Quantification of the Impact of GHG Emissions on Unit Commitment in Microgrids

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Abstract—The global climate change creates a dire need to mitigate greenhouse gas (GHG) emissions from thermal generation resources (TGRs). While microgrids enable the deeper penetration of renewable resources, their capabilities in combating climate change can fully come to fruition only through short-term planning approaches that expressly assess the entire breadth of impact of GHG emissions. To this end, we propose a novel unit commitment (UC) approach that enables the representation of GHG emissions from TGRs, the stipulation of GHG emission constraints, and the ex-ante evaluation of carbon tax payment. We quantify the relative merits of the proposed approach vis-à-vis the classical UC approach using representative studies. The results indicate that the proposed UC approach yields lower costs than does the classical UC approach and achieves a greater reduction in costs as carbon tax rate increases. Further, increasing carbon tax rates can markedly disincentivize TGR generation under the proposed approach.

Index Terms—carbon tax, microgrids, power generation planning, unit commitment

I. INTRODUCTION

A microgrid is a cluster of loads, distributed generation resources (DGRs), and electric storage resources (ESRs) that operate in coordination to supply electricity in a reliable manner. Typically integrated to its host power system at the distribution level, a microgrid is perceived by its distribution system as a single entity responding to appropriate signals [1]. For all intents and purposes, a microgrid is a microcosm of a bulk power system that retains most of its innate operational characteristics.

The DGRs in a microgrid can be broadly bifurcated into two categories: thermal generation resources (TGRs) and variable energy resources (VERs). TGRs include microturbines, fuel cells, and reciprocating internal combustion engines with generators and are especially common in microgrids in rural areas, developing nations, and military premises [2]. TGRs have controllable power output but can undergo only gradual temperature changes and hence are subject to minimum uptime, minimum downtime, and ramping constraints [3].

VERs, such as photovoltaic (PV) panels and wind turbines, are characterized by a renewable fuel source that can be neither stored nor controlled. VERs cannot be similarly situated to TGRs, since VER power outputs are highly time-varying, intermittent, and uncertain. Further, microgrids with integrated ESRs, such as batteries, ultracapacitors, and flywheels, possess various capabilities, including the hallmark capability to store electric energy for later use.

Similar to bulk power systems, the short-term planning of a microgrid can be determined via unit commitment (UC) and economic dispatch (ED) decisions [4]. The classical unit commitment (CUC) approach seeks minimum cost strategies to determine the start-up and shut-down of TGRs based on expected load, equipment limitations, and operational policies [3]. The equipment limitations of TGRs and the inter-temporal constraints of microgrid physical asset operations render UC a time-coupled problem, and necessitate that the UC decisions be taken typically one-hour to one-week ahead of operations based on the uncertain data/information available at the time of decision. The injections levels of TGRs are subsequently determined by the solution of the ED problem after most of the uncertainty unravels.

Microgrids lend themselves as conducive environments to enabling the deeper penetration of VERs without unduly exacerbating the stress on transmission systems. As such, microgrids, aided by UC approaches that evaluate the full breadth of impact of greenhouse gas (GHG) emissions, can play a pivotal role in combating global climate change.

The thorough assessment of GHG emissions in short-term microgrid operations hinges on practical UC approaches that expressly include GHG emission models. Such approaches further need to have the capability to stipulate explicit constraints on the amount of GHG emissions over a study period.

Another major requirement, brought on especially with the advent of carbon pricing schemes, is the analysis of the monetary impacts of GHG emissions. Carbon tax sets a specific price on the amount of emitted carbon dioxide equivalent (CO$_2$e) to internalize the negative externalities of TGR generation. The prevalence of carbon pricing has been soaring in recent years, with the price reaching $139/ton CO$_2$e in Sweden [5].

The CUC approach does not consider GHG emissions and so does not take into account the carbon tax payment due to the GHG emissions from TGRs at the time of decision. As such, the carbon tax payment, for which the microgrid is liable, is evaluated ex-post under the CUC approach, thereby potentially bringing about dire economic implications. The UC

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**Nomenclature**

- \( \mathcal{H} \) set of simulation time periods
- \( \mathcal{G} \) set of distributed generation resources (DGRs)
- \( \mathcal{VER} \) set of variable energy resources (VERs)
- \( \mathcal{TGR} \) set of thermal generation resources (TGRs)
- \( Y \) set of electric storage resources (ESRs)
- \( g \) index of an hourly time period
- \( \gamma \) distributed generation resource \( g \)
- \( \sigma_s \) electric storage resource \( s \)
- \( \left[p_{\gamma g}^{\text{max}}\right] \) minimum power output of DGR \( \gamma \) \( g \) (kW)
- \( \left[p_{\gamma g}^{\text{max}}\right] \) maximum power output of DGR \( \gamma \) \( g \) (kW)
- \( [T_{\gamma g}^{\text{up}}] \) minimum uptime of TGR \( \gamma \) \( g \) (hrs)
- \( [T_{\gamma g}^{\text{down}}] \) minimum downtime of TGR \( \gamma \) \( g \) (hrs)
- \( \vec{e}_{\gamma g}, \vec{d}_{\gamma g}, \vec{c}_{\gamma g} \) quadratic (\$/kW\(^2\)h), linear (\$/kW\(h\)) and fixed (\$/h) fuel cost parameter of TGR \( \gamma g \)
- \( \mu_{\gamma g} \) start-up cost of TGR \( \gamma \) \( g \) (\$
- \( \overline{k}_{\gamma g}, \overline{c}_{\gamma g}, \overline{c}_{\gamma g} \) quadratic (kgCO\(_2\)e/kW\(^2\)h), linear (kgCO\(_2\)e/kWh), and fixed (kgCO\(_2\)e/h) GHG emission parameter of TGR \( \gamma g \)
- \( [\kappa]^M \) maximum GHG emission limit for the study period (kgCO\(_2\)e)
- \( \psi \) carbon tax rate (\$/kgCO\(_2\)e)
- \( \nu_{\gamma g} \) GHG emissions of TGR \( \gamma g \) over the study period (kgCO\(_2\)e)
- \( \kappa \) total GHG emissions from all microgrid TGRs over the study period (kgCO\(_2\)e)
- \( \left[p_{\sigma_s}^{\text{min}}\right] \) minimum discharging power of ESR \( \sigma \) \( s \) (kW)
- \( \left[p_{\sigma_s}^{\text{max}}\right] \) maximum discharging power of ESR \( \sigma \) \( s \) (kW)
- \( \left[p_{\sigma_s}^{\text{min}}\right] \) minimum charging power of ESR \( \sigma \) \( s \) (kW)
- \( \left[p_{\sigma_s}^{\text{max}}\right] \) maximum charging power of ESR \( \sigma \) \( s \) (kW)
- \( E_{\gamma g}^{\text{min}} \) minimum energy storage limit of ESR \( \sigma \) \( s \) (kWh)
- \( E_{\gamma g}^{\text{max}} \) maximum energy storage limit of ESR \( \sigma \) \( s \) (kWh)
- \( n_{\sigma_s}^1 \in [0,1] \) discharging efficiency of ESR \( \sigma \) \( s \)
- \( n_{\sigma_s}^2 \in [0,1] \) charging efficiency of ESR \( \sigma \) \( s \)
- \( P_{\gamma g}^{\text{load}}[h] \) total microgrid load in hour \( h \) (kW)
- \( \lambda[h] \) the price at which the microgrid purchases (resp. sells) energy from (resp. to) the distribution company in hour \( h \) (\$/kW\(h\))
- \( [R[h]] \) spinning reserve requirement for hour \( h \) (kW)
- \( p_{\gamma g}^1[h] \) power generation of DGR \( \gamma \) \( g \) in hour \( h \) (kW)
- \( u_{\gamma g}^1[h] \) commitment status of TGR \( \gamma \) \( g \) in hour \( h \)
- \( r_{\gamma g}[h] \) spinning reserve of TGR \( \gamma \) \( g \) in hour \( h \)
- \( u_{\sigma_s}[h] \) injection status of \( \sigma \) \( s \) in hour \( h \)
- \( u_{\sigma_s}^0[h] \) withdrawal status of \( \sigma \) \( s \) in hour \( h \)
- \( p_{\sigma_s}[h] \) power injection of \( \sigma \) \( s \) in hour \( h \) (kW)
- \( P_{\sigma_s}^1[h] \) power withdrawal of \( \sigma \) \( s \) in hour \( h \) (kW)
- \( p_{\sigma_s}^2[h] \) net power injection of \( \sigma \) \( s \) in hour \( h \) (kW)
- \( E_{\sigma_s}[h] \) energy stored in \( \sigma \) \( s \) in hour \( h \) (kWh)
- \( P_{\sigma_s}^0[h] \) net power injection of the distribution system to the microgrid in hour \( h \) (kW)
- \( \xi_{\gamma g}^1 \) fuel cost of TGR \( \gamma \) \( g \) over the study period (\$
- \( \xi_{\gamma g}^2 \) total start-up cost of TGR \( \gamma \) \( g \) over the study period (\$
- \( \xi_{\sigma} \) total net cost for the exchange of power with the distribution company (\$
- \( \xi_{\gamma g} \) carbon tax payment (\$

Approaches for microgrids must conduct an ex-ante evaluation of the carbon tax payment that will have been incurred, as per the effective carbon pricing schemes. The ex-ante evaluation of carbon tax payments permits a more thorough quantification of the benefits of taking UC decisions that favor the greater utilization of VERs jointly with ESRs in lieu of TGRs.

While economic mechanisms can serve as prime movers for major change, a key issue that needs to be investigated is whether carbon tax rates can effectively deter the use of TGRs and incentivize the further utilization of VERs in conjunction with ESRs. As such, the analytical study of the influence of carbon pricing schemes on UC decisions can provide useful guidance for policy makers addressing global warming.

**A. Related Work**

There is a growing body of literature on UC approaches for microgrids. In [4], the authors propose a UC approach for microgrids with integrated TGRs, VERs, and ESRs, yet the proposed approach does not consider the GHG emissions from integrated TGRs or evaluate the monetary impacts of GHG emissions. The frameworks presented in [6], [7] consider ESRs, TGRs, and VERs in the UC of a microgrid; nonetheless, they do not model the GHG emissions from TGRs or their economic implications.

In [8], the UC decisions for microgrids with integrated TGRs and VERs have been studied, where the GHG emissions from TGRs are modeled. However, [8] does not include an explicit constraint on the amount of GHG emissions, study carbon tax rates, or include ESRs—which are key to enable the greater utilization of VERs and so to mitigate GHG emissions. While the approach presented in [9] models the GHG emissions from TGRs of a microgrid, it does not impose any constraints on the amount of GHG emissions or evaluate the impact of carbon tax rates. In [10], the UC of a microgrid is studied, where the GHG emissions from TGRs and carbon emission costs are modeled. However, the authors of [10] do not study the influence of carbon tax rate on UC decisions or model an explicit constraint for GHG emissions from TGRs in the UC problem formulation.

**B. Contributions of the paper**

The general contributions and novel aspects of this paper are as follows:

1. We propose a novel UC approach that comprehensively evaluates the full range of impact of GHG emissions, and not just the carbon tax. We refer to this approach as environmental unit commitment or EUC. To the best of our knowledge, this is the first approach that simultaneously models GHG emissions, allows the stipulation of a constraint on GHG emission amount, and conducts an ex-ante evaluation of the carbon tax payment. We conduct representative studies and demonstrate the effectiveness of the proposed EUC approach on real-world data.

2. We examine the sensitivity of the UC decisions to carbon tax rate and study the extent to which carbon tax can

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1 The source code is available at: https://github.com/oyurdakul/euc
influence the operation of microgrid TGRs, ESRs, and power exchange with the distribution grid. Our findings regarding the influence of carbon tax rate on short-term microgrid operations could prove useful for policy makers in judiciously determining carbon tax rate.

This paper contains four additional sections. In Section II, we develop models for the microgrid physical, economic, and environmental aspects. In Section III, we present the mathematical formulations of the EUC and CUC approaches. We illustrate the capabilities and effectiveness of the proposed EUC approach in Section IV with representative studies and discuss the results. We summarize the paper and provide directions for future work in Section V.

II. MICROGRID MODELING

We devote this section to the delineation of the microgrid models. We discretize the time axis and adopt one hour as the smallest indecomposable unit of time. In line with [11], we decompose the study period into \( H \) non-overlapping hours and define the study period by the set \( \mathcal{H} := \{ h : h = 1, ..., H \} \).

A. Physical Asset Models

We consider a microgrid interfaced with the distribution system and denote by \( \mathcal{G} \) the set of DGRs in the microgrid. We define the subsets \( \mathcal{G}_{\text{VER}} \) and \( \mathcal{G}_{\text{TGR}} \) to denote the set of VERs and TGRs, respectively, and we write the relation \( \mathcal{G} = \mathcal{G}_{\text{VER}} \cup \mathcal{G}_{\text{TGR}} \). We define by \( p^i_{\gamma_g}[h] \) the kW power injection of \( \gamma_g \) in \( \mathcal{G} \) in hour \( h \).

The binary variable \( u^i_{\gamma_g}[h] \in \{0, 1\} \) denotes the commitment status of TGR \( \gamma_g \) in \( \mathcal{G}_{\text{TGR}} \) in hour \( h \). \( u^i_{\gamma_g}[h] = 1 \) if \( \gamma_g \) is up in hour \( h \), and 0 otherwise. We define by \(\bar{r}^i_{\gamma_g}[h] \) the spinning reserve of TGR \( \gamma_g \) in \( \mathcal{G}_{\text{TGR}} \) in hour \( h \). We denote by \( p^s_{\sigma_s}[h] \) the total kW load of the microgrid in hour \( h \).

We consider that an ESR may inject power, withdraw power, or remain idle in hour \( h \). Let \( u^s_{\sigma_s}[h] = 1 \) if the ESR \( \sigma_s \) withdraws power in hour \( h \), and 0 otherwise. Similarly, let \( u^w_{\sigma_s}[h] = 1 \) if \( \sigma_s \) injects power in hour \( h \), and 0 otherwise. We denote by \( p^i_{\sigma_s}[h] \) and \( p^w_{\sigma_s}[h] \) the power injection and power withdrawal of \( \sigma_s \) in hour \( h \) respectively. We define by \( p^0_{\sigma_s}[h] := p^i_{\sigma_s}[h] - p^w_{\sigma_s}[h] \) the net power injection of \( \sigma_s \) in hour \( h \). Let \( E_{\sigma_s}[h] \) denote the energy stored in the \( \sigma_s \) at the end of hour \( h \), or equivalently, at the beginning of hour \( h+1 \).

We assume that the distribution company (DisCo) is the sole owner and operator of the distribution system with which the microgrid is interfaced. Let \( p^0_{\mathcal{G}}[h] \) denote the net power injection of the distribution system to the microgrid in hour \( h \). We adopt the convention that if the distribution system injects (resp. withdraws) power to (resp. from) the microgrid in hour \( h \), then \( p^0_{\mathcal{G}}[h] > 0 \) (resp. \( p^0_{\mathcal{G}}[h] < 0 \)). If there is no exchange of power between the microgrid and the distribution system in hour \( h \), then \( p^0_{\mathcal{G}}[h] = 0 \).

B. Environmental Models

We devote this subsection to the development of the models for GHG emissions from the microgrid TGRs. We explicitly represent the total \( kgCO_2 e \) GHG emission of each TGR \( \gamma_g \) over the study period by the relation

\[
\zeta_{\gamma_g} = \sum_{h \in \mathcal{H}} \left[ \left( \bar{K}_{\gamma_g} (p^i_{\gamma_g}[h])^2 + K_{\gamma_g} (p^i_{\gamma_g}[h]) + c_{\gamma_g} \right) u^i_{\gamma_g}[h] \right] (1 \text{ hr}),
\]

based on the GHG emission modeling in [8]. The terms \( \bar{K}_{\gamma_g} \), \( K_{\gamma_g} \) and \( c_{\gamma_g} \) in (1) denote the quadratic (\( kgCO_2 e/kW^2 h \)), linear (\( kgCO_2 e/kW h \)), and fixed (\( kgCO_2 e/h \)) GHG emission parameter of the TGR \( \gamma_g \), respectively.

We further express the total \( kgCO_2 e \) GHG emissions from all microgrid TGRs over the study period by

\[
\kappa = \sum_{\gamma_g \in \mathcal{G}_{\text{TGR}}} \zeta_{\gamma_g},
\]

The proposed EUC approach allows the stipulation of an upper limit on the total GHG emissions from microgrid TGRs over the study period. Such an upper limit ensures that, independent of the economic factors, the generation of microgrid TGRs is explicitly constrained by the resulting GHG emissions. To this end, we model by \( [\kappa]M \) the maximum GHG emission limit for the study period.

C. Economic Models

In this subsection, we model the costs and benefits associated with the microgrid operation over the study period. We express the fuel cost of TGR \( \gamma_g \) over the study period by

\[
\xi^1_{\gamma_g} = \sum_{h \in \mathcal{H}} \left[ \bar{K}_{\gamma_g} (p^i_{\gamma_g}[h])^2 + K_{\gamma_g} (p^i_{\gamma_g}[h]) + c_{\gamma_g} \right] u^i_{\gamma_g}[h] \right] (1 \text{ hr}),
\]

based on [4]. We express the total start-up cost of TGR \( \gamma_g \) over the study period by

\[
\xi^2_{\gamma_g} = \sum_{h \in \mathcal{H}} \left[ \mu_{\gamma_g} (1 - u^i_{\gamma_g}[h]) \right] (1 \text{ hr}),
\]

We consider that the DisCo uses time-of-use rates and utilizes net metering as the billing mechanism. We express the total net cost \( (i.e., \text{ total cost minus total benefit}) \) associated with the exchange of power with the DisCo by

\[
\xi_{\mathcal{G}} = \sum_{h \in \mathcal{H}} \left[ \lambda[h] p^0_{\mathcal{G}}[h] \right] (1 \text{ hr}).
\]

The CUC approach evaluates only \( \xi^1_{\gamma_g} \) and \( \xi^2_{\gamma_g} \) as the costs associated with the operation of TGR \( \gamma_g \). A key source of cost that is not captured by the CUC approach is the carbon tax payment associated with the GHG emissions from TGRs over the study period. Our objective is to enable the ex-ante evaluation of carbon tax payment simultaneously with \( \xi^1_{\gamma_g} \) and \( \xi^2_{\gamma_g} \). As such, we expressly model the carbon tax payment in the proposed EUC approach.

We denote by \( \psi \) the carbon tax rate, which is the price for each unit of \( kgCO_2 e \) emitted, evaluated in $/kgCO_2 e$. Utilizing \( \psi \), as well as the total GHG emissions from the microgrid TGRs \( \kappa \) modeled in Subsection II-B, we express
the carbon tax payment for the GHG emissions from microgrid TGRs over the study period by the relation
\[ \xi_u = \psi \kappa. \]  

(6)

III. EUC Problem Formulation

In this section, we present the EUC problem formulation using the physical asset models, environmental models, and economic models developed in Section II. The general EUC problem formulation is stated as:

\[
\text{EUC: } \begin{array}{ll}
\text{minimize} & \sum_{\gamma_\sigma \in \mathcal{G}_{\text{TGR}}} \left[ \xi_{\gamma_\sigma} + \xi_{\gamma} + \xi_u \right], \\
\text{subject to} & \begin{align*}
\gamma_{\sigma} & \leq [\kappa]M, \\
\sum_{\gamma_\sigma \in \mathcal{G}_{\text{TGR}}} \gamma_{\sigma} & \leq \gamma_{\gamma}, \\
\gamma_{\sigma} & \geq \gamma_{\gamma} \\
\end{align*}, \\
\end{array}
\]  

(7)

where we take into account the constraints (8)-(18) \( \forall h \in \mathcal{H} \), the constraints (8)-(11) \( \forall \gamma_\sigma \in \mathcal{G}_{\text{TGR}}, \) and the constraints (12)-(16) \( \forall \sigma \in \mathcal{J} \).

The EUC approach seeks to minimize the carbon tax payment, jointly with the fuel and start-up costs of TGRs, and the net cost associated with the exchange of power with the DisCo, as expressed by the objective function (7). The EUC problem formulation explicitly considers the constraints on TGR outputs by (8) and (9). TGR minimum uptime and minimum downtime constraints are expressed by (10) and (11), respectively. We represent the constraint that ESRs may not both inject and withdraw power at the same time by (12). The constraints on the power injection and withdrawal of ESRs are expressed by (13) and (14), respectively. We express the intertemporal operational constraint of ESRs by (15). The constraints on the energy stored in ESRs are expressed by (16). The power balance of the microgrid is ensured by (17). We state the constraints on spinning reserve requirements by (18).

The constraint (19) stipulates a limit on the allowable GHG emissions over the study period, which may effectively restrict the generation of TGRs.

To illustrate the quantitative improvements imparted by the proposed EUC approach, we present the CUC problem formulation, which does not consider the GHG emissions at the time of decision. CUC problem formulation is stated as:

\[
\text{CUC: } \begin{array}{ll}
\text{minimize} & \sum_{\gamma_{\sigma} \in \mathcal{G}_{\text{TGR}}} \left[ \xi_{\gamma_{\sigma}} + \xi_{\gamma} + \xi_u \right], \\
\text{subject to} & (8)-(18).
\end{array}
\]  

IV. Case Study and Results

In this section, we illustrate the application and effectiveness of the proposed EUC approach on representative studies.

A. Case Study Data

We consider a microgrid connected to the low-voltage side of the distribution transformer to power residential loads. We consider that the microgrid includes a diesel generator denoted by \( \gamma_1 \), a PV panel denoted by \( \gamma_2 \), and an ESR denoted by \( \gamma_3 \). The peak load of the microgrid is 37 kW.

The \( \gamma_1 \) has a peak capacity of 50 kW. The \( \gamma_1 \) cost parameters are \( \xi_{\gamma_1} = 4.20 \times (10^{-3})/kW^{*}h \), \( \xi_{\gamma_1} = \$0.208/kWh \), and \( \psi_{\gamma_1} = 3.2/h \). Further, the \( \gamma_1 \) GHG emission parameters are \( \gamma_{\gamma_1} = 3.03 \times (10^{-4}) \text{ kgCO}_2e/kW^{*}h \), \( \gamma_{\gamma_1} = 0.53 \text{ kgCO}_2e/kW^{*}h \), and \( \gamma_{\gamma_1} = 8.09 \text{ kgCO}_2e/h \). The data for \( \gamma_1 \) and \( \gamma_3 \) are extracted from [4], [12] and presented in Table I. The peak capacity of \( \gamma_2 \) is 17 kW. The load and PV generation data are extracted from [13] and contain measurements for an anonymous house in New York. Since the load and PV data are collected in New York, to ensure consistency, we consider the time-of-use rates offered by Con Edison, viz.: 21.97¢/kWh from 8 a.m. to midnight and 1.55¢/kWh from midnight to 8 a.m. [14]. We consider a 15% minimum reserve requirement measured with respect to the microgrid peak load over the study period provided solely by TGR \( \gamma_1 \). We explicitly stipulate a constraint on the allowable GHG emissions over the study period and take \( [\kappa]M = 220 \text{ kgCO}_2e \). We further consider that the carbon tax rate is \( \psi = 500 \text{¢}/\text{kWh} \).

| TABLE I |
| -- | -- |

| CASE STUDY DATA FOR TGR \( \gamma_1 \) AND ESR \( \gamma_3 \) |

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| \( [\rho_{\gamma_1}] \) | 5 kW | \( [\rho_{\gamma_3}] \) | 50 kW |
| \( [\sigma_{\gamma_1}] \) | 2 hrs | \( [\sigma_{\gamma_3}] \) | 2 hrs |
| \( u_{\gamma_1[0]} \) | 0 |
| \( [\rho_{\gamma_3}] \) | 0 kW | \( [\rho_{\gamma_3}] \) | 0 kW |
| \( [\sigma_{\gamma_3}] \) | 12 kW | \( [\sigma_{\gamma_3}] \) | 12 kW |

B. Load and PV Forecasting

The computation of the numerical solutions of the EUC and CUC problems requires the numerical representation of VER generation and microgrid load over the study period. To this
end, in this section, we utilize the methodology presented in [15] to forecast $PV$ generation and microgrid load over the study period. The utilized methodology leverages a sequence-to-sequence (S2S) architecture that comprises two long short-term memory (LSTM) networks, viz.: encoder and decoder, which can effectively grasp intertemporal relationships [16].

We construct one S2S architecture for each of the two forecasting tasks. We provide each S2S architecture with the measurements for the previous 24 hours as well as the hour of the day and the day of the week of the forecasted time periods. Further, each S2S architecture generates forecasts for the subsequent 24 hours. It is worth emphasizing that, since the data in [13] were anonymized and the exact location of the house was not disclosed, we did not provide the S2S architectures with relevant weather data, such as cloudiness index or temperature. Nevertheless, different studies can utilize other forecasting methodologies, probability distributions, or historical data in the implementation of the EUC approach.

The dataset of each S2S architecture contains measurements collected between May 1, 2019 and July 29, 2019 at one-hour resolution. Each dataset is split into training (60%), validation (20%), and test (20%) sets, and we use the validation sets to tune the hyperparameters of the S2S architectures. We pick Adam as the optimizer, and to prevent the networks from overfitting, utilize dropout with a probability of 0.5. The S2S architecture to forecast the microgrid load achieves an $RMSE$ of 0.5825 on the test set. Fig. 1 depicts the S2S architecture forecasts for the study period along with the corresponding actual measurements. The S2S architecture forecasts for July 29, 2019 are utilized in the EUC and CUC solutions to represent $\gamma_2$ generation and microgrid load over the study period.

### C. Unit Commitment Results

The EUC problem formulation described by (7)-(19) is a mixed-integer-programming (MIP) problem known to be NP-hard. We solve the EUC problem using Gurobi 8.1 on a 2.6 GHz Intel Core i7 CPU with 16 GB of RAM for the study period. Fig. 2 presents the optimal injections and withdrawals under the EUC and CUC approaches. In both formulations, $\sigma_1$ tends to charge (resp. discharge) when the DisCo electricity rates are low (resp. high), thereby exploiting intraday price variation and capitalizing on arbitrage opportunities.

![Fig. 1. Forecasted and actual $\gamma_2$ generation and microgrid load](image1)

![Fig. 2. Optimal operations under the EUC and CUC approaches](image2)

The marked difference between the EUC and CUC approaches manifests itself in the optimal operations from hour 9 to hour 24. The optimal EUC solution generates less energy from the TGR compared to the optimal CUC solution, since the EUC approach is cognizant of the carbon tax payment while taking UC decisions. On the flip side, the CUC approach does not consider the carbon tax payment while taking UC decisions and so needs to conduct an ex-post evaluation of the carbon tax payment for which the microgrid is liable. Owing to this ex-ante evaluation of carbon tax payment, the total costs for the study period are 16.9¢ lower under the EUC approach than those under the CUC approach.

While the simulation depicted in Fig. 2 is performed for the specific carbon tax rate $\psi = \$0.07/kgCO_2e$, we also would like to examine the influence of the carbon tax rate on the quantifiable benefits of the EUC approach. To this end, we study the sensitivity of the total costs to changes...
From in the carbon tax rate. We vary the carbon tax rate $\psi$ in 2018 of $0.139/\text{kgCO}_2\text{e}$ implemented in Sweden, in $0.010/\text{kgCO}_2\text{e}$ increments.

Fig. 3 illustrates the energy generation from the TGR $\gamma_1$ over the study period under the EUC and CUC approaches, as a function of $\psi$. Under EUC approach, while the lowest simulated carbon tax rate resulted in a TGR generation of 184.86 kWh, the highest simulated carbon tax rate resulted in a significantly lower TGR generation of 120 kWh. The TGR generation under the CUC approach, however, does not vary with carbon tax rate and attains the constant value of 191.33 kWh, because the CUC approach does not consider the impact of carbon tax rate at the time of decision. The plots make clear that the carbon tax rate can effectively disincentivize TGR generation under the EUC approach in comparison with the CUC solution.

Fig. 3 also presents the difference between the total costs obtained by the EUC and CUC approaches, i.e., the total costs under the CUC approach minus the total costs under the EUC approach, as a function of $\psi$. The results indicate that, for all considered carbon tax rates, the total costs under the EUC approach are lower than those under the CUC approach. We further observe that, as $\psi$ increases, the reduction in total costs under the EUC approach vis-à-vis the CUC approach also increases. This observation can be attributed to the fact that the EUC approach optimizes the microgrid operation by taking into account the carbon tax payment based on varying carbon tax rates. The CUC approach, however, can only evaluate the impact of increasing carbon tax rate ex-post, which inevitably results in higher costs with increasing carbon tax rates. These results underscore the importance of the explicit consideration of the monetary impacts of GHG emissions by UC approaches.

V. Conclusion

In this paper, we propose a UC approach that expressly assesses the GHG emissions from TGRs as well as their monetary impacts. The proposed EUC approach enables the stipulation of a constraint on GHG emissions from TGRs over the study period and the ex-ante evaluation of carbon tax payment jointly with all other costs and benefits. The results indicate that the proposed approach yields lower costs than does the classical UC approach. Further, it was observed that the TGR operation could be attenuated via an economic mechanism, i.e., carbon tax rate, when the carbon tax payment is ex-ante evaluated. The performed sensitivity analysis provides valuable insights into the impact of carbon tax rate on the EUC and CUC approaches.

In our future studies, we plan to incorporate emissions trading schemes to the proposed EUC approach. To evaluate a wider range of costs and benefits, we further plan to represent the participation of microgrids in wholesale energy and ancillary services markets under the EUC approach.

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