made by the `Customer-to-PowerPlant` method is also added to each matrix. Regarding the scalability of the framework, given that although the number of customers in a small/medium city may reach the order of thousands or more, however, since the framework is semi-decentralized and executed in various independent feeders in parallel, it is possible to scale it up, since each feeder serves only a small sub-set of customers in the grid.

As Fig. 6 shows, first, for each feeder f_k, corresponding buyer agents start negotiating with corresponding seller agents. Second, an unsatisfied buyer, who still needs some energy, negotiates with sellers connected to other feeders. Finally, the power plant undertakes the remaining demand of unsatisfied buyers. These steps will completely satisfy the buyers' full demand satisfaction and sellers' limited surplus energy constraints (see Eqs. (2) and (5)). Then, the two-stage price updating mechanism updates electricity prices accordingly. In conclusion, the output is an acceptable power matching solution.

To perform each trading method, Algorithm 1 proposes a negotiation procedure. This procedure is incorporated into all trading methods. For the `Inside-Feeder` method, $k = g$ while for the `Feeder-to-Feeder` method $k \neq g$. Obviously, electricity distribution loss is considered prior to making any transfer over time. The reason is that the power transferred in the system is lower than the actual contracted amount. RNSGA-II, to produce Q solutions together as a parent population, performs the following three power trading methods, as described in Fig. 6.

Algorithm 1: The Negotiation Procedure

if $q^t_{s_{j,g}} \geq \left(d^t_{b_{i,k}} \times \left(1 + loss_{b_{i,k}\,s_{j,g}}\right)\right)$ **then**
  $q^t_{s_{j,g}} = q^t_{s_{j,g}} - \left(d^t_{b_{i,k}} \times \left(1 + loss_{b_{i,k}\,s_{j,g}}\right)\right)$;
  $x^t_{b_{i,k}\,s_{j,g}} = d^t_{b_{i,k}} \times \left(1 + loss_{b_{i,k}\,s_{j,g}}\right)$;
  $d^t_{b_{i,k}} = 0$;
else
  $x^t_{b_{i,k}\,s_{j,g}} = q^t_{s_{j,g}}$;
  $d^t_{b_{i,k}} = d^t_{b_{i,k}} - \left(q^t_{s_{j,g}} \times \left(1 - loss_{b_{i,k}\,s_{j,g}}\right)\right)$;
  $q^t_{s_{j,g}} = 0$;
end

4.1.1. Inside-feeder power trading

Algorithm 2 demonstrates the `Inside-Feeder` power trading method. One of the main challenges in the power matching problem is to find an optimal order of buyers and sellers to start the negotiation. The best permutation of buyers and sellers results in an optimal power allocation. However, since this paper focuses on the multi-objective power matching approach, obviously, it is impossible to find this unique set. For instance, one method is to start with those buyers whose contracts might have more electricity distribution losses. This happens when they have to purchase from sellers connected to other feeders. This method obviously violates the equality of buyers since we assume all are residential customers. As a result, we randomly generate a permutation set of buyers and sellers at the feeder's level.

Algorithm 2: Inside-Feeder Power Trading

for $k = 1$ *to* K **do**
  Randomly select a permutation of buyers and sellers say $\left(b_{1,k}, b_{2,k}, \dots, b_{N_k,k}\right)$ and $\left(s_{1,k}, s_{2,k}, \dots, s_{M_k,k}\right)$, respectively;
  for $i = 1$ *to* N_k **do**
    for $j = 1$ *to* M_k **do**
      if $\left(q^t_{s_{j,g}} > 0\right)$ *and* $\left(d^t_{b_{i,k}} > 0\right)$ **then**
        Run Algorithm 1;
      end
    end
  end
end

4.1.2. Feeder-to-feeder power trading

Algorithm 3 describes how an unsatisfied buyer, who still needs some energy, is searching for sellers, connected to other feeders. Here, a random permutation of feeders is also generated. Due to the electricity distribution loss, customers intend to negotiate with close neighbors connected to other feeders. Since the negotiation is only based on the minimization of electricity distribution loss, therefore, a larger distance implies more loss.

Algorithm 3: Feeder-to-Feeder Power Trading

Select a random permutation of feeders, say $\left(f_1, f_2, \dots, f_K\right)$;
for $k = 1$ *to* K **do**
  if $\exists b_{i,k} \in f^B_K$ *such that remaining* $d^t_{b_{i,k}} > 0$ **then**
    Sort Euclidean distances among buyer $b_{i,k}$ connected to feeder f_k, and all sellers, connected to other feeders, ascendingly;
    for $c = 1$ *to* K **do**
      if $\left(\left(\sum_{h=1}^{M_c} q^t_{s_{h,c}}\right) > 0\right)$ *and* $(c \neq K)$ **then**
        for $h = 1$ *to* M_c **do**
          if $q^t_{s_{h,c}} > 0$ **then**
            Run Algorithm 1;
          end
        end
      end
    end
  end
end

4.1.3. Customer-to-PowerPlant power trading

After executing Algorithms 2 and 3, Algorithm 4 shows how the power plant satisfies the remaining load demand of unsatisfied buyers. Considering this plant alone does not completely prevent the electrical grid from any black-outage (Amin and Wollenberg, 2005). This emphasizes the necessity of paying a sufficient attention to some electricity demand thresholds for feeders and households to shape load consumptions (Azar et al., 2015).

Algorithm 4: Customer-to-PowerPlant Power Trading

```
for k = 1 to K do
    if ∃b_{i,k} ∈ f_k^B such that remaining d^t_{b_{i,k}} > 0 then
        x^t_{b_{i,k} ξ} = d^t_{b_{i,k}} × (1 + loss_{b_{i,k} ξ});
        d^t_{b_{i,k}} = 0;
    end
end
```

4.1.4. Robustness analysis of various challenges in producing the initial parent population

Constructing a robust procedure to produce a good parent population is a challenging issue. In particular, robustness can have various connotations in different circumstances. In the problem under investigation, it could allude to the possible failures that could occur while the electricity is distributed among the agents. The following describes some challenging scenarios, RNSGA-II can face at each time interval. A reliable solution follows each scenario.

First Scenario: Let us suppose the total load demand at a time interval is greater than the total surplus energy. There will be, at least, one unsatisfied buyer after running the first two power trading methods (see Algorithms 2 and 3). According to full demand satisfaction constraint (see Eq. (2)), the framework has to find a way to supply the remaining demand. This proves the reason of having a backup power plant, as Algorithm 4 describes. In fact, buyers' welfare will not be optimized since the electricity distribution loss of and purchasing cost from the power plant are high.

Second Scenario: The best case of the problem occurs, when the total demand at each time interval meets the total supply. Here, all buyers, without purchasing any electric energy from the power plant, will be satisfied through sellers. Furthermore, in this condition, sellers are completely satisfied since they can sell all their surplus energy. As a result, continuous occurrence of this situation maximizes the social welfare of all customers globally.

Third Scenario: The last scenario happens, when the total surplus energy at each time interval is greater than the total demand. In this circumstance, buyers are again satisfied through sellers while some sellers cannot sell all their surplus production. Here, buyers are able to optimize their social welfare, nevertheless, sellers are unable to do so due to having, at least, one seller who still has some electric energy to sell.

Next, we clarify how the exploitation and exploration procedures in each generation are applied to the parent population to create the children population.

4.2. Exploitation and exploration

The diversity of a population is known as one of the utmost important factors to reach a near-optimal Pareto-front. To obtain that diversity, the exploitation procedure, used in evolutionary approaches, disregards low and keeps high fitness solutions found so far while exploration procedures combine selected parent solutions in order to make (possibly better) new child solutions (Črepinšek et al., 2013). Although reaching an optimal balance between these two procedures is a challenging issue, however, it can be managed by some proper control parameter settings, such as probabilistic execution. When the probability of calling the exploitation procedure is very high, a majority of good solutions survive and the search space is remained unexplored. On the other hand, when the probability of calling exploration procedures is high, most of the objective space is explored, but the probability of neglecting a majority of good solutions is relatively high.

4.2.1. Exploitation

The traditional NSGA-II, to increase the quality of solutions surviving in each generation, uses the simple tournament selection. We again apply a new multi-objective constrained tournament selection procedure. It receives two completely random solutions, chosen from the parent population, say φ_1 and φ_2, as inputs. Then, it selects φ_1 if it is better in, at least, one objective and not worse in the others compared to φ_2. In equal situation, one that has lower total electricity distribution loss is chosen.

4.2.2. Exploration

The following presents two "linear crossover" and "exchange mutation" procedures proposed to stabilize the necessary diversity.

Linear Crossover: The tournament selection procedure delivers two solutions say φ_1 and φ_1 to the linear crossover procedure This delivery is performed with the probability of $p_c \in [0,1]$. The crossover procedure chooses a "random" time interval say $\tau \in \{1,2,\dots,T\}$. Then, it produces two child solutions named σ_1 and σ_2, as follows:

$$\begin{aligned} \sigma_1 &= \left\{ \bigcup_{t=1}^{\tau} \mathbb{C}^t_{\varphi_1} \right\} \cup \left\{ \bigcup_{t=\tau+1}^{T} \mathbb{C}^t_{\varphi_2} \right\}, \\ \sigma_2 &= \left\{ \bigcup_{t=1}^{\tau} \mathbb{C}^t_{\varphi_2} \right\} \cup \left\{ \bigcup_{t=\tau+1}^{T} \mathbb{C}^t_{\varphi_1} \right\}. \end{aligned} \tag{16}$$

Eventually, it finds the Pareto-fronts of these four solutions (φ_1, φ_2, σ_1, and σ_2). Here we apply a greedy method. If there are only two solutions in the first Pareto-front, it exports them as the outputs. Otherwise, if there are more than two solutions in the first Pareto-front, it calculates their crowding distance value and exports the solutions with the two highest crowding distance values accordingly. Finally, if there is only one solution in the first Pareto-front, it will be one of the output solutions. The same procedure is applied to the second Pareto-front to obtain the other solution.

Exchange Mutation: Mutation is an evolutionary operator used to preserve variety from one solution to the other solution, where each solution component may change entirely from its previous version. The exchange mutation procedure is applied to each output (child solution) of the linear crossover with the probability of $p_m \in [0,1]$. This procedure chooses two random buyers, say $b_{i,k}$ and $b_{i',k'}$, and two random sellers, say $s_{j,g}$ and $s_{j',g'}$. Here, we apply a greedy method, where it sorts peer-to-peer Euclidean distances of these four agents. Then, the highest amount of electric energy transferred between them is assigned to agent with the lowest distance and so on.

Indeed, the modifications done by exploration procedures may produce infeasible child solutions. Therefore, there should be an effective refiner to handle the framework constraints and make the solutions feasible.

4.3. Constraint handling

An effective constraint handling procedure is a key element in designing competitive evolutionary algorithms to solve multi-objective optimization problems (Deb, 2000). As Algorithm 5 describes, this paper proposes a greedy constraint handling procedure to refine solutions that need a refinement. This helps the power matching framework converge to a near-optimal Pareto-front while running the power matching algorithm. Let us consider $\mathbb{Q}' = \left\{\varphi'_1, \varphi'_2, \dots, \varphi'_Q\right\}$ is the set of children's population. It includes Q solutions as parent population $\mathbb{Q}$ has. The following clarifies each probable problems, shown in Algorithm 5, accompanied with their possible algorithmic solution.

Algorithm 5: Constraint Handling

for $t = 1$ *to* T **do**
  $Feasibility = 0$;
  while $Feasibility = 0$ **do**
    for $k = 1$ *to* K **do**
      for $i = 1$ *to* N_k **do**
        if $d_{b_{i,k}} > 0$ **then**
          `// Unsatisfied Buyer`
          Run Algorithm 6;
        else
          if $d_{b_{i,k}} < 0$ **then**
            `// Overbought Buyer`
            Run Algorithm 7;
          end
        end
      end
      for $j = 1$ *to* M_k **do**
        `// Oversold Seller`
        Run Algorithm 8;
      end
      `// Exceeding the EDT`
      Run Algorithm 9;
    end
    if $\{\exists b \in F^B | d_b^t \neq 0\} \wedge \{\exists s \in F^S | q_b^t < 0\} \wedge \{\exists f_k \in F | EDT_k^t < 0\}$ **then**
      Feasibility = 1;
    end
  end
end

Algorithm 6: Constraint Handling: Unsatisfied Buyer

`// Inside-Feeder Trading Method`
Randomly select a permutation of sellers say $\left(s_{1,k}, s_{2,k}, \dots, s_{M_k,k}\right)$;
$j = 1$;
while $\left(q_{s_{j,k}}^t > 0\right) \wedge \left(j \leq M_k\right)$ **do**
  Run Algorithm 1;
  $j = j + 1$;
end
`// Feeder-to-Feeder Trading Method`
if $d_{b_{i,k}}^t > 0$ **then**
  Select a random permutation of feeders, say $\left(f_1, f_2, \dots, f_{k-1}, f_{k+1}, \dots, f_K\right)$;
  $c = 1$;
  while $c \leq (K-1)$ **do**
    Sort Euclidean distances among buyer $b_{i,k}$ and sellers, connected to feeder f_c, ascendingly;
    $h = 1$;
    while $\left(q_{s_{h,c}}^t > 0\right) \wedge \left(h \leq M_c\right)$ **do**
      Run Algorithm 1;
      $h = h + 1$;
    end
    $c = c + 1$;
  end
end
`// Customer-to-PowerPlant Trading Method`
if $d_{b_{i,k}}^t > 0$ **then**
  Run Algorithm 4;
end

4.3.1. Unsatisfied buyer

Algorithm 6 describes how the constraint handling procedure meets unsatisfied buyers' demands. Each unsatisfied buyer should try to buy the remaining load demand using the `Inside-Feeder` trading method. Afterwards, sellers, who are connected to other feeders, will suggest their remaining surplus energy. Finally, the power plant will satisfy the unsatisfied buyers' demand.

4.3.2. Overbought buyer

Algorithm 7 shows how the overbought amount of energy is deducted from contracts. For each overbought buyer, first, the total electricity purchased from the power plant is reduced. Then, the same process is performed for negotiations done with sellers connected to different feeders. Finally, it is investigated in contracts made by sellers connected to the same feeder as the overbought buyer is.

4.3.3. Oversold seller

Algorithm 8 describes how the limited surplus energy of oversold sellers is respected. The oversold amount of each seller will be decreased from those contracts, which include `Feeder-to-Feeder` transfers. Then, the same process will be checked for the contracts including `Inside-Feeder` transfers.

4.3.4. Exceeding the EDT

Algorithm 9 ensures that, during any time interval, the grid will not overload. If the total electric power transmitted through a feeder exceeds the corresponding EDT, the amount of excessive energy will be deducted from the `Customer-to-PowerPlant` transactions. Then, the same process will be applied to `Feeder-to-Feeder` and `Inside-Feeder` exchanges, until satisfying the corresponding EDT.

5. Simulation setup and analysis

This section first provides the default simulation setup and then, analyzes the simulation results.

5.1. Simulation setup

We create four environmental scenarios $\mathbb{ES}_{1\sim4}$, including different sets of customers, as Table 2 expresses. The reason for choosing such scenarios is to analyze the impact of "customer participation percentage" on the framework. We believe real cases will fall in one of these practical assumptions. To make scenarios more realistic, it is considered that in each feeder, a subset of customers are willing to utilize such framework. In $\mathbb{ES}_1$, the idea is to analyze how having insufficient number of sellers influences the buyers. In contrast, in $\mathbb{ES}_2$, the same analyze is applied when we have a very low buyers' participation percentage. Afterwards, $\mathbb{ES}_3$ and $\mathbb{ES}_4$ are designed to investigate how the disparate distribution of customers' location affects the grid's balance over time.

Table 3 lists the default values of simulation parameters. Each customer's location in the grid is uniformly randomly assigned, within the range of 2.5 km^2. The operable range of electricity price offers are captured from the electricity prices in New York City (Anon, 2018). We assume sellers own a set of solar panels to first, satisfy their demands and then, sell the surplus energy (Hummon et al., 2012). Electricity consumption patterns of customers are captured from Englert et al. (2013). The simulations are spanned over only one day, due to the daily basis of patterns. To ensure buyers of having their demands fully satisfied at each time interval, we assume $EDT_k^t = PAC_k^t$, where PAC_k^t

Algorithm 7: Constraint Handling: Overbought Buyer

```
// Customer-to-PowerPlant transfer
if x^t_{b_{i,g} ξ} > 0 then
    if x^t_{b_{i,g} ξ} ≥ |d^t_{b_{i,k}}| then
        x^t_{b_{i,g} ξ} = x^t_{b_{i,g} ξ} − |d^t_{b_{i,k}}|;
        d^t_{b_{i,k}} = 0;
    else
        d^t_{b_{i,k}} = d^t_{b_{i,k}} + x^t_{b_{i,g} ξ};
        x^t_{b_{i,g} ξ} = 0;
    end
end
// Feeder-to-Feeder transfer
if d_{b_{i,k}} < 0 then
    Calculate the electricity distribution loss of applicable
    Feeder-to-Feeder transfers and sort the corresponding
    contracts descendingly, say χ = (x^t_{b_{i,k} s_{j,g}}, ..., x^t_{b_{i,k} s_{j',g'}}, ...),
    where k ≠ {g, g'};
    j = 1;
    while (d_{b_{i,k}} < 0) ∧ (j ≤ |χ|) do
        if χ(j) ≥ |d^t_{b_{i,k}}| then
            χ(j) = χ(j) − |d^t_{b_{i,k}}|;
            d^t_{b_{i,k}} = 0;
        else
            d^t_{b_{i,k}} = d^t_{b_{i,k}} + χ(j);
            χ(j) = 0;
        end
        j = j + 1 ;
    end
end
// Inside-Feeder transfer
if d_{b_{i,k}} < 0 then
    Calculate the electricity distribution loss of applicable
    Inside-Feeder transfers and sort the corresponding
    contracts descendingly, say χ = (x^t_{b_{i,k} s_{1,k}}, x^t_{b_{i,k} s_{2,k}}, ...);
    c = 1;
    while (d_{b_{i,k}} < 0) ∧ (c ≤ |χ|) do
        if χ(c) ≥ |d^t_{b_{i,k}}| then
            χ(c) = χ(c) − |d^t_{b_{i,k}}|;
            d^t_{b_{i,k}} = 0;
        else
            d^t_{b_{i,k}} = d^t_{b_{i,k}} + χ(c);
            χ(c) = 0;
        end
        c = c + 1 ;
    end
end
```

is the peak aggregated consumption of customers. For more information regarding utilizing multi-objective load scheduling approaches on demand response programs, i.e., where $EDT^t_k < PAC^t_k$, the reader is referred to Azar and Jacobsen (2016). We simulate the framework with Matlab in a personal computer with a single Intel Core i7-2.0 GHz CPU and 6 GB memory. Since the proposed evolutionary multi-objective algorithm is stochastic in nature, 50 trials have been performed for each simulation case. The results have been averaged across the trials.

Algorithm 8: Constraint Handling: Oversold Seller

```
// Feeder-to-Feeder transfer
Calculate the electricity distribution loss of applicable
Feeder-to-Feeder transfers and sort the corresponding
contracts descendingly, say χ = (x^t_{b_{i,g} s_{j,k}}, ..., x^t_{b_{i',g'} s_{j,k}}, ...), where
k ≠ {g, g'};
c = 1;
while (q_{s_{j,k}} < 0) ∧ (c ≤ |χ|) do
    if χ(c) ≥ |q^t_{s_{j,k}}| then
        χ(c) = χ(c) − |q^t_{s_{j,k}}|;
        q^t_{s_{j,k}} = 0;
    else
        q^t_{s_{j,k}} = q^t_{s_{j,k}} + χ(c);
        χ(c) = 0;
    end
    c = c + 1 ;
end
// Inside-Feeder transfer
if q_{s_{j,k}} < 0 then
    Calculate the electricity distribution loss of applicable
    Inside-Feeder transfers and sort the corresponding
    contracts descendingly, say χ = (x^t_{b_{1,k} s_{j,k}}, x^t_{b_{2,k} s_{2,k}}, ...);
    c = 1;
    while (d^t_{b_{i,k}} < 0) ∧ (c ≤ |χ|) do
        if χ(c) ≥ |q^t_{s_{j,k}}| then
            χ(c) = χ(c) − |q^t_{s_{j,k}}|;
            q^t_{s_{j,k}} = 0;
        else
            q^t_{s_{j,k}} = q^t_{s_{j,k}} + χ(c);
            χ(c) = 0;
        end
        c = c + 1 ;
    end
end
```

5.2. Simulation results

The following analyzes the effectiveness and significance of the proposed framework according to different criteria both quantitatively and qualitatively.

5.2.1. Fitness diagrams and customers' social welfare

Fig. 7 demonstrates the fitness diagram of each environmental scenario in the objective space. Each diagram presents the Pareto-front obtained from the last generation of RNSGA-II. Numbers, shown on vertical and horizontal axes, are fitness values of all buyers and sellers corresponding to each solution resting on the Pareto-front. Their near constant slopes are due to the fixed but time-dependent electricity market's price, which the two-stage price updating mechanism sets to use in both objectives over time (see Eq. (9)). It is worthwhile emphasizing that by changing the pricing policy and objective functions accordingly, the fitness diagrams can change to non-linear vectors. Furthermore, three different points, named **A**, **B**, and **C**, are marked on each diagram. The solution, corresponding to point A, indicates that the market operator favors buyers more than sellers. In this situation, their overall fitness decreases simultaneously, as expected. Conversely, both objectives are maximized, when the market operator favors sellers (i.e., point B). Finally, point C indicates the situation, where the market operator pays

Algorithm 9: Constraint Handling: Exceeding the EDT

// `Customer-to-PowerPlant transfer`
Calculate the electricity distribution loss of applicable `Customer-to-PowerPlant` transfers and sort the corresponding contracts descendingly, say $\chi = \left(x^t_{b_{1,k}\,\xi}, x^t_{b_{2,k}\,\xi}, \dots\right)$;
$j = 1$;
while $\left(EDT^t_k < 0\right) \wedge (j \le |\chi|)$ **do**
  if $\chi(j) \ge \left|EDT^t_k\right|$ **then**
    $\chi(j) = \chi(j) - \left|EDT^t_k\right|$;
    $EDT^t_k = 0$;
  else
    $EDT^t_k = EDT^t_k + \chi(j)$;
    $\chi(j) = 0$;
  end
  $j = j + 1$;
end
// `Feeder-to-Feeder transfer`
if $EDT^t_k < 0$ **then**
  Calculate the electricity distribution loss of applicable `Feeder-to-Feeder` transfers and sort the corresponding contracts descendingly, say $\chi = \left(x^t_{b_{1,k}\,s_{1,g}}, \dots, x^t_{b_{1,k}\,s_{1,g''}}, \dots\right)$, where $k \ne \{g, g'\}$;
  $c = 1$;
  while $\left(EDT^t_k < 0\right) \wedge (c \le |\chi|)$ **do**
    if $\chi(c) \ge \left|EDT^t_k\right|$ **then**
      $\chi(c) = \chi(c) - \left|EDT^t_k\right|$;
      $EDT^t_k = 0$;
    else
      $EDT^t_k = EDT^t_k + \chi(c)$;
      $\chi(c) = 0$;
    end
    $c = c + 1$;
  end
end
// `Inside-Feeder transfer`
if $EDT^t_k < 0$ **then**
  Calculate the electricity distribution loss of applicable `Inside-Feeder` transfers and sort the corresponding contracts descendingly, say $\chi = \left(x^t_{b_{1,k}\,s_{1,k}}, x^t_{b_{2,k}\,s_{2,k}}, \dots\right)$;
  $c = 1$;
  while $\left(EDT^t_k < 0\right) \wedge (c \le |\chi|)$ **do**
    if $\chi(c) \ge \left|EDT^t_k\right|$ **then**
      $\chi(c) = \chi(c) - \left|EDT^t_k\right|$;
      $EDT^t_k = 0$;
    else
      $EDT^t_k = EDT^t_k + \chi(c)$;
      $\chi(c) = 0$;
    end
    $c = c + 1$;
  end
end

a near-equal attention to them. Table 4 shows average values of buyers' power purchase cost and sellers' power selling benefit with respect to these three specific points in each environmental scenario.

Fig. 7(a) illustrates that $\sum_{k=1}^{K}\sum_{i=1}^{N_k} d^t_{b_{i,k}} \gg \sum_{k=1}^{K}\sum_{j=1}^{M_g} q^t_{s_{j,g}}$. Thus, almost all buyers have to satisfy their demands through the power plant. Then, not only are corresponding contracts expensive due to the higher electricity price, but also, they have a higher electricity distribution loss. With respect to the random permutation, described in Section 4.1.1, the Pareto-front includes ten distinct power matching solutions. Since there is only one seller in $\mathbb{ES}_1$, the surplus energy is completely sold. The seller's daily benefit range, i.e., \$[4.72,7.79], in each solution, is obtained by contracting with different buyers. When a buyer makes an `Inside-Feeder` contract with a seller, the benefit would be relatively high compared to a `Feeder-to-Feeder` contract due to the lower electricity distribution loss. From the buyers' perspective, the buyer succeeds to satisfy all or a major part of the demand from the seller, then, the electricity cost will be lower compared to the situation, where the buyer has to satisfy all the demand through the power plant. Fig. 7(b) demonstrate the fitness diagram, when there is only one buyer and 25 sellers. Obviously, $\sum_{k=1}^{K}\sum_{i=1}^{N_k} d^t_{b_{i,k}} \ll \sum_{k=1}^{K}\sum_{j=1}^{M_g} q^t_{s_{j,g}}$ and thus, the buyer is able to satisfy his/her demands through a subset of sellers. Solutions on the Pareto-front emphasizes that the buyer, by just making `Inside-Feeder` contracts with two sellers, is successful in satisfying the load demand. These solutions only differ in the permutation order of their sellers and the surplus energy volume sellers can provide. Therefore, as Table 3 shows, the cost range for buyers is very narrow. Indeed, only two sellers, located in feeder f_2, are able to increase their social welfare while others cannot even sell anything. Hence, their fitness range is also narrow. In this environmental scenario, there is no `Customer-to-PowerPlant` transaction.

Figs. 7(c) and 7(d) are almost the same. The main difference is that the probability of not having sufficient surplus energy in $\mathbb{ES}_3$ is higher than in $\mathbb{ES}_4$, i.e., $\sum_{k=1}^{K}\sum_{i=1}^{N_k} d^t_{b_{i,k}} > \sum_{k=1}^{K}\sum_{j=1}^{M_g} q^t_{s_{j,g}}$. Therefore, the density in the upper half of the fitness diagram, shown in Fig. 7(c), is high. The reason is that sellers perhaps will completely sell their surplus energy.

Table 2
Environmental scenarios.

			f_1	f_2	f_3	f_4
$\mathbb{ES}_1$	$\lvert\mathbb{B}\rvert = 25$	→	$N_1 = 4$	$N_2 = 6$	$N_3 = 7$	$N_4 = 8$
	$\lvert\mathbb{S}\rvert = 1$	→	$M_1 = 0$	$M_2 = 0$	$M_3 = 0$	$M_4 = 1$
$\mathbb{ES}_2$	$\lvert\mathbb{B}\rvert = 1$	→	$N_1 = 0$	$N_2 = 1$	$N_3 = 0$	$N_4 = 0$
	$\lvert\mathbb{S}\rvert = 25$	→	$M_1 = 10$	$M_2 = 2$	$M_3 = 1$	$M_4 = 12$
$\mathbb{ES}_3$	$\lvert\mathbb{B}\rvert = 40$	→	$N_1 = 15$	$N_2 = 5$	$N_3 = 12$	$N_4 = 8$
	$\lvert\mathbb{S}\rvert = 25$	→	$M_1 = 4$	$M_2 = 9$	$M_3 = 11$	$M_4 = 1$
$\mathbb{ES}_4$	$\lvert\mathbb{B}\rvert = 25$	→	$N_1 = 16$	$N_2 = 4$	$N_3 = 0$	$N_4 = 5$
	$\lvert\mathbb{S}\rvert = 40$	→	$M_1 = 3$	$M_2 = 6$	$M_3 = 9$	$M_4 = 22$

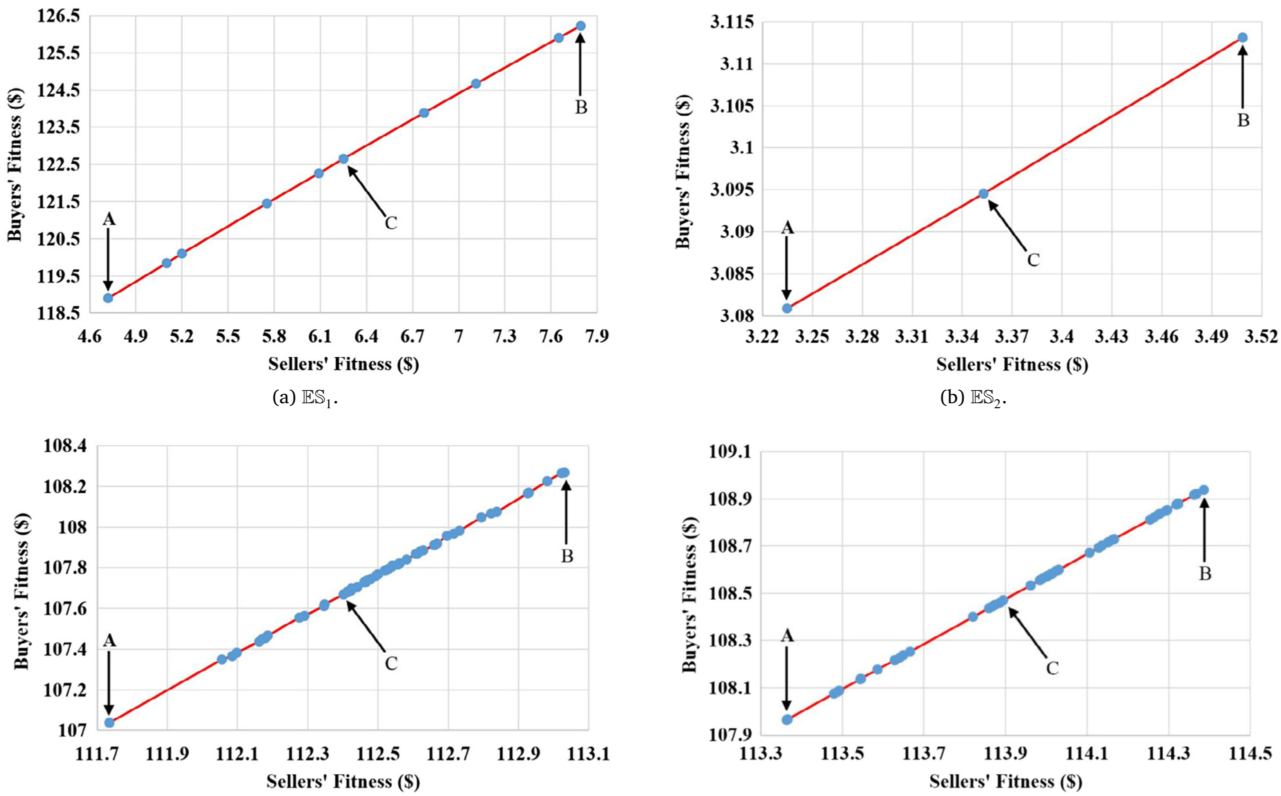
Table 3
Default values of simulation parameters.

Parameter	Value	Parameter	Value
Area	10×10 km^2	K	4
p_l	0.03 (\$/kWh)	p_u	0.1(\$/kWh)
pm	2 (\$/kWh)	ELF_f	0.05
ELF_ξ	0.15	d^t	$[1,9]^*$ (kWh)
q^t	$[2,13]^*$ (kWh)	EDT^t_k	PAC^t_k
T	24	Q	100
W	100	p_c	0.8
p_m	0.2	γ	$(0,1)^*$
δ	$(0,1)^*$	pb^1	$(p_l, p_u)^*$
ps^1	$(p_l, p_u)^*$		

* The value is uniformly randomly chosen.

Table 4
Average values of buyers' purchasing cost and sellers' selling benefit in a 24 h period.

			Point A	Point B	Point C
$\mathbb{ES}_1$	$\mathbb{B}$	→	\$4.75	\$5.04	\$4.90
	$\mathbb{S}$	→	\$4.72	\$7.79	\$6.25
$\mathbb{ES}_2$	$\mathbb{B}$	→	\$2.67	\$2.71	\$2.69
	$\mathbb{S}$	→	\$2.83	\$2.87	\$2.85
$\mathbb{ES}_3$	$\mathbb{B}$	→	\$4.31	\$4.35	\$4.33
	$\mathbb{S}$	→	\$4.46	\$4.52	\$4.49
$\mathbb{ES}_4$	$\mathbb{B}$	→	\$3.08	\$3.11	\$3.09
	$\mathbb{S}$	→	\$3.25	\$3.35	\$3.30



(a) $\mathbb{ES}_1$.

(b) $\mathbb{ES}_2$.

(c) $\mathbb{ES}_3$.

(d) $\mathbb{ES}_4$.

Fig. 7. Fitness diagrams of environmental scenarios in the objective space.

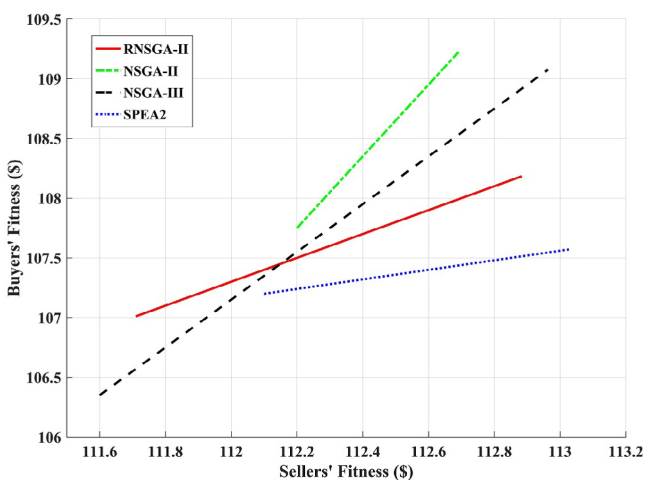


Fig. 8. Comparison of fitness diagrams of the proposed RNSGA-II, NSGA-II, NSGA-III, and SPEA2.

On the contrary, Fig. 7(d) includes an almost uniformly distributed solutions. Here, since probably $\sum_{k=1}^{K}\sum_{i=1}^{N_k} d^t_{b_{i,k}} < \sum_{k=1}^{K}\sum_{j=1}^{M_g} q^t_{s_{j,g}}$, then, all buyers are satisfied through available sellers. On one hand, since $|\mathbb{S}|$ in $\mathbb{ES}_3$ is lower than $|\mathbb{S}|$ in $\mathbb{ES}_4$, the probability of finding the optimal permutation of sellers in $\mathbb{ES}_3$ is high. Therefore, buyers can comparatively make cost-effective contracts. For the same reason, sellers in $\mathbb{ES}_3$ benefits relatively more than sellers in $\mathbb{ES}_4$.

This part compares the proposed RNSGA-II with the traditional NSGA-II (Deb et al., 2000), *Reference-Point-Based* NSGA-II referred as NSGA-III (Deb and Jain, 2014), and Improved Strength Pareto Evolutionary Algorithm (SPEA2) (Zitzler et al., 2001). The main difference between NSGA-II and NSGA-III is the maintenance of diversity among population members. The former utilizes the crowding distance operator while the latter supplies and adaptively updates a number of well-spread pre-defined reference points to ensure the diversity in obtained solutions. We use a systematic approach that places points on a normalized hyper-plane, which is equally inclined to two-objective axes and has an intercept of one on each axis. We consider three divisions, where four reference points are equally spread out along each objective.

Table 5
Average values of buyers' purchasing cost and sellers' selling benefit in a 24 h period achieved in different algorithms.

			Point A	Point B	Point C
RNSGA-II	$\mathbb{B}$	→	$4.31	$4.35	$4.33
	$\mathbb{S}$	→	$4.46	$4.52	$4.49
NSGA-II	$\mathbb{B}$	→	$4.33	$4.75	$4.61
	$\mathbb{S}$	→	$4.47	$4.50	$4.49
NSGA-III	$\mathbb{B}$	→	$4.28	$5.49	$4.56
	$\mathbb{S}$	→	$4.43	$4.55	$4.50
SPEA2	$\mathbb{B}$	→	$4.30	$4.32	$4.31
	$\mathbb{S}$	→	$4.41	$4.47	$4.52

Fig. 8 shows this comparison in the objective space considering $\mathbb{ES}_3$ and default setup listed in Table 3. Table 5 shows average values of buyers' power purchase cost and sellers' power selling benefit achieved in different algorithms mentioned above. Points A, B, and C are selected according to the procedure described earlier. NSGA-II and SPEA2 achieve a narrow diversity while NSGA-III hosts more diverse solutions. These diagrams show the first Pareto-front obtained

Table 6
Average electricity cost of buyers and benefit of sellers when the number of customers increases.

		Number of buyers				
		10	20	30	40	50
Number of sellers	10	$\frac{\$(11.77,11.84,11.81)}{\$(11.22,11.28,11.25)}$	$\frac{\$(11.64,11.69,11.66)}{\$(22.42,22.52,22.46)}$	$\frac{\$(9.75,9.60,9.58)}{\$(27.83,27.93,27.88)}$	$\frac{\$(7.69,7.72,7.71)}{\$(29.95,30.04,30.01)}$	$\frac{\$(6.58,6.60,6.59)}{\$(30.02,32.14,32.08)}$
	20	$\frac{\$(6.00,6.07,6.03)}{\$(2.86,2.89,2.87)}$	$\frac{\$(5.75,5.81,5.78)}{\$(5.48,5.45,5.05)}$	$\frac{\$(6.07,6.10,6.09)}{\$(8.70,8.74,8.72)}$	$\frac{\$(5.84,5.86,5.85)}{\$(11.25,11.27,11.26)}$	$\frac{\$(5.18,5.20,5.19)}{\$(6.71,6.73,6.71)}$
	30	$\frac{\$(3.90,4.01,3.96)}{\$(1.23,1.27,1.25)}$	$\frac{\$(4.00,4.06,4.03)}{\$(2.54,2.58,2.56)}$	$\frac{\$(4.02,4.06,4.04)}{\$(3.83,3.87,3.85)}$	$\frac{\$(3.98,4.00,3.99)}{\$(5.05,5.08,5.07)}$	$\frac{\$(4.19,4.21,4.20)}{\$(6.71,6.73,6.71)}$
	40	$\frac{\$(2.99,3.05,3.03)}{\$(0.71,0.72,0.72)}$	$\frac{\$(2.93,2.95,2.94)}{\$(1.39,1.40,1.40)}$	$\frac{\$(3.00,3.03,3.01)}{\$(2.14,2.16,2.15)}$	$\frac{\$(2.97,3.00,2.98)}{\$(2.83,2.85,2.84)}$	$\frac{\$(3.03,3.04,3.04)}{\$(3.61,3.62,3.62)}$
	50	$\frac{\$(2.43,2.47,2.45)}{\$(0.46,0.47,0.46)}$	$\frac{\$(2.38,2.42,2.40)}{\$(0.90,0.92,0.91)}$	$\frac{\$(2.41,2.43,2.37)}{\$(1.38,1.39,1.38)}$	$\frac{\$(2.36,2.38,2.37)}{\$(1.79,1.81,1.80)}$	$\frac{\$(2.35,2.36,2.36)}{\$(2.24,2.25,2.25)}$

in the last generation. Pareto-fronts of RNSGA-II and NSGA-II include 95 unique solutions. However, RNSGA-II provides the market operator with more flexibility in selecting the final solution. Fitness diagram of the NSGA-III hosts 52 unique solutions. This algorithm behaves slightly better in providing a wider range of solutions. Fitness diagram of the SPEA2 possesses 35 unique solutions. The difference in the gradient of these diagrams is due to the nature of exploitation and exploration procedures. However, RNSGA-II results in having more solutions, which are in almost near-equal benefit of both buyers and sellers. NSGA-II and NSGA-III provides more solutions, in which sellers' social welfare is not maximized. SPEA2 behaves the reverse and buyers' social welfare are almost equal in that 35 solutions.

5.2.2. Stability analysis of RNSGA-II

This part analyzes the stability of the RNSGA-II according to the correlation between "customers' social welfare" and "number of customers." Table 6 summarizes the average buyers' electricity purchase cost and sellers' benefit when the number of customers increases. Each cell includes a fraction $\frac{\$(x,y,z)}{\$(x',y',z')}$. The numerator (denominator) involves the average cost (benefit) of buyers (sellers) corresponding to points A, B, and C, respectively. When the number of buyers is constant, as the number of sellers increases, both values decrease. On one hand, buyers have more `Customer-Customer` trading opportunities, which results in decreasing the amount of `Customer-to-PowerPlant` transactions. On the other hand, sellers, to encourage buyers to have a trading with them, have to offer lower electricity prices. This results in obtaining lower cost values on average. However, as the number of buyers increases, the probability of finding a buyer to sell the surplus energy to him/her also increases. This maximizes the sellers' benefit. For buyers, the best situation happens when $|\mathbb{B}| = 50$ and $|\mathbb{S}| = 50$ while for sellers it is $|\mathbb{B}| = 50$ and $|\mathbb{S}| = 10$. As the former, with very high probability, the buyers are satisfied with `Customer-Customer` contracts, particularly with the Inside-Feeder trading method. They have more options in making contracts to minimize their electricity cost. As the latter, sellers attempt to find buyers who offer high electricity prices. Since buyers have to satisfy their demand, then, the probability of selling all or, at least, the majority of the total surplus energy is high.

Table 7 analyzes the stability of the evolutionary algorithm according to the correlation between the "number of generations" and the "population size." Let

$$SEF_{\mathbb{P}} = \sqrt{\left(\frac{1}{|\mathbb{P}|-1}\right) \times \sum_{a=1}^{|\mathbb{P}|} \overline{\left(\psi - \psi_a\right)}^2}, \quad \psi_a = \min_{a \neq a} \left\{ \left| G\left(\varphi_a\right) - G\left(\varphi_{a'}\right) \right| + \left| H\left(\varphi_a\right) - H\left(\varphi_{a'}\right) \right| \right\}, \quad \left\{a, a'\right\} \in \{1, 2, \dots, |\mathbb{P}|\}, \tag{17}$$

where $SEF_{\mathbb{P}}$ is the variance of the distance between each solution φ_a in the Pareto-front $\mathbb{P}$ and its closest neighbor $\varphi_{a'}$ in the objective space obtained in the last generation. $\overline{\psi}$ is the mean of all ψ_a. G and H are the objective functions of the market operator with input φ (see Eq. (6)). A value of zero for $SEF_{\mathbb{P}}$ expresses that all solutions, resting on $\mathbb{P}$, are equidistantly spaced. Furthermore, ($|\mathbb{P}|$) shows the number of solutions on the Pareto-front $\mathbb{P}$ and CT is the computation time of the algorithm.

Each cell in Table 7 includes a fraction $\frac{x}{y}$. x equals the value of the corresponding criterion when the number of generation increases while the population size is constant, i.e., $Q = 100$. y refers to the value of the corresponding criterion when the population size increases while the number of generations is constant, i.e., $W = 100$. The environmental scenario $\mathbb{ES}_4$ is also selected for this analysis.

Table 7
Stability analysis of the algorithm based on three efficiency criteria when the number of generations and population size increase.

$Q = 100$	$SEF_{\mathbb{P}}$	$\|\mathbb{P}\|$	CT (s)	$W = 100$
$W = 50$	$\frac{0.14}{0.12}$	$\frac{75}{35}$	$\frac{549.96}{637.82}$	$Q = 50$
$W = 100$	$\frac{0.12}{0.12}$	$\frac{69}{73}$	$\frac{9.57}{13.51}$	$Q = 100$
$W = 150$	$\frac{0.12}{0.08}$	$\frac{69}{73}$	$\frac{13.04}{20.15}$	$Q = 150$
$W = 200$	$\frac{0.07}{0.05}$	$\frac{64}{125}$	$\frac{17.74}{25.44}$	$Q = 200$
$W = 250$	$\frac{0.04}{0.02}$	$\frac{64}{196}$	$\frac{23.34}{30.04}$	$Q = 250$
$W = 300$	$\frac{0.04}{0.02}$	$\frac{63}{254}$	$\frac{29.54}{38.01}$	$Q = 300$

Table 8
Stability analysis of the algorithm based on three efficiency criteria when crossover and mutation probabilities increase.

$\{Q, W\} = 100$ $p_m = 0.2$	$SEF_{\mathbb{P}}$	SS (%)	CT-CH (s)	$\{Q, W\} = 100$ $p_c = 0.8$
$p_c = 0.2$	$\frac{0.14}{0.12}$	$\frac{15}{7}$	$\frac{251.98}{116.77}$	$p_m = 0.2$
$p_c = 0.4$	$\frac{0.05}{0.12}$	$\frac{16}{8}$	$\frac{427.98}{196.75}$	$p_m = 0.4$
$p_c = 0.6$	$\frac{0.08}{0.13}$	$\frac{19}{10}$	$\frac{779.11}{348.67}$	$p_m = 0.6$
$p_c = 0.8$	$\frac{0.12}{0.14}$	$\frac{22}{12}$	$\frac{976.02}{441.22}$	$p_m = 0.8$
$p_c = 1.0$	$\frac{0.14}{0.14}$	$\frac{23}{12}$	$\frac{1227.64}{512.12}$	$p_m = 1.0$

When $Q = 100$, while we increase the number of generations, $SEF_{\mathbb{P}}$ decreases. This shows the optimality of the algorithm since as we run more, we spread the solutions on the Pareto-front more. However, $|\mathbb{P}|$ decreases since the algorithm, in each generation, attempts to improve solutions. Therefore, with respect to the dominance rule and also the default setting mentioned in Table 3, the algorithm is interested in just surviving dominant solutions. This helps the market operator choose an effective solution since $SEF_{\mathbb{P}}$ also decreases, which proves the sufficient dispersion. This makes a trade-off for the market operator since the computation time of running the algorithm also increases. When $W = 100$, while we increase the population size, we enhance the $SEF_{\mathbb{P}}$ and increase the number of solutions resting on the Pareto-front $\mathbb{P}$, as expected. The same situation with CT is also applicable here.

Table 8 analyzes the algorithm when the probability of exploration procedures varies independently. Here, SS refers to the average percentage of survival of an explored child solution in the Pareto-front obtained in each generation. CT-CH is the average computation time of the constraint handling (CH) procedure running in each generation. Each cell includes a fraction $\frac{x}{y}$. x equals the value of the corresponding criterion, when the crossover probability increases while the mutation probability is constant, i.e., $p_m = 0.2$. y refers to the value of the corresponding criterion, when the mutation probability increases while the crossover probability is constant, i.e., $p_c = 0.8$. It should be noted that the environmental scenario $\mathbb{ES}_4$ is selected for this analysis. While we keep increasing the crossover probability, the greedy linear crossover procedure produces good solutions since SS increases. This

Table 9
Average electricity prices offered by customers and the market operator in each environmental scenario.

			Point A	Point B	Point C
$\mathbb{ES}_1$	$\mathbb{B}$	→	$0.04	$0.07	$0.05
	$\mathbb{S}$	→	$0.07	$0.09	$0.08
	MO	→	$1.81	$1.84	$1.83
$\mathbb{ES}_2$	$\mathbb{B}$	→	$0.03	$0.04	$0.03
	$\mathbb{S}$	→	$0.03	$0.05	$0.04
	MO	→	$0.03	$0.05	$0.04
$\mathbb{ES}_3$	$\mathbb{B}$	→	$0.04	$0.05	$0.04
	$\mathbb{S}$	→	$0.06	$0.08	$0.06
	MO	→	$0.03	$0.04	$0.04
$\mathbb{ES}_4$	$\mathbb{B}$	→	$0.03	$0.04	$0.03
	$\mathbb{S}$	→	$0.05	$0.06	$0.05
	MO	→	$0.04	$0.05	$0.05

increase requires calling the constraint handling procedure more as CT-CH follows. These explanations are also applicable to the greedy mutation procedure. However, high values of mutation implies that the evolutionary search changes from a guided to a purely blind one. By this change, the algorithm, in each generation, confronts no new good solutions, since not only are these solutions not good enough, but also they require more computation time in the constraint handling step. Hence, its influence on the criteria compared to the crossover is relatively negligible, as expected.

5.2.3. Effects of the two-stage price updating mechanism on RNSGA-II

Table 9 analyzes the performance of the two-stage price updating mechanism and its effects on RNSGA-II. It elaborates average electricity prices offered by customers ($\mathbb{B}$ and $\mathbb{S}$) and the market price announced by the market operator (MO). In $\mathbb{ES}_1$, as described before, since the main party, in most of the contracts, is the power plant, therefore, the market price is close to its offered electricity price. In $\mathbb{ES}_2$, since $|\mathbb{B}| \ll |\mathbb{S}|$ and according to Eq. (9), buyers dominate the market, which results in a lower market price. Sellers, to encourage buyers to make a contract with them, have to offer a relatively lower electricity prices. Otherwise, they are in charge of paying more for the energy storage. Results for scenarios $\mathbb{ES}_3$ and $\mathbb{ES}_4$ are almost the same. Nevertheless, in the former, buyers offer lower while sellers offer high electricity prices. The reason is that buyers attempt to make `Customer-Customer` contracts, which avoid them to pay more to the power plant while sellers provide high electricity price offers since $|\mathbb{B}| > |\mathbb{S}|$. This also proves the reason that the market operator announces the market price near the buyers' average electricity price offer. In the latter, the situation differs since $|\mathbb{B}| < |\mathbb{S}|$. Both buyers and sellers offer relatively lower electricity prices, which lead the market operator to provide the market price near the sellers' average electricity price offer.

According to Section 3.3, the malleability rate plays a key role in the two-stage price updating mechanism. Its influence, as Table 9 reflects, differs in each environmental scenario. For instance, in $\mathbb{ES}_1$, let us suppose $pb^1 = p_l$, $ps^1 = p_u$, and $\{\gamma, \delta\} = 0.001$. In this situation, buyers will not save more since they have to satisfy most of their demands through the power plant, which provides constant and high electricity price. Since the single seller's surplus energy is sold completely, its benefit is maximized. In $\mathbb{ES}_2$, let us assume $\{pb^1, ps^1\} = p_l$, $\gamma = 0.001$, and $\delta = 0.999$. As discussed in Section 3.3.2, $pd^t \cong \overline{pb}^t$ since $|\mathbb{B}| \ll |\mathbb{S}|$ and $\sum_{k=1}^{K}\sum_{i=1}^{N_k} d^t_{b_{i,k}}$. As a result, buyer's purchasing cost and sellers' selling benefit will decrease together.

Fig. 9 displays price updating diagrams of customers and the market operator at consecutive time intervals considering $\mathbb{ES}_3$. As Fig. 9(a) demonstrates, on one hand, while a buyer $b_{i,k}$ offers a lower electricity price to start purchasing, according to Eq. (7), the malleability rate enables that agent to offer $pb^{t+1}_{i,k}$ near $\overline{pb}^t$, at time interval t. On the other hand, when another buyer $b_{i',k}$ offers an initial electricity price $pb^1_{i',k}$ near the average operable price, i.e., $\frac{p_l+p_u}{2} = \frac{0.03+0.1}{2} = 0.065$, there will be no concrete reason to modify the next intervals' prices rapidly.

Fig. 9(b) illustrates the sellers' electricity price offers in a 24-hour. Let us suppose two sellers $s_{j,g}$ and $s_{j',g'}$ provide $ps^1_{j,g}$ and $ps^1_{j',g'}$ close to each other and higher than the average operable electricity price. If their malleability rate values are different, statuses of their electricity price updating will also be different. Considering another seller $s_{j'',g''}$, who offers $ps^1_{j'',g''} \cong p_l$, he/she, to increase the probability of selling the major part of the surplus energy, has to change it rapidly at future time intervals. Now, the main question is: why sellers should change their electricity price offers to get close to the weighted average of electricity price offers? There are two reasons. First, if they offer "very low" or "very high" electricity prices, with a high probability, there will be no or, at least, some few buyers who are interested in having any negotiation with them. Second, making offers as close to the weighted average of electricity price offers as possible increases the possibility of having more balanced and effective contracts. It also results in optimizing the customers' objectives.

Fig. 9(c) exhibits the electricity market's fixed price calculated at each time interval by Eq. (9). It can be seen that the market operator is interested in keeping the electricity market in a stable condition. When pd^t is slightly higher than the average operable electricity price at each time interval t, the market operator attempts to return it to the stable condition. It helps the power matching framework not only facilitate the electricity production and distribution, but also prevent the grid from unwilling outages. Let

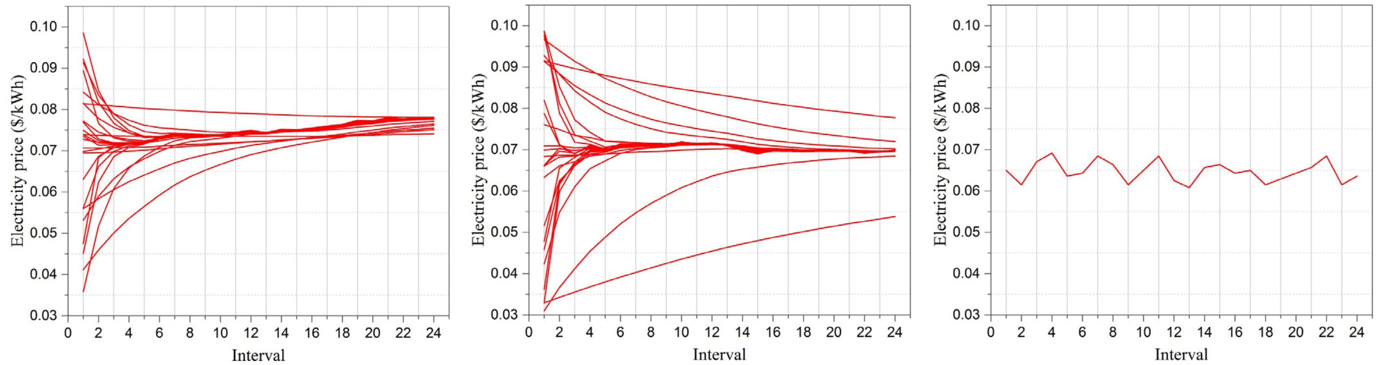
$$\left\{\exists\tau \in \{1,2,\dots,T\} \mid \left(\left|\overline{pb}^{\tau} - pd^{\tau}\right| < \epsilon\right) \wedge \left(\left|\overline{ps}^{\tau} - pd^{\tau}\right| < \epsilon\right)\right\}, \quad 0 \le \epsilon \le \left((p_u - p_l) \times T\right), \tag{18}$$

where τ is a time interval, at which the difference between weighted averages of electricity price offers with the market's price is less than $\epsilon \in \mathbb{R}^*$. The sooner τ is found, the quicker the market converges to equilibrium. This is the market operator's responsibility to adjust the ϵ.

Fig. 10 displays the performance comparison between the proposed two-stage price updating mechanism (referred as TSPUM in the legend) with different approaches proposed in HomChaudhuri and Kumar (2011) and Endo et al. (2016) (referred as Ref 1 and Ref 2 in the legend, respectivley). We assume all buyers offer the lowest possible electricity price, i.e., $p_l = 0.03$, at the first time interval. At the same time, sellers offer the highest possible electricity price, i.e., $p_u = 0.1$. We assume $\epsilon = 0.5$. According to simulation results, TSPUM reaches a acceptable equilibrium at time interval $\tau = 18$, where $\left|\overline{pb}^{18} - pd^{18}\right| = 0.457 < 0.5$ and $\left|\overline{ps}^{18} - pd^{18}\right| = 0.479 < 0.5$. In Endo et al. (2016), $\tau = 21$ while in HomChaudhuri and Kumar (2011) no τ is found. Since $|\mathbb{B}| > |\mathbb{S}|$ in $\mathbb{ES}_3$, all sellers' surplus energy is sold. They get benefit more since there is no critical competition among themselves. Therefore, their price offers are slightly higher than the average. In contrast, buyers need to compete with each other to increase `Customer-Customer` contracts. The pricing scheme proposed in Endo et al. (2016) behaves similarly. However, buyers face higher electricity costs while sellers receive lower benefits. In the mechanism developed in HomChaudhuri and Kumar (2011), buyers' criterion for buying electricity is only the sellers' location, not their price. Sellers' strategy to update their price offers depends on the number buyers currently bidding for it.

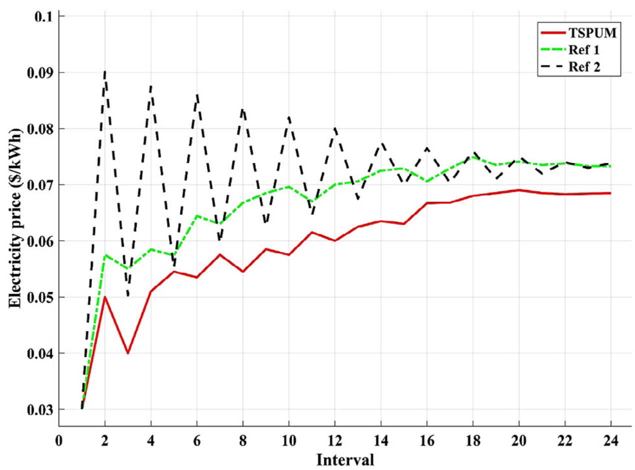
5.2.4. Computation time

Fig. 11 compares the computation time of RNSGA-II compared to algorithms proposed in HomChaudhuri and Kumar (2011) and Endo et al. (2016), when the number of customers increases (default setting). We consider $|\mathbb{B}| = |\mathbb{S}|$ in each case. The results have been averaged across the 50 trials performed for each case. RNSGA-II, to return the solution (i.e., the first Pareto-front obtained in the last generation), takes a shorter time than the algorithm proposed in Endo et al. (2016). Also, its computation complexity does not grow linearly, which confirms its scalability. The algorithm averagely uses 35% of the CPU and 10% of

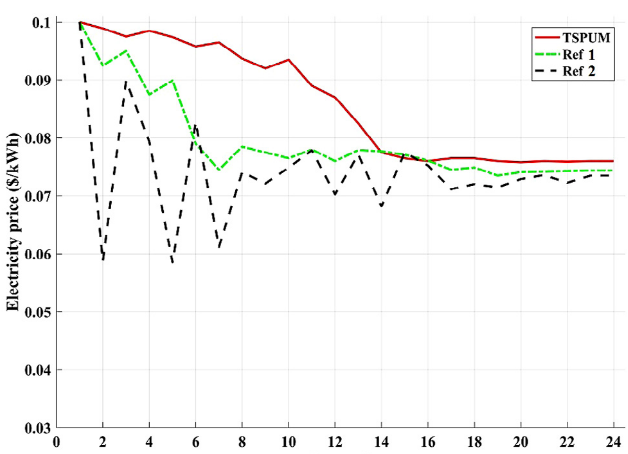


(a) Buyers' electricity price offers. (b) Sellers' electricity price offers. (c) Fixed electricity market price.

Fig. 9. Price updating diagrams of customers and the market operator using the two-stage price updating mechanism based on ES3.



(a) Buyers' average electricity price offers.



(b) Sellers' average electricity price offers.

Fig. 10. The performance comparison between the proposed two-stage price updating mechanism (referred as TSPUM in the legend) with other similar approaches proposed in HomChaudhuri and Kumar (2011) and Endo et al. (2016) shown as Ref 1 and Ref 2, respectively.

the memory. We apply the constraint handling procedure on all of the child solutions. Although this yields to have more diversity in solutions, nevertheless, it is known as the most computation intensive task in RNSGA-II.

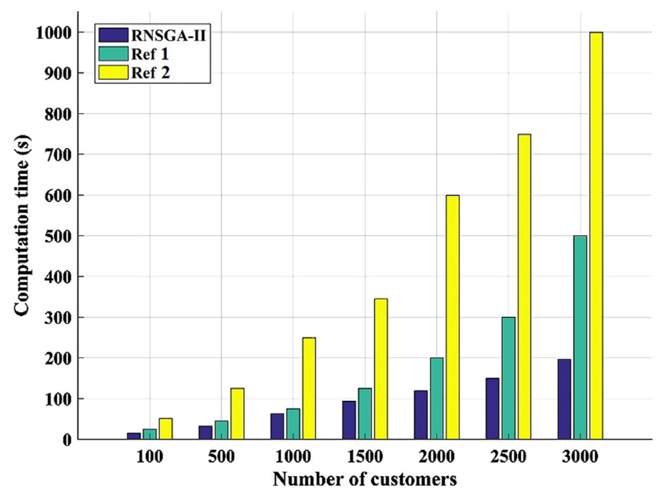


Fig. 11. Computation time of simulating RNSGA-II compared to algorithms proposed in HomChaudhuri and Kumar (2011) and Endo et al. (2016) shown as Ref 1 and Ref 2 in the legend, respectively.

6. Conclusions

This paper presented a market-driven framework formulating the power matching problem into a multi-objective optimization context. The framework attempted to match the buyers' demands with the sellers' produced power using an efficient power matching algorithm. A smart grid environment was considered including some electrical feeders. The negotiations among customers were done through three consecutive methods named Inside-Feeder, Feeder-to-Feeder, and Customer-to-PowerPlant. The last method worked as a backup to make the framework more reliable. Minimizing buyers' purchasing cost while maximizing sellers' benefit were the considered conflicting objectives.

A new two-stage iterative price updating mechanism was proposed to update the electricity price offers. Buyers and sellers were offering their desirable electricity purchasing prices to the market operator over time. Then, the market operator was responsible for equilibrating these prices and announcing an electricity market price to make negotiation contracts. Finally, a multi-objective evolutionary algorithm was developed to make the contracts considering the minimization of electricity distribution loss while respecting imposed grid stability constraints.

Simulation results discussed different environmental scenarios based on a default setup. It was shown that RNSGA-II clearly achieved better results compared to other algorithms in terms of customers' social welfare and diversity of solutions in the Pareto-front. Different stability analysis parameters were provided to challenge the performance of RNSGA-II, when number of customers increased, or evolutionary parameters were fluctuated. Then, the effects of the two-stage price updating mechanism on RNSGA-II were studied. Meanwhile, a convergence parameter was proposed to evaluate its performance compared to similar approaches proposed in the literature. Finally, computation time of running the framework with different number of customers was analyzed. It was shown that the framework was successful to scale the number of customers up with a reasonable computation time compared to other contributions.

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