A Quasi-Feed-In-Tariff policy formulation in micro-grids: A bi-level multi-period approach

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HIGHLIGHTS

• We present a bi-level optimization problem formulation for Quasi-Feed-In-Tariff (QFIT) policy. 

• QFIT dictates that subsidy prices dynamically vary over time depending on conditions. 

• Power grid’s physical characteristics affect optimal subsidy prices and energy generation. 

• To maximize welfare, policy makers ought to increase subsidy prices during the peak-load.

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ABSTRACT

A Quasi-Feed-In-Tariff (QFIT) policy formulation is presented for micro-grids that integrates renewable energy generation considering Policy Makers' and Generation Companies' (GENCOs) objectives assuming a bi-level multi-period formulation that integrates physical characteristics of the power-grid. The upper-level problem corresponds to the PM, whereas the lower-level decisions are made by GENCOs. We consider that some GENCOs are green energy producers, while others are black energy producers. Policy makers incentivize green energy producers to generate energy through the payment of optimal time-varying subsidy price. The policy maker’s main objective is to maximize an overall social welfare that includes factors such as demand surplus, energy cost, renewable energy subsidy price, and environmental standards. The lower-level problem corresponding to the GENCOs is based on maximizing the players' profits. The proposed QFIT policy differs from the FIT policy in the sense that the subsidy price-based contracts offered to green energy producers dynamically change over time, depending on the physical properties of the grid, demand, and energy price fluctuations. The integrated problem solves for time-varying subsidy price and equilibrium energy quantities that optimize the system welfare under different grid and system conditions.

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1. Introduction

The objective in the paper is to develop a bi-level multi-period decision making formulation in micro-grids for energy markets that integrates renewable energy generation considering different Policy Makers'(PM) and Generation Companies'(GENCOs) objectives, while taking into consideration the effect of power line characteristics and the physical constraints in the system. The policy maker (or in some cases, the independent system operator) represents the governing and monitoring body of the grid, that is concerned with the welfare of the power grid, rather than the profitability. In the bi-level problem, the upper-level problem corresponds to the PMs, whereas the lower-level decisions are made by competing market players or GENCOs. The goal of the PM is to maximize an overall social welfare (OSW) measure which depends on overall system reliability, price stability, supply surplus, percentage of renewable energy generation, and other factors. On the other hand, GENCOs are profit maximizing entities. GENCOs' plants are subject to physical constraints in terms of line loading capabilities, Power Transfer Distribution Factors (PTDFs), as well as profitability considerations. We study the short-term (hourly, daily) planning and the interaction between the PM and GENCOs in a micro-grid, as well as the effect of different line...
parameters on the optimal generation, and the eventual price according to the demand. A better understanding of the interaction between PMs and GENCOs would enable the design of policies towards improved grid performance.

The formulation presented in this paper takes into account the integration of renewable energy standard (RES, also called Renewable Portfolio Standard) into the smart-grid infrastructure (Weisenmiller et al., 2012a). Through providing incentives for the green energy producers (GEPs), the PM targets achieving a certain level of renewable energy production. Feed-In-Tariff (FIT) and Tradable Green Certificate (TGC) are examples of policies that encourage GENCOs to invest in green energy production. A FIT is an energy-based policy that provides long-term incentives for GENCOs through payment of a regular subsidy price per unit of green energy generated (Couture et al., 2010). This policy accelerates the investment in green energy production. FIT policy’s other objectives are job creation, decreasing electricity prices, growing the overall economy, building environment-friendly plants, managing waste streams, and attracting new investments (Couture and Cory, 2009). TGC policy is different than FIT policy in the sense that TGC GEPs are offered certificates proportional to the green energy produced. GENCOs utilizing TGC policy can trade these certificates independently of electricity (Tamas et al., 2010). FIT and TGC policies’ common objective is to achieve a certain level of renewable energy production. Albeit policies like FIT and TGC have numerous advantages and benefits, some arguments could be raised against such policies. As discussed by Couture et al. (2010), difficulty controlling overall policy costs, near-term upward pressure on electricity prices, and distortion of wholesale electricity market prices are some of the disadvantages of FIT policy. In addition, shortage of capital leading to the exclusion of smaller participants from the market, price instability of TGCs when the system is near a target level and uncertainty in future energy prices are some potential TGC disadvantages (Poputoaia and Fripp, 2008).

The bi-level formulation developed in this paper utilizes the integration of these policies in the micro-grid economies. It also incorporates the impact of line parameters on the optimal power flow (OPF) in the system. The Quasi-FIT (QFIT) policy proposed in this paper is different from the usual FIT policy in the sense that the subsidy price-based contracts offered to green energy producers are varying over time, depending on the physical properties of the power-network (such as line-losses and minimum and maximum generation), demand, and energy price fluctuation, rather than being held constant over a long-term contract.

The paper is organized as follows. In Section 2, we present the relevant work and background in the area of computational modeling in energy markets. We also give an overview of OPF in micro-grids. Research gaps, price function, some underlying assumptions and preliminaries, and QFIT PM’s and GENCO’s optimization problem formulation are presented in Section 3. In Section 4, a solution strategy for the bi-level, multi-period problem is outlined. Simulation results for different system characteristics and scenarios are included in Section 5. Section 6 presents closing comments and conclusions.

2. Background

In this section we provide a succinct background on the relevant research areas covered throughout the paper. A simple model of the lower-level non-cooperative game and decision making problem for GENCOs is discussed in Section 2.1. The optimization methodology used to model constrained non-cooperative games along with an overview of tools used to solve the optimization problem is reviewed in Section 2.2.

2.1. GENCOs’ interaction as a Nash–Cournot game

We model the lower-level problem as a non-cooperative, Nash–Cournot game where players make decisions independently. The Nash equilibrium of the non-cooperative games is generally used as a solution for problems associated with several players. The Nash equilibrium is a solution that guarantees that no player can individually improve their profits by changing their own strategies (Osborne and Rubinstein, 1994). The Nash–Cournot game (Hobbs, 2001; Han and Liu, 2013) is widely used in modeling non-cooperative games in energy markets. In this paper, we assume that the lower-level problem is modeled as Nash–Cournot game.

2.2. Bi-level problem formulation

In this paper, we develop a multi-period bi-level problem formulation in energy markets. The upper-level decision problem corresponds to the PM, while the lower-level optimization problem corresponds to the GENCOs. We first derive the equilibrium constraints on the lower-level problem. In the problem formulation, we assume various constraints for both the lower- and upper-level decision problems. Formulating the First Order Necessary Conditions (FONC) of optimality is the first step in finding the optimal solution to any non-cooperative constrained optimization problem. These optimality conditions are also called the Karush–Kuhn–Tucker (KKT) conditions. The FONC formulation results in a complementarity problem (Ferris and Pang, 1997). The complementarity problem is either a linear (LCP) or a nonlinear complementarity problem (NCP), depending on the nature of the constraints and the objective function. The solution can be found through methods developed for complementarity problems. Complementarity problems find the problem solution, as well as the optimization problem’s multipliers (Murty and Yu, 1997). Murty and Yu (1997), Duan et al. (2010), and Gabriel et al. (2012) provide various algorithms that are used to solve both LCPs and NCPs.

In this paper, we formulate the nonlinear complementarity problem using the KKT conditions. These conditions, resulting from the lower-level optimization problem, are used as a set of constraints in the upper-level PM’s decision making problem. This integration of the lower-level problem’s optimality conditions results in a mathematical problem with equilibrium constraints (MPEC) (Pieper, 2001; Hawthorne and Panchal, 2012). Due to the lack of convexity and nonlinearity of MPECs, the solution derived for the upper-level problem can be combinatorial (Hawthorne and Panchal, 2012). The non-linearity of the problem and the non-convexity of the feasible space make the feasible space too small and hence the formulated problem a challenging one to solve. Efficient algorithms have been developed for solving MPEC problems. Penalty interior-point algorithm (PIPA), piece-wise sequential quadratic programming (PSQP), smoothing SQP, and some implicit function based methods are all algorithms that have been developed to solve such MPECs (Pieper, 2001). Gabriel et al. (2012) provided an extensive review on LCPs and MPECs, with applications modeling natural gas markets. In this paper, the MPEC’s main objective is to solve for the time-varying optimal generation quantities and subsidy prices for the QFIT bi-level policy, considering price fluctuations, peak demand periods, and physical properties of the power-network.

2.3. Optimal power flow

The optimal power flow (OPF) problem seeks to control generation/consumption to optimize certain objectives such as minimizing the generation cost or power loss in the network. It is one of the fundamental problems in power system operation (Gan
and Low, 2013). In this section, we address the power flow aspect of the energy market.

2.3.1. Transmission losses

The physical characteristics of transmission lines, represented by the resistance and inductance, lead to electrical losses whenever electric power is transmitted through these lines. Transmission losses are proportional to the current passing through the line, and despite the significant reduction that high-voltage transmission achieves, these losses still impact the overall system and the cost of energy production (Benedict et al., 1992). This effect can be seen in the power balance equation that governs the operation of the power system:

$$\sum_{j=1}^{m} P_{Gj} = P_D + P_L(P_{G1}, P_{G2}, ..., P_{Gm}),$$  

where $P_{Gj}$ is the power generated by the $j$th GENCO, $P_D$ is the power demanded by the market and $P_L(P_{G1}, ..., P_{Gm})$ is the aggregate lost power in the transmission lines (Benedict et al., 1992). High transmission losses imply that a higher generation is required to satisfy the total demand, leading to higher costs and hence higher prices on the consumer side. For that reason, the PM tries to minimize transmission losses in an attempt to increase the overall welfare of the system.

2.3.2. Transmission lines capacity and congestion

Congestion occurs in electrical power systems when power transmission over a line is constrained by the maximum allowable flow in that line (PJM, 2010). Going above that limit can increase the losses and may jeopardize the stability of the overall system.

2.3.3. Power transfer distribution factors (PTDF)

In power systems, a transaction between nodes $m$ and $n$ is defined as a power injection by the generator at node $m$ that is removed by the load at node $n$. By definition, the PTDF is the fraction of the amount of a transaction from one zone to another that flows over a given transmission line (Christie et al., 2000). It is studied in order to understand the effect of a transaction on the state of all branches in the system, namely in terms of congestion. The power flow in line $l-k$ due to a 1MW transaction between node $m$ and node $n$ in a power grid is given by

$$\text{PTDF}_{lm, mn} = \frac{X_{in} - X_{km} - X_{ln} + X_{kn}}{X_{km}},$$

where $X_{km}$ is the reactance on transmission line $l-k$ and $X_{kn}$ is the entry on the $l$th row and $m$th column of the reactance matrix (Huang, 2011). Since micro-grids are in fact a small-scale version of the larger macro-grid, we assume that the different GENCOs in the micro-grid have a single load to feed in the form of the PM, who is then responsible for feeding energy to consumers. Hence, all power flows in the system are between the $j$th GENCO and a fixed load. The PTDF can therefore be simplified to $\text{PTDF}_{l-k}^{(j)}$, which is defined as the power flow in line $l-k$ due to a 1MW generation by the $j$th stakeholder.

3. Problem formulation

The work presented in this paper is an extension of Hawthorne and Panchal (2012) and Taha and Panchal (2013a, b), which was focused on the policy design problems related to decentralized energy infrastructure for multiple technologies, considering the uncertainty in stakeholders' preferences and targeting long-run policy goals. In this paper, we focus on the short-run objectives for the system operators such as sustaining a certain level of overall social welfare, while considering price and demand fluctuations during multiple periods. Through data from the UK, Tamas et al. (2010) studied FIT and Tradable Green Certificate (TGC) policies and derived the equilibrium expressions for the generation quantities and subsidy prices. In our formulation, we use a similar social welfare function. The formulation in Tamas et al. (2010) does not take into account the time-varying demand in the energy market, nor the variation of demand in the decision problem. This limitation is addressed in this paper. As mentioned in Section 1, the main objective of the paper is to develop a bi-level formulation in micro-grids that integrates renewable energy generation considering different PMs' and GENCOs' objectives, transmission line parameters and the power-network topology. However, formulations in the area of policy decision making in micro-grids are based on studying individual entities, one at a time (Masters, 2004; Kirschen and Strbac, 2004). In this paper, we address this limitation by studying the interaction between the two major decision making entities in the power markets, taking into account the physical properties of the grid.

In this section, we provide a bi-level mathematical formulation of the optimization problems corresponding to PMs and GENCOs. This formulation takes into consideration real-time energy pricing and multi-period decision making. In Section 3.1, the underlying assumptions and preliminaries are stated. In Sections 3.2 and 3.3, we present upper and lower level formulations of the problem by the PM and GENCOs, respectively.

3.1. Assumptions and preliminaries

The formulation presented in this paper corresponds to short-term planning in decentralized, deregulated energy markets. Short-term planning aims to optimize the hourly/daily operation of the micro-grid. Key issues in the short-term planning framework are: supply–demand balance, fair electricity pricing, and maintaining overall system reliability (Kirschen and Strbac, 2004). We consider a scenario with $n$ time periods. Index $i$ represents a specific time-period. In this paper, we assume that a time-period is defined over $1 h$ (the PM solves for generation dispatch quantities and GENCOs generate these quantities for a given price). We solve the bi-level, multi-objective optimization problem in each period $i$, based on hourly update signals from the PM. We assume that there are $m$ distinct GENCOs. Index $j$ represents a specific GENCO. Out of the $m$ GENCOs, $k$ of them are Green Energy Producers (GEP), thus $(m-k)$ produce non-renewable fossil fuel based energy or Black Energy Producers (BEP). The energy quantity supplied by the $j$th GENCO in the $i$th time-period is denoted by $q_{ij}^{(m)}$ for BEPs, $q_{ij}^{(m)}$ for GPs. This distinction is important since we assume that renewable energy generating companies receive a subsidy per unit energy generated. Let $q_{ij}$ be defined as the total quantity generated during the $i$th time-period. Let the sets $\mathcal{J}$ and $\mathcal{J}^*$ be the index sets of GEPs and BEPs. We also assume that there are $o$ energy consumers. The consumer index is notated as $u$. The quantity demanded by $i$th consumer in the $i$th time-period is denoted by $d_{iu}^{(o)}$. The electricity price is updated in each time-period. Consumers adjust their consumption based on their needs and based on the market prices for electricity. In addition, GEPs are rewarded with a subsidy price $\Delta_{ij}^{(o)}$ which varies during different time-periods and among different renewable energy production types. The main objective of the formulation is to solve for the dynamically optimal subsidy prices and energy generation quantities for each GENCO during all time-periods, whilst demand and energy market price change. Furthermore, as highlighted in Tamas et al. (2010) and Newbery (1998), we assume that the electricity demand is defined by a linear inverse demand function, $p_{ij} = \alpha - \beta q_{ij}$, where $p_{ij}$ is the price paid by consumers and $q_{ij}$ is the total amount of green and black energy produced in the $i$th time-period.
3.2. Upper-level QFIT policy problem formulation: PM’s objectives and constraints

In this section, we formulate the objectives of the PM along with the underlying constraints. A PM is a non-profit organization, hence it’s main goal is to improve overall social welfare (Tamas et al., 2010), rather than overall profitability, as mentioned earlier in Section 1.

The overall social welfare (OSW) measure used in this formulation is adapted from Tamas et al. (2010) and is defined as

\[ \text{OSW}_i = \mu_{CS} C_i - \mu_{F} F_i - \mu_{E} E_i \]

where

- \( C_i \) is the Consumption Surplus (or the surplus in supply); \( C \) is basic energy cost; \( F \) is the Renewable Energy Policy Price (total subsidy price); \( E \) is the Environmental Damages Cost (which is directly proportional to the black energy production quantities (multiplied by a constant \( k \)).

The PM’s main objective is to maximize the OSW in each time-period \( [4] \), where \( \mu_{CS,CF,E} \) are weight parameters that depend on the PM’s preferences, subject to multiple constraints (4):

\[
\text{maximize : } \text{OSW}_i = \mu_{CS} C_i - \mu_{F} F_i - \mu_{E} E_i \\
\text{subject to : } 0 \leq \sum_{k=1}^{q_{\text{max}}} (q_l^k - q_l) - \sum_{k=1}^{d_l^k} \leq U_l \\
q_l = \sum_{k=1}^{q_{\text{max}}} (q_l^k - q_l) - \sum_{k=1}^{d_l^k} \geq q_{\text{min}} \\
r_j = \sum_{k=1}^{d_l^k} \leq q_{l_{\text{max}}} \\
\text{OSW}_{\text{max}} \leq \text{OSW}_i \\
0 \leq \sum_{j=1}^{m} \Delta_j \leq \Delta_{\text{max}}
\]

The power flow in line \( l \) – \( k \) during the \( j \)th time-period is defined as \( q_{l_{-k}} \); \( q_{l_{-k_{\text{max}}}} \) is the maximum power flow capability of branch \( l \) – \( k \); \( g_{l_{-k}} \) is the power loss factor in line \( l \) – \( k \); \( \text{PTDF}_{l_{-k}} \) is the power flow in line \( l \) – \( k \) due to 1MW generation by \( j \)th stakeholder; \( q_{l_{-k}} \) are the total losses in the transmission lines. \( U_l \) is an upper bound on the surplus in supply; \( \rho \) is the regulatory percentage of the total energy produced from green energy sources (California Renewables Portfolio Standard (RPS) states that \( \rho = 0.33 \) by 2020, Weisenmiller et al., 2012b); \( \text{OSW}_{\text{min}} \) is the minimum overall social welfare determined by the PM; \( \Delta_{\text{max}} \) is the maximum subsidy price that the PM is willing to pay for the GEPs. The PMs solve this optimization problem in each time-period \( i \). In the next section, we formulate the GENCOS’ optimization problems.

3.3. Lower level problem formulation: GENCOS’ objectives and constraints

As mentioned in Section 3.1, we assume that there are \( m \) GENCOS, out of which \( k \) are GEPs and \( (m-k) \) are BEPs. We also assume that the lower-level problem is modeled as Nash–Cournot game, which is widely used in modeling non-cooperative games in energy markets. Generators have generation and ramping constraints that lead to a minimum power limit below which the generator cannot operate efficiently. First, large generating units cannot remain stable (i.e., maintain their online status) when operating at very low power, hence the minimum output power below which the generator is completely switched off (offline). Additionally, the start-up of large generators is a gradual and costly process, and startup cannot take up to several hours (Sumbera, 2011), during which costs are incurred without any power produced. Consequently, generation companies tend to keep their generators at a minimum power production, \( q_{\text{min}} \) unless the unit is not planned to be used in the short term future. A GENCO’s objective is to maximize its net profits subject to three constraints \( [5] \):

\[
\text{GENCO’s optimization problem : } \\
\text{maximize : } V_i^0 = q_l^0 (p_l + \Delta_l^0 - C_{\text{min}} - f^0) - f^0 \\
\text{subject to : } g_l^0 : q_l^0 \leq q_{\text{max}} \\
\text{subject to : } g_l^0 : q_{\text{min}} \leq q_l^0 \\
\text{subject to : } g_l^0 : V_{\text{max}} \leq V_i^0
\]

where \( V_i^0 \) is the payoff function to be maximized, \( q_{\text{max}} \) and \( V_{\text{min}} \) are the generation capacity limit and the minimum profit margin for the \( j \)th stakeholder, respectively. \( C_{\text{min}} \) is the sum of operation and maintenance cost per unit production; \( f^0 \) is the capital investment cost; \( f_i^0 \) is the fixed cost of production for each GENCO, which is independent on the level of energy production (such as mortgage costs and fixed taxations).

4. Solution methodology

In this section, we outline the methodology used to solve the bi-level, multi-period optimization problem. First, we derive the KKT conditions of optimality for the lower-level GENCOS’ optimization problem. We treat these conditions as constraints in the upper-level problem corresponding to the QFIT PM decision problem. Second, we append these conditions to the upper-level problem. Finally, we solve the augmented optimization problem using existing algorithms for solving MPECs.

The PM pays no subsidy price for the black energy producers \( q_{l_{-k}} \). As mentioned in Section 4, we solve the optimization problem for each time-period. Hence, for simplicity we drop the time-index \( (i) \). We can reformulate the GENCO’s payoff function as given in the following equation:

\[
V_i^0 = q_l^0 \left( \alpha - \beta \left( \sum_{k=1}^{q_{\text{max}}} q_l^k + \sum_{k=1}^{d_l^k} - \Delta_l^0 - C_{l_{-k}} \right) - f^0 \right), \quad j \in \mathcal{J}
\]

\[
\tilde{V}_i^0 = \tilde{q}_l^0 \left( \alpha - \beta \left( \sum_{k=1}^{q_{\text{max}}} \tilde{q}_l^k + \sum_{k=1}^{d_l^k} - C_{l_{-k}} - f^0 \right) \right) - f_{\text{min}}, \quad j \in \mathcal{J}
\]

Let

\[ \mathbf{g}(q^0) = [\mathbf{g}_l(q_l) \mathbf{g}_f(q_f)]^\top = [q_l^0 - q_{\text{max}} \mathbf{q}_{\text{min}} - q_l^0 \mathbf{V}_{\text{min}} - V_i^0] \]

be the vector of constraints formulated from \( (5) \). The GENCO optimization problem can be rewritten as

\[
\text{minimize : } -V_i^0 \\
\text{subject to : } \mathbf{g}(q^0) \leq 0.
\]
The KKT optimality conditions for the constrained GENCO problem can be formulated as

$$\begin{aligned}
\mu^w = [\mu^w_1, \mu^w_2, \mu^w_3]^T \succeq 0 \\
0 = \partial \ell^0 / \partial q^w + \mu^w - \gamma^w \frac{\partial g(q^w)}{\partial q^w} \\
\mu^w \succeq 0 \\
\frac{g(q^w)}{\partial q^w} \leq 0.
\end{aligned}$$

KKT conditions:

$$\begin{aligned}
\mu^w_1 - \mu^w_2 + (1 + \mu^w_3) \left( 2 \beta q^w - (\alpha + \Delta^0 - \bar{c}_m^0 - \bar{p}^0 - \beta \sum_{j \in J} q^w) \right) = 0, & \quad j \in \hat{J}, \\
\mu^w_1 - \mu^w_2 + (1 + \mu^w_3) \left( 2 \beta q^w - (\alpha - \bar{c}_m^0 - \bar{p}^0 - \beta \sum_{j \in J} q^w) \right) = 0, & \quad j \in \hat{J},
\end{aligned}$$

Deriving the second KKT condition, we get the following equations:

$$\begin{aligned}
\mu_1^w - \mu_2^w + (1 + \mu_3^w) \left( 2 \beta q^w - (\alpha + \Delta^0 - \bar{c}_m^0 - \bar{p}^0 - \beta \sum_{j \in J} q^w) \right) = 0, & \quad j \in \hat{J}, \\
\mu_1^w - \mu_2^w + (1 + \mu_3^w) \left( 2 \beta q^w - (\alpha - \bar{c}_m^0 - \bar{p}^0 - \beta \sum_{j \in J} q^w) \right) = 0, & \quad j \in \hat{J}.
\end{aligned}$$

The third KKT condition can be written as in the following equations:

$$\begin{aligned}
\mu_1^w (q^{w_0} - \hat{q}_{\text{max}}) + \mu_2^w (q_{\text{min}} - q^{w_0}) + \mu_3^w (\hat{V}_{\text{min}} - \hat{V}(0)) = 0, & \quad j \in \hat{J}, \\
\mu_1^w (q^{w_0} - \hat{q}_{\text{max}}) + \mu_2^w (q_{\text{min}} - q^{w_0}) + \mu_3^w (\hat{V}_{\text{min}} - \hat{V}(0)) = 0, & \quad j \in \hat{J}.
\end{aligned}$$

This system of equations produces $m$ unknowns corresponding to the equilibrium production quantities ($q^{0}$), and $3m$ unknowns corresponding to the KKT multipliers. The system of equations is undetermined with a total of $4m$ unknowns and $2m$ equations. As mentioned in Section 4, these KKT optimality conditions (are also referred to as equilibrium conditions) are added to the PM optimization problem. For a fixed time-period $i$, the corresponding upper-level optimization problem formulation can be re-written as in the following equation:

$$\begin{aligned}
\text{maximize : } & \quad OSW_i = c_{CS} C_i - \mu_c C_i - \mu_s F_i - \mu_e E_i \\
\text{subject to : } & \quad 0 \leq \sum_{j=1}^n (q^{0}_j - q_{l}) - \sum_{u=1}^m d^{(u)}_i \leq U_i \\
& \quad q_{l} = \sum_{l=1}^n \sum_{k=1}^m (f_{l-k} q_{l-k}) \\
& \quad q_{l-k} = \sum_{j=1}^m \sum_{k=1}^m \text{PTDF}_{j,k} q^{0}_l \leq q_{l-k, \text{max}} \\
& \quad \rho \sum_{j=1}^m q^{0}_j \leq \sum_{j=1}^m q^{0}_j \\
& \quad OSW_{\text{min}} \leq OSW_i \\
& \quad 0 \leq \sum_{j=1}^m q^{0}_j \leq \Delta_{\text{max}} \\
& \quad \mu^w = [\mu^w_1, \mu^w_2, \mu^w_3]^T \succeq 0 \\
& \quad \mu_1^w - \mu_2^w + (1 + \mu_3^w) \left( 2 \beta q^w - (\alpha + \Delta^0 - \bar{c}_m^0 - \bar{p}^0 - \beta \sum_{j \in J} q^w) \right) = 0, & \quad j \in \hat{J}, \\
& \quad \mu_1^w - \mu_2^w + (1 + \mu_3^w) \left( 2 \beta q^w - (\alpha - \bar{c}_m^0 - \bar{p}^0 - \beta \sum_{j \in J} q^w) \right) = 0, & \quad j \in \hat{J}, \\
& \quad \mu_1^w (q^{w_0} - \hat{q}_{\text{max}}) + \mu_2^w (q_{\text{min}} - q^{w_0}) + \mu_3^w (\hat{V}_{\text{min}} - \hat{V}(0)) = 0, & \quad j \in \hat{J}, \\
& \quad \mu_1^w (q^{w_0} - \hat{q}_{\text{max}}) + \mu_2^w (q_{\text{min}} - q^{w_0}) + \mu_3^w (\hat{V}_{\text{min}} - \hat{V}(0)) = 0, & \quad j \in \hat{J}.
\end{aligned}$$

This formulated optimization problem, which includes optimality conditions from lower-level problems, is called a Mathematical Program with Equilibrium Constraints (MPEC). The decision variables in this MPEC problem are the subsidy price ($\Delta^{(0)}$) and equilibrium generation quantities ($q^{0}$) for a given time-period and all stakeholders. The objective function to be optimized (OSW) is a quadratic function of the decision variables. Some of the constraints in (10) are linear (such as bounds on $OSW, \Delta, V, q$). Other equality constraints, such as the equilibrium constraints, are non-linear. The formulated MPEC (10) can be rewritten as minimize:

$$\begin{aligned}
\text{subject to : } & \quad c_i(x_i) = 0 \\
& \quad 0 \leq \mu_i \leq c_m(x_i) \geq 0 \\
& \quad x_i \leq x_i \leq x_i \\
& \quad (i, 1, 2, \ldots, n),
\end{aligned}$$

where

$$\begin{aligned}
& \quad \mu = [\mu_1^{(1)} \ldots \mu_i^{(k)} \ldots \mu_n^{(m)} \Delta_1^{(1)} \ldots \Delta_1^{(k)}]^T \\
\end{aligned}$$

is the inequality constraint vector we are solving for, $c_i(x_i)$ is the inequality constraints vector (demand-supply balance limit and renewable electricity standard), $c_m(x_i)$ represents the lower-level equilibrium constraints, resulting in the complementarity problem, and $[x, x]$ are the bounds on the decision variables.

5. Simulation results

Based on the MPEC formulation (10) and fixing the market and GENCO parameters for generic values, we provide results that explore and analyze the optimal values for the subsidy price ($\Delta^{(0)}$) and generation quantities ($q^{0}$) for all GENCOs during each time-period, under different testing conditions: normal conditions, low capacity and high losses on a branch. Through the results, we also illustrate the feasibility of the solution and validate market scenarios.

5.1. System modeling

The model of the studied system is shown in Fig. 1. The system is composed of four GENCOs (nodes 1, 2, 3 and 4) and a single load.
The entry maximum power that can flow through a particular branch in the system. These simulation results are assumed for a micro-grid (node 5) that represents the PM, encapsulating the demand side of the system. These simulation results are assumed for a micro-grid that supplies energy to a small city with a population of 10,000–12,000. As mentioned in Section 5.1, we assume that there are four main GENCOs (2 BEPs, 2 GEPs). GENCO 1 and 2 are assumed to be GEPs while GENCO 3 and 4 are assumed to be BEPs. As seen in the figure, all GENCOs are directly connected to the load, while GENCOs of similar energy production type are also interconnected. Furthermore, a link between GENCOs 1 and 3 ensures the coherence of the system and the ability to overcome any outage in some parts of it. The single load represents the consumer side of the system, ultimately embodied by the PM. The model structure is meant to represent an energy system where similar generation units are in close proximity to one another.

The line characteristics are taken into consideration in the form of line loss factors ($\gamma$) the line loading capability ($q_{i \rightarrow k, \text{max}}$) and the system PTDF matrix parameters (PTDF). Loss factors ($\gamma$) indicate the percentage of the power flow in a certain branch that is lost in transmission. For instance, a 5% loss factor of branch 1–5 means that only 95 kV out of 100 kW sent through that line arrive to the load. The line loading capability ($q_{i \rightarrow k, \text{max}}$) is the maximum power that can flow through a particular branch in the system. The entry $p_{j}$ of the PTDF matrix is the proportion of power flowing along line $i$ as the result of an injection at node $j$ (e.g., $p_{11} = 0.25$ states that 0.25 units of power will flow along line 1–2 at the result of a 1 unit injection at node $G_{2}$, to be withdrawn at the load node). Table 1 displays the PTDFs for the adapted 5-node model.

Table 1

<table>
<thead>
<tr>
<th>PTDF values</th>
<th>Branch</th>
<th>$G_{1}$</th>
<th>$G_{2}$</th>
<th>$G_{3}$</th>
<th>$G_{4}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1–2</td>
<td>0.2381</td>
<td>-0.381</td>
<td>0.0952</td>
<td>0.0476</td>
<td></td>
</tr>
<tr>
<td>1–3</td>
<td>0.2857</td>
<td>0.1429</td>
<td>-0.2857</td>
<td>-0.1429</td>
<td></td>
</tr>
<tr>
<td>1–5</td>
<td>0.4762</td>
<td>0.2381</td>
<td>0.1905</td>
<td>0.0952</td>
<td></td>
</tr>
<tr>
<td>2–5</td>
<td>0.2381</td>
<td>0.6391</td>
<td>0.0952</td>
<td>0.0476</td>
<td></td>
</tr>
<tr>
<td>3–4</td>
<td>0.0952</td>
<td>0.0476</td>
<td>0.2381</td>
<td>-0.381</td>
<td></td>
</tr>
<tr>
<td>3–5</td>
<td>0.1905</td>
<td>0.0952</td>
<td>0.4762</td>
<td>0.2381</td>
<td></td>
</tr>
<tr>
<td>4–5</td>
<td>0.0952</td>
<td>0.0476</td>
<td>0.2381</td>
<td>0.0476</td>
<td></td>
</tr>
</tbody>
</table>

An essential characteristic in any power flow calculation is the adopted demand curve. In the simulations, we use the National Grid New York electricity company’s posted demand curve to estimate the hourly demand for the demand from the Standard Service in New York (National Grid, 2013). We use the hourly projected load profile for the year 2013 to compute the average hourly demand for the year (averaged value through all days and hours for a year). Fig. 2 shows the resultant demand curve.

5.2. Demand curve

As mentioned in Section 3.2, the overall optimization problem is an MPEC (10) which solves for the QFIT policy parameters: the optimal time-varying generation quantities and subsidy prices. To solve for the derived MPEC (11) decision variables ($q, \Delta$), we use the Network-Enabled Optimization System (NEOS) server online solver. Different solvers on NEOS server were tested. In the simulations, we use the KNTIO nonlinear complementarity optimization problem solver. KNTIO solver provided optimal solutions compared to other optimization problem solvers such as CONOPT, MINOS, and filter. The coding language used to model our MPEC and simulate the problem through KNITRO is AMPL. Other simulation packages such as MATLAB’s fmincon has been also tested, providing unfeasible solutions.

Table 2 shows the simulation results for a standard case under normal conditions that illustrates the feasibility of some of NEOS solver’s optimization problem solvers. Table 4 includes the problem’s parameters for this simulation. To test for different micro-grid scenarios, we change some parameters from Table 4 in Section 5.4. We list the changed parameters in the relevant subsection of Section 5.4.

The variables listed in Table 2 ($q_{ij}, \Delta, CSW, CS, RE$) are the averaged outputs of the optimization problem solver for each solver (i.e., $\bar{q}_{ij} = \sum_{t=1}^{24} q_{ij}^{(t)}/T$). Under normal conditions, PATH solver produces a higher total subsidy price than the one allowed ($\bar{\Delta}j + \bar{\Delta}f = 17.32 \sigma > \Delta_{\text{max}} = 10 \sigma$), as well as a higher average supply surplus (consumption surplus) than the upper bound on CS ($\bar{CS} = 564 \text{ kW} > U = 500 \text{ kW}$). In addition, CONOPT and filter solvers...
produce negative values for the OSW function for many time-periods and a significantly high Renewable Energy percentage (RE).

Table 3 shows the optimal generation quantities for all time-periods with the variation of demand. As shown in Table 3, KNITRO provides the most feasible solutions. It is observed that the fluctuations in the generation quantities between two consecutive time-periods is lower than the fluctuations for the generation quantities produced by filterMPEC. Precisely, between the 8th and 9th time-periods, $q_3$ increases from 300 kW to 2384 kW. This could cause stability problems for GENCO 3. Using KNITRO solver, energy generation is distributed evenly among the GENCOs, satisfying all the constraints and bounds of the formulated MPEC (10). Thus, we use KNITRO solver to simulate the overall problem for different grid and system conditions.

### 5.4. Sample results

To analyze the effect of transmission line parameters on the generation quantities and optimal subsidy prices for the QFIT policy and the overall social welfare function, we consider different test cases to simulate the overall problem. In Section 5.4.1, we simulate the formulated model for standard transmission line parameters. Section 5.4.2 includes simulation results when changing the maximum capacity of one of the transmission lines. This allows us to test the impact of line loading capability constraints on generation quantities and the social welfare measure. In Section 5.4.3, we study the effect of high transmission line...
losses in couple branches on the optimal generation quantities and market price.

5.4.1. Standard case, normal conditions

The standard case will be used as a benchmark for all simulations. Table 4 contains the adopted values for most problem parameters used in the simulations. The only changed parameter for this simulation is $\Delta_{\text{max}} = 0.05$.

Transmission losses are 5% per line across the system. This assumption represents normal operating conditions and takes into consideration various losses throughout transmission. The maximum subsidy price ($\Delta_{\text{max}}$) is equal to $0.1$, $\alpha$ and $\beta$ are set to $0.1$ and $0.000001$, respectively. The line loading capabilities are set to 7000 kW across the system. We assume that GENCOs 1 and 2 have higher investment, operation and maintenance costs, and consequently higher required profitability margin. This assumption is meant to give the optimization problem a renewable energy prioritization aspect that we will observe later on. Finally, the maximum and minimum generation levels for the GENCOs are set to be 5000 kW and 300 kW, respectively, except for GENCO 1 ($q_{\text{max}} = 6000$ kW), for reasons explored in the next section. The minimum generation capacity is set to 300 kW for all units. In addition, the renewable energy generation percentage ($\rho$) is set to 30%.

Fig. 3 shows the optimal generation quantities for all GENCOs and the PM’s objective function (OSW) under normal conditions as a function of time. The inverse relationship between the high demand and OSW function can be seen. As the demand increases, the overall social welfare decreases due to tighter constraints on GENCOs and the PM. GENCOs produce more energy while operating within their generation capacity limits, transmission line constraints, and profitability margins, while the PM has to pay higher subsidy prices for GEPs, and higher environmental damage is caused due to high energy production from BEPs.

Moreover, GENCO 1 generates over 50% of the supplied demand, while operating at maximum capacity, as the optimal solution shows. Generated power is transmitted through transmission line 1–5 and through the following paths: 1–2–5, 1–3–5, and 1–3–4–5. GENCO 2 produces roughly 32% of the demand, ensuring that the minimum renewable energy standard is satisfied. GENCOs 1 and 2 produce more energy due to the higher minimum profitability value ($V^{(1)}_{\text{min}} = 45$, while $V^{(4)}_{\text{min}} = 20$), hence a need to produce more which is reflected by the solver’s optimal solution. GENCO 3 is operated at the minimum generation level and GENCO 4 is limited to just 20% of the generation. As demand increases, the reliance on the BEPs (GENCOs 3 and 4) increases as seen in Fig. 4.

This change is paralleled with a decrease in the output of GENCO 1, which despite being the most economical source of energy at low loads, cannot satisfy high demands single handedly, and is therefore phased out to allow for the other GENCOs to distribute the required generation amongst them. This can be observed between 9h00 and 17h00 when the demand goes above the 15,000 kW mark. The decrease in generation from GENCO 1 is also met with an increase with the output of GENCO 2 that ensures the Green Energy Generation is still above the required level.

Fig. 5 shows the time-varying optimal subsidy prices ($\Delta_1, \Delta_2$) for the QFIT policy. The first observation is that $\Delta_1$ and $\Delta_2$ are highly correlated with the nature of the demand curve. For the QFIT policy proposed, the subsidy prices for both generators increase from 1.8 to 1.9 $\alpha$ for low demand time-periods, and increase to 2.4 $\alpha$ at peak loads. This increase in subsidy prices is a response to system’s attempt to incentivize GEPs into more energy production, leading to the satisfying of the formulated MPEC’s constraints in (10); satisfying the increased demand, and maintaining the decreasing green energy production above the minimum RES, as seen in Fig. 4. Another observation is the fact that $\Delta_2$ exceeds $\Delta_1$ for all time-periods when the load is lower than 14,600 kW. This is reflected by a dominance of $q_1$ over $q_2$ in these
same time-periods. In fact, with $q_1$ already at the maximum generation limit, a high QFIT subsidy price ($\Delta_2$) must be paid for $q_2$ in order to ensure that both the demand and the RES constraint are met simultaneously.

In order to test the feasibility of the solution under different system conditions, we vary some parameters in different test cases. This allows us to observe the impact of these parameters on the system performance, generation quantities and transmission lines loading, as well as the GENCOs’ profitability and market prices.

5.4.2. Low capacity on line 1–5

In order to test the impact of line loading capability constraints on system performance, we change the capacity of line 1–5 from 7000 kW to 4000 kW while keeping all other system parameters unchanged. The optimal generation quantities for all GENCOs as a function of time is plotted in Fig. 6.

Decreasing the capacity constraint of line 1–5 impacts the generation of all units. Under low-load conditions, the reliance on GENCO 1 as the main generator decreases from 9 time-periods
to 7 time-periods (a time-period is defined as 1 h). This is due to
the fact that the power generated from GENCO 1 and transmitted
through the line is decreased due to the lower maximum capacity
on that line. Consequently, starting at 7h00, using the three other
units for generation becomes more economical than relying on
GENCO 1 as the main provider. GENCO 1 is therefore phased out,
with its output going below the 5500 kW mark by 7h00, as seen in
Fig. 7a below.

GENCOs 3 and 4 increase their output to the maximum of
5000 kW, leading to an increase in the power flow in lines 3–4,
3–5 and 4–5. This increase is due to the increase in load and the
decrease in the reliance on GENCO 1 and line 1–5. In fact,
compared to the standard case, GENCO 4 generates over the
1000 kW mark for four additional time-periods in the low line
capacity case, as seen in Fig. 7b. The need to maintain a minimum
of 30% green energy production results in increasing GENCO 2’s
generation to its maximum possible output, particularly between
10h00 and 17h00 when peak load conditions occur. The Renew-
able Energy Standard (RES) is thus satisfied despite the dominance
of black energy producers during peak hours, as illustrated in
Fig. 8.

In addition, the decrease in the generation of GENCO 1 leads to
an increase in the subsidy price paid to that unit: the PM is willing
to offer a higher subsidy price (Δ₁) to give GENCO 1 an incentive to
produce more, and hence satisfying the RES. This is mostly
observed during peak-load conditions, as shown in Fig. 9. Further-
more, decreasing the capacity of a line imposes additional con-
straints on the solution. The overall system solution is no less
favorable to the PM compared to normal conditions. The PM has to
pay higher subsidy prices for the GEPs to ensure that both the
demand and the minimum green energy production constraint are
continuously met as previously discussed. This leads to an overall
decrease in the OSW, particularly at peak demand time-periods.

5.4.3. High losses

In order to understand the impact of faulty conditions and the
high line losses on the overall system, we increase the loss
coefficient of lines 1–2 and 2–5 from 0.05 to 0.4 (γ₁₂ = γ₂₅ = 0.4).
This allows us to understand the impact of high losses on the
optimal generation quantities of the GENCO that is most
affected by these changes (in this case, GENCO 2). Since no feasible
solution could be found using the original generation upper bound
constraint, the maximum power generation is changed to
8000 kW for all generating units.

The chosen high-loss lines are both connected to the two GEPs,
who are therefore the most affected by this high line loss
condition. As seen in Fig. 11, the output of GENCO is approximately
6700 kW throughout the day. This value is high enough to ensure
that the GEP percentage constraint is met for all demand values,
regardless of all the variations in q₂, as observed in Fig. 11.

Furthermore, simulation results show that as in the case for
low capacity on line 1–5 in the previous section, the optimal QFIT
policy subsidy prices increase compared to the subsidy prices for
the standard case. GENCOs 2 and 4 start the day generating
4000 kW. However, as demand increases, GENCO 2 is phased
out, while GENCO 4 dominates the generation (producing
6000 kW by 9h00). As shown in Fig. 11, GENCO 2 is practically
shut down during the peak load conditions, operating at minimum
generation between 13h00 and 21h00. The latter, combined with a
constant q₁, leads to the domination of BEPs under high load
conditions, and a subsequent decrease in the OSW. In fact, an
increased reliance on GENCO 4 that makes up for the simultaneous
phasing out of GENCO 2 can be seen in Fig. 10. GENCO 4 is

![Fig. 10. Generation quantities comparison between normal and high losses condition. (a) q₁ and q₂. (b) q₃ and q₄.](image)

![Fig. 11. Generation quantities under high line loss conditions.](image)
complementing GENCO 2’s production level by increasing energy production when \( q_2 \) is low, despite the absence of a physical connection between the two units. This decreased reliance on GEPs throughout the day, and particularly during peak demand, leads to a decrease in the OSW.

Transmission lines 1–2 and 2–5 become too costly under high line loss conditions. Hence, the optimal solution under high-loss conditions avoids these lines as much as possible, and focuses the line loss conditions. Hence, the optimal solution under high-loss conditions during peak hours, as shown in Fig. 12. Furthermore, increasing the loss factors in lines 1–2 and 2–5 leads to a decrease in \( q_2 \). The 40% decrease in the power flow in paths 2–5 highlights the decreased reliance on GENCO 2 as a direct energy supplier in the system. As depicted in Fig. 12, the power flow direction in line 1–2 changes under high loss conditions, with the increase in \( q_1 \), causing power to be transmitted from node 1 to node 2. In addition, the increase in power flow for BEPs (GENCos 3 and 4) highlights an increase in generation and transmission, as can be seen by the 6800 kW and 5600 kW transmitted in lines 4–5 and 3–5. The PM relies more on GENCos 1 and 4 for energy production.

6. Future work and conclusions

The second lower-level problem in our formulation corresponds to large-scale consumers, represented by manufacturing firms and commercial entities. In this paper, we assumed that the demand is static. In the future work, we are interested in studying demand response: the variability and deviation in the consumers’ energy consumption in response to the change in the market price of electricity over time. According to the Federal Energy Regulatory Commission (FERC), demand response is defined as the variability and deviation in the consumers’ energy consumption in response to the change in the market price of electricity over time. In addition, demand response also incorporates changing the consumers’ behavior (decreasing energy consumption), through incentivising end-users to consume less whenever system reliability is under jeopardy. It is estimated that a 5% lowering of demand would result in a 50% price reduction during the peak hours of the California electricity crisis in 2000–2001. The market also becomes more resilient to intentional withdrawal of offers from the supply side.

6.1. Optimal demand backlogging problem

In this section, a formulation is presented for the optimal energy backlogging problem developed in Roozbehani et al. (2011) for the low-level decision problem of the large-scale consumers. The formulation incorporates this model into the bi-level optimization problem proposed in this paper. This will lead to a better response by consumers during peak-demand periods, which will cause overall social welfare to increase. In the following formulation, assume that the demand from any consumer \( u \) in time-period \( i \) is defined as

\[
d_i^{(u)} = d_i^{(u)} + d_{i}\,\text{ where } i = 1, \ldots, n, u = 1, \ldots, o,
\]

where \( d_i^{(u)} \) is the shiftable demand and \( d_{i}\,\text{ is the firm demand which cannot be postponed. The firm demand } d_i^{(u)} \text{ needs to be fulfilled in the } ith \text{ time-period, whereas shiftable demand can be satisfied in subsequent time-periods (any period } t, \text{ where } t \\in [i + 1, \ldots, n].) \text{ Let } e_i^{(u)} \text{ be the amount of electricity the consumer allocates to fulfilling some or all of their shiftable demands (} d_i^{(u)} \text{) at time } i. \text{ Our goal is to find the optimal } e_i^{(u)} \text{ for all time-periods. Denote by } x_i^{(u)} \text{ the amount of backlogged accumulated demand. Define } y_i^{(u)} \text{ as the total consumed energy. We also define a penalty function } J_i(x_i^{(u)}) \text{ which represents a quantification for the inconvenience caused by the backlogging of the user demand. Hence, the dynamic optimization problem for the } ith \text{ consumer can be formulated as}

\[
\begin{array}{ll}
\text{minimize:} & \sum_{i=1}^{n} J_i(x_i^{(u)}) + p_i(y_i^{(u)}) \\
\text{subject to:} & x_{i+1}^{(u)} = x_i^{(u)} + (e_i^{(u)} - d_i^{(u)}) \\
& y_i^{(u)} = d_i^{(u)} + e_i^{(u)}
\end{array}
\]

(12)

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Given a price signal $p_i$ and information from consumers about their preferences ($d_i^{(u)}, d_i^{(w)}, j_i$), the goal of the dynamic optimal backlogging problem is to solve for the optimal allocated demand ($j_i^{(w)}$). After solving for the optimal demand, this quantity is incorporated in the PM optimization problem (4) by setting $d_i^{(w)} = d_i^{(w)} + j_i^{(w)}$ for all time-periods.

6.2. Summary and conclusions

Micro-grids and decentralized energy systems are complex large-scale systems that use the information supplied by different interacting blocks, such as producers' and consumers' behavior and preferences, to autonomously improve the overall social welfare and reliability. A better interaction between the different cooperating blocks (PMs, GENCOs) leads to a better sustainability of micro-grid energy resources. Hence, it is crucial to formulate and analyze the interaction between the different stakeholders in these energy systems, while implementing a certain renewable energy policy or standard.

In this paper, we present a multi-period bi-level problem formulation of the decisions made by the PM and GENCOs, resulting in non-linear constrained MPEC, that formulates a Quasi-Feed-In-Tariff model. We assume that some GENCOs are GEPs, while others are BEPs. PM’s main objective is to maximize an overall social welfare utility function that includes meeting a certain renewable energy production standard and supply-demand balancing, as well as satisfying the physical constraints of the transmission lines. The GENCOs’ goal is to maximize their profits under certain capacity constraints. The necessary conditions of optimality for the lower-level optimization problem are also derived. The problem’s objective is to solve for optimal time-varying generation quantities and QFIT policy subsidy per unit under different conditions such as peak-demand and high disturbance/losses in the power-network.

Simulation examples are shown to analyze and compare the results under different conditions, in order to understand the effect of line characteristics and system parameters on the performance of the overall grid, as well as the impact on the generation levels for the GENCOs, the optimal subsidy prices, and the energy price. We consider a simplistic market with two GEPs, two BEPs, and a load. The primary objective of the formulated optimization problem is to solve for the optimal generation quantities and dynamically varying subsidy prices (for GENPs), assuming a generic demand function. In order to solve the formulated bi-level MPEC, we simulate the system using different optimization problem solvers. Simulation results show the effect of the solvers used on the feasibility of the proposed solution. KNITRO provided feasible solutions for all time-periods. Furthermore, results illustrate that the OSW function decreases during peak demand time-periods due to the increase in the QFIT policy subsidy price and generation quantities, and thus the environmental risks associated with the BEP. Similarly, tightening the constraints on the GENCOs by line losses or low line capacities lead to less favorable conditions that decrease the OSW of the system. This subsequently results in an increase in the price. The results show that GENCOs must receive a higher subsidy price during peak-demand time-periods. These results illustrate the appropriateness of the welfare function choice under different conditions and constraints. In addition, the implementation of a time-varying subsidy price for GEPs (that depends on the grid and demand conditions) through the QFIT policy would increase the social welfare of the micro-grid.

In future work, our goal is to integrate a real-time analysis for the demand side of a micro-grid as formulated in Section 6.1, where the consumers adjust their consumption optionally according to a time varying price function. In addition, we will consider constrained OP problems for GENCOs and PMs that include power-flow constraints, voltage stability analysis, and other technical constraints. We also aim to study the stochastic nature of the demand-side to achieve a better understanding of the interaction between the consumers and other smart-grid blocks, as well as the uncertainty in the bi-level problem parameters.

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References


