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Abstract

This manuscript presents the Generator Fleet Characteristics Model (GFCM), a general purpose tool for the analysis of power system operations, economics, and resilience. The GFCM is a collection of MATLAB functions that use publicly available data with national coverage to produce year-long (8760 hour) analyses of the electric grid at the balancing authority level. As the name implies, the GFCM builds up a series of snapshots of electric grid conditions and outcomes using the economics of the generator fleet as a starting point for understanding system complexity and dynamics. While the synchronous inertia application we present here uses the GFCM to build a detailed picture of the present state of electric grid operations and market outcomes, the model is designed to facilitate counterfactual study through the comparison of model outputs by an analyst that systematically varies inputs. The GFCM forms a modeling framework intended to aide in the formulation of "what if" questions regarding how the grid might operate under changing ambient conditions while harnessing evolving technologies.

Keywords

Economics; Electricity; Generator Fleet; Infrastructure; Interoperability; Operations; Power Systems; Resilience; Smart Grid; Synchronous Inertia.

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1. Introduction

Public and private investment in the electric grid creates value for a diverse array of sectors and stakeholder communities. In turn, these reliable and resilient systems for the generation and delivery of abundant, low-cost electricity improve the competitiveness of the American economy. The reliability and resilience of the electric grid requires thoughtful management of complexity and attendant costs as many stakeholders engage in what amounts to perpetual integration of new components and systems. These complexity costs extend beyond the physical system to the very models and tools used to analyze and operate the grid. As the need grows for grid operators to improve their capacity for hosting emerging technologies, our ability to create inclusive opportunities for such stakeholder contributions may be limited by the scarcity of publicly available and economically accessible tools for conducting critical assessments. The work presented in this document concerns the development and use of one such tool.

Performance requirements for critical infrastructure and utilities increase monotonically with societal expectations. Going forward, an increasing share of solutions to operational problems will be drawn from technologies for which relative costs and characteristics compare favorably to the legacy infrastructure of the grid. The characteristics of the grid will change accordingly. If we are to measure what this change portends for the effectiveness of current and prospective operating strategies, we need tools for understanding patterns of change emanating from the characteristics of the generating fleet.

The Generator Fleet Characteristics Model (GFCM) is designed to sketch an efficient production frontier for electricity generation and, through the characteristics of individual generators, understand what is possible when the grid has high levels of physical and digital interoperability. The GFCM provides a framework for constructing counterfactuals that facilitate analysis of systemic change in the grid, and lets the analyst ask how the grid's opportunities for value creation would look if the current constraints on information and power flow over communications and physical networks were relaxed through improved interoperability.

The costs of developing understanding rise with the complexity of the tools we employ. The GFCM was designed to be simple in structure, employ public data resources extensively, and offer the opportunity for greater specification and complexity as needed by the analyst. As an initial demonstration reflecting the original point of departure for this research effort, the GFCM is used to understand how system inertia from synchronous generation varies hourly over the course of a year. Inertia from synchronous generation is one of several factors that influence system stability.[1]

The GFCM allocates generation according to observed patterns in load and net generation by energy source, allowing for simple aggregation of inertial contributions by online generating units. Hourly time series of total inertial contributions and other key operating and economic variables for a given balancing authority (BA) are produced for a full year with the GFCM. In time, the GFCM can be used to evaluate changes in system inertia with the reorganization of some grid operations

[1] Other factors include load inertia and damping, contingency size, under frequency load shedding settings, and frequency response speed [1].

and improvements to interoperability that relax presently binding constraints on coordinated fleet operations. The GFCM is validated against data for the Electric Reliability Council of Texas (ERCOT) by modulating assumed inputs to recover inertia time series that obtain sufficient fidelity to data made public by that BA.

1.1. Changing Composition of Useful Phenomena

We begin by offering some clarification regarding our use of the term *inertia*, differentiating between its use in a loose practical sense as it relates to electric power system operations, and its strictly formal use to describe fundamental physical phenomenon of inertia. For electric power systems, the presence of inertial contributions from synchronous generation and load supports frequency stability and system security. The quantity of inertia varies with the changing set of generators and loads interconnected with the grid. The physical phenomenon of inertia is that which relates to Newton's first law of motion and the resistance of a physical object to a change in velocity. In the rest of this document, we use the word inertia in the systemic sense rather than that of the narrow and explicit textbook definition, all while acknowledging the terminological overlap.

The concepts of physical and electric system inertia intersect in the traditional mechanisms for producing and consuming inertia. Generators built from large turbines have physical inertia and control feedback loops that together stabilize electrical output in the face of system disturbances. Similarly, traditional analog loads can involve some physical inertia for motors and other large machines, but also naturally adjust and continue to function through small signal perturbations. This combination of physical inertia and electrical stability provided by traditional generators and loads manifests as the inertia of the power system.

However, as the technology set capable of economically supplying electricity and ancillary services admits new members, the composition of physical phenomena actively harnessed to provide useful functionalities to the grid increasingly turns to the technical solutions enjoying significant cost improvements. The value propositions of inverter-based resources, sensors, edge computing, and advanced power electronics continue to improve. These rising technology sets trade the well-characterized performance of synchronous generators for the ability to contribute to grid operations without producing emissions or requiring extensive operations and maintenance costs. Furthermore, the cost structures of electric grid infrastructure are transitioning from that of steel and fuel to that of silicon and communications. This manuscript describes the GFCM and develops insights into the market structures and cycles that influence the inertial contributions available to support grid stability.

The discussion surrounding inertia would benefit from improved transparency into its historical presence, alleged disappearance, and a characterization of its value to grid operations more broadly. While we acknowledge that the potential quantity of inertial contributions from synchronous generation is likely to decline in some segments of the electric grid, we also draw attention to typical diurnal fluctuations in inertia and the changes in the cost of that inertia which is contributed. Furthermore, our model offers insight into other industry trends that are likely to impact the inertia available to grid operators going forward.

1.2. A Simple Model of Generating Fleet Characteristics

A simple metric is needed to track the evolution of generator-based inertia on the U.S. electric grid. The inertia of each generator is a consequence of its design and is therefore specific to individual generating units. Data on the inertial characteristics of individual generators is generally proprietary. However, the physical differences between technologies are sufficient that average values for generators of each technology group may be used for characterizing their inertial contribution to the bulk electric system. The sum of these inertial contributions available to support grid stability is of interest to us.

The inertia constant (H) of a generator, reported in seconds, expresses the duration that a synchronous generator may provide its rated power using only its kinetic energy [2]. Average values by technology group for the inertia constant of generators operating within the ERCOT footprint are presented in [3]. We employ these average values of the inertia constant in estimating the inertial contribution (MWs) of each generator reported as operational in the Energy Information Administration (EIA) Electric Power Monthly (EPM). The EPM data reports each generator that is operational as of a given date (August 2019 in our case). Information on initial operating month and planned retirement month are incorporated to ensure that the operable fleet, as modeled for any given month, reflects ongoing changes to technological composition of generation resources.

Each generator is assigned an inertia constant from the ERCOT data by rough matching on the prime mover code and technology group listed in the EPM. Assignment is made based on prime mover code with ambiguities resolved by looking at the data contained in the technology variable. Some assignments are cleaner than others, and the diversity of generator design implies that average inertia constant values may not be completely representative of specific generating units.

We use inertia constant values for generator groups as baseline inputs to calculate the inertial contribution of each generating unit. The sum of all inertial contributions available to the grid will depend on which generators are allocated to serve load. In actual wholesale markets, generating unit commitment and dispatch is conducted in a manner that respects the security constraints of the system. True dispatch, therefore, depends on the economics of generating units and the physical constraints on system operations.

Our model ranks generating units in order of increasing marginal generating costs ($\$/MWh$). Barring other constraints, the smallest set of the lowest marginal cost generators capable of meeting system load is allocated. We initially focus on the marginal cost of an inertial contribution as a valuation of the replacement cost of inertia. The full marginal cost of generation must be paid to obtain an inertial contribution from a generator. The marginal cost of generation ($\$/MWh$) is calculated using data on fuel costs, heat rates, and variable operating and maintenance costs. Another cost-adder based on the location of a given generator within the grid's network structure may also be modeled and included in the marginal cost calculation that informs merit order in the GFCM. For the base version of the GFCM, the network component of marginal cost is derived using a random number generator. The data inputs for marginal cost calculations are presented in Table 4 in Appendix B. The marginal cost of an inertial contribution ($\$/MWs$) is calculated using the marginal cost of generation and inertial contribution data. After marginal cost estimates are obtained for all generating units, we construct a supply (industry marginal cost) curve for generation and inertial contributions. The set of operable generators that supply power in any period is determined by the level of load. It is for this group of allocated generating units that we estimate historical inertia conditions with the GFCM.

System inertia may be influenced by anything that changes the set of generating units that are supplying energy and ancillary services to the grid. Grid operating constraints include minimum stable generation levels, ramp rates, minimum up and down times, startup costs, and fuel costs [4]. While the model thus far developed and presented in this manuscript does not incorporate all constraints, it is designed so that future iterations of the model may benefit from their inclusion. In its present iteration, the model accounts for the differing cost structures (including fuel) of assorted generating technologies, load levels, and intermittent generation from wind and solar resources. The estimates of generator-based inertial contributions to the grid describe the limiting case in which physical constraints such as ramping rates or transmission capacity limits between regions do not bind. That is, the base model presented here considers the regions of the grid encompassed by balancing authorities independently.

While this manuscript focuses on conventional inertial contributions, the model is designed to accommodate the inclusion of technical substitutes in service of grid stability. The search for and refinement of technical substitutes for synchronous inertia is an active area of research. A growing body of literature surveys the diversity of technical solutions that have been developed in different operating environments as a response to changing inertia [5–16].

2. Model

Guiding our modeling philosophy is the realization that there is too much complexity and heterogeneity to produce a high-fidelity, broadly applicable, and parsimonious model. Even if such a model could be specified satisfactorily, the data requirements would likely prove so onerous as to obviate some of the value of the modeling exercise. Instead, the model presented in this manuscript uses publicly available data with national coverage to form a framework for examining the set of resources supplying energy and ancillary services to electricity markets organized as BAs. The approach focuses on developing a series of static analyses of electricity markets and does not explicitly model inter-hourly operating dynamics such as ramp rates and start-up times.

Present inputs have been limited to those necessary to develop an understanding of system inertia, but we recognize that the analysis of resource-based inertial contributions is only one possible application of the model. Modeling additional market complexity such as line congestion and dynamic operating constraints is left for future work. An open-source approach ensures the model developed is not limited by overfit to a narrow segment of the electric grid, current operating conditions (including climate), or governance structures. While the MATLAB software with which the GFCM is built is proprietary, it is commonly available to and already used by researchers in academia, government, and industry.

The chosen design preserves the model's flexibility for addressing geographically and structurally distinct settings. The design also maintains the headroom to increase model specificity where results are sensitive to uncertainty or variability in assumptions. Ongoing improvements to the EIA application programming interface (API) have enabled the design of a relatively lightweight model that can draw on new electric grid operating data as it becomes available.[2] The GFCM obtains hourly data on the ambient operating conditions of generating units using the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) data resource. Reanalysis data access is currently managed through a series of requests submitted to the Climate Data Store (CDS). Minimizing the number of core data inputs ensures the flexibility necessary to model a diverse set of anticipated and unanticipated scenarios as they emerge from an evolving electric grid. At present, the ambient condition data represents the largest single data input to the GFCM, as well as the greatest potential source of analytical augmentation.

2.1. Model Purpose

The model is tuned to investigate the question of how system inertia evolves over time and is modulated by market structure and conditions. Model parsimony is maintained through a focus on the primary influences that determine the set of generators serving load and offering non-market stability services like inertia. Principal among these influences is system load or level of demand for electricity, the fleet of operable generating units, and cost structures of assorted generating technologies.

2.2. Primary Data Inputs

The primary data inputs consist of a collection of static EIA data tables, which detail the characteristics of the generator fleet; hourly operating data (e.g., system load and net generation by fuel source) from assorted BAs obtained through the EIA API; and user-provided parameters in the form of the specification table (.xlsx). Figure 1 presents the temporal support for selected data resources.

The first objective of data acquisition efforts for the GFCM is to obtain a comprehensive list of the operable generators capable of serving load and providing ancillary and implicit services to the grid. We construct the list for each month in our study period from downloaded EIA Form-860M data. We acquire a list of operable generators in a reference month and then construct a group of data sets for each other study month (before and after the reference month), adjusting the set of operable generators to include those planned to have come online and remove those planned to retire in the intervening months. The chosen reference month of August 2019 may be changed by the analyst with minimal adjustments to data inputs and code. A comprehensive list of generator retirements since 2002 is included in the monthly version of the EIA Form-860 starting in 2017. More information on the EIA data can be found in [18].

[2] The EIA API occasionally supplies time series with gaps due to reporting outages. The inertia model uses autoregressive modeling tools from the MATLAB Signal Processing Toolbox to fill in the gaps in the API data. For additional discussion regarding working with EIA demand data, see [17].

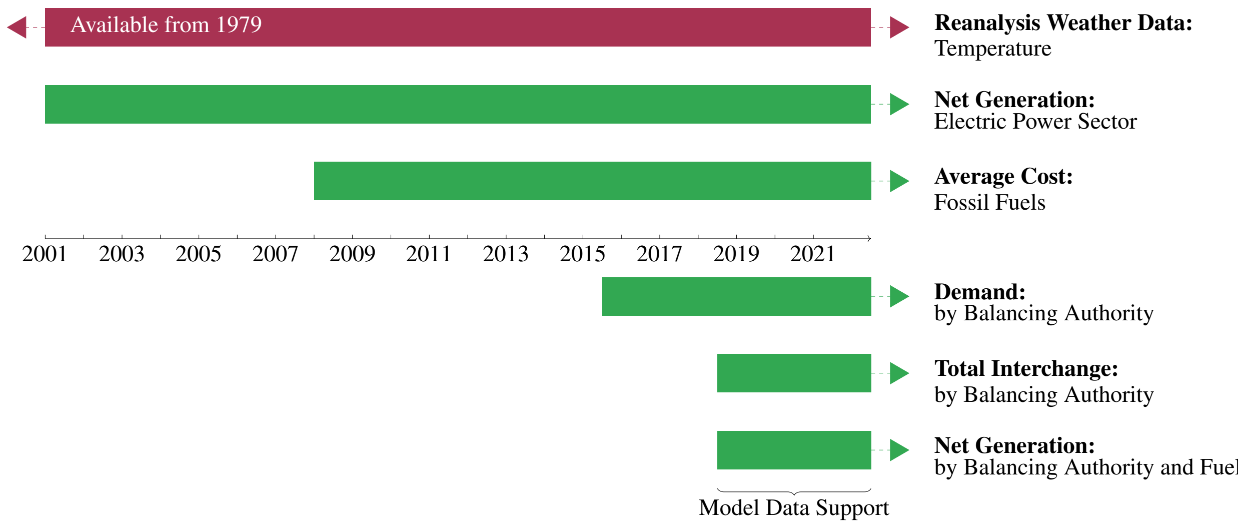


Fig. 1. Temporal Data Support: Complete for July 2018 to Present

2.2.1. Static EIA Data

The generator data from EIA Form 860 constitutes the foundation of the GFCM. The data contains names and identifier numbers at the entity (organization), plant, and generator level, as well as categorical representations of generating technology, including a prime mover code for each generator.[3] An accounting of the static data inputs to the GFCM is located in Table 4 in Appendix B. The scenario specification data is described in Section 2.2.3. The generator data comes from the EIA Form 860 data as of August 2019. The 2019 EIA Electric Power Annual (EPA) is the source of several data sets containing heat rate and operating cost information as well as general reference information.

2.2.2. EIA API Data

The GFCM obtains electric system operating data through multiple API calls to the EIA. While developmental iterations of the GFCM used Version 1 of the EIA API, the published form of the GFCM employs only Version 2 of the EIA API. Perhaps the most important model input obtained though the EIA API is the top-level hourly load series. No variable more closely tracks movements in modeled inertia than the demand that system operators allocate power plants to match. Hourly net generation by energy source is also crucial to the GFCM allocation modeling strategy. The energy source groups are defined simply by the terms: coal, natural gas, nuclear, hydro, wind, solar, petroleum, and other. Total net interchange between the focal BA and adjacent peer entities is also obtained from the EIA API. The fossil fuel cost data that informs marginal cost calculations is obtained through several API calls.

[3]The EIA Glossary provides the following definition for *prime mover*: “The engine, turbine, water wheel, or similar machine that drives an electric generator; or, for reporting purposes, a device that converts energy to electricity directly (e.g., photovoltaic solar and fuel cells)” [19].

An additional note on the data series obtained through the EIA API is warranted here. In the test case for the ERCOT BA, there are several periods in which net generation classified as from natural gas dips precipitously in concert with offsetting rises in net generation from the other category. Whether these generators operated using alternative fuels during these periods, or as is more likely, the discrete jumps reflect an incorrect coding of generation source, a simple algorithm is implemented to prevent the model from trying to allocate more generation to the other category than its installed capacity could deliver. Optionally, the analyst may filter out and replace other net generation values that exceed a set number of standard deviations above the mean.

2.2.3. Scenario Specification

The specification for a GFCM scenario run is encapsulated in a single *.xlsx* file. Each scenario is first specified with respect to the BA and time period of focus. By default, the specification table lists 12 scenarios, one for each month in 2019. The second group of scenario parameters contains the inertia constants, which are presented for the baseline scenario in Table 1. A power factor of 1 is assumed in the specification. If a plant retirement date is unknown, operating life defaults to 50 years. Additional parameters allow the analyst to fine-tune the modeling of auxiliary sources of inertia, set default dispatch levels for different technologies, and adjust how combined cycle plants are handled.

Table 1. Baseline Inertia Constants

Technology	H Constant (s)	Technology	H Constant (s)
Combustion Turbine	5.29	Geothermal BT	1.00
Combined Cycle	4.97	Flywheel	1.00
Nuclear	4.07	Pumped Storage	0.00
Gas Steam Turbine	2.94	Compressed Air Energy Storage	0.00
Coal	2.63	Solar Thermal	1.00
Hydro	2.40	Fuel Cell	0.00
Wind	0.00	Energy Storage	0.00
Solar PV	0.00	Battery	0.00
Steam Other	1.00	Internal Combustion Engine	1.00
Geothermal ST	1.00		

The first eight values taken from the average values by technology group for the inertia constant of generators operating within the ERCOT footprint are presented in [3]. H constants for all other technologies are assumed to be either nonexistent (zero) or minimal (one).

2.3. Auxiliary Data Inputs

In addition to the core fleet characteristics and operating data obtained from the EIA, the GFCM incorporates data on typical inertial contributions from load and private use networks as well as ambient weather conditions. Simple point estimates for the inertial contributions from load and private use networks are taken directly from the literature as described below. In contrast, the ambient weather component of the GFCM takes advantage of comprehensive modern reanalysis products to use a single resource with complete spatial and temporal data support for all BAs in the contiguous U.S.

2.3.1. Inertia from Motor Loads

Non-generator-based inertial contributions are as mutable as any economy served by the electric grid and therefore constitute a source of potential uncertainty for the model. Without hard data on these contributions, the analyst is left to test the sensitivity of model results to assumed values. Where possible, assumed values are drawn directly from the literature. Inertia from industrial motor loads varies with the demand for electricity to operate such devices and generally scales up in times of peak demand while remaining low overnight when loads diminish [20]. Accurate modeling of inertia from load requires effective modeling of the loads themselves. The extensive literature on modeling loads is summarized in [21]. The adoption of new or improving technologies can change the characteristics of the loads that the electric grid must meet. For example, increasing use of variable frequency drives (VFD) will change the temporal profile of inertia from load. The rising deployment of VFD will decrease the energy use and inertial contributions of motor loads as it decouples these devices from the synchronous grid.

2.3.2. Inertia from Private Use Networks

The large and energy-intensive industrial base of Texas operates considerable private use network (PUN) resources for which load is not explicitly metered by wholesale market operators. While these PUN entities generally do not (net of their own generation) consume energy from the wholesale market, they are synchronously connected with the grid and therefore contribute to system inertia at a non-negligible level. Most PUN generating units in ERCOT employ combined cycle, combustion turbine simple cycle, or gas steam technologies [22]. An ERCOT report on system inertia found that PUN generating units, ancillary service providers, and always-online nuclear plants make considerable baseline inertial contributions to the ERCOT grid. From 2013 to 2018, inertial contributions from PUN never fell below 32 GW•s. Ancillary service providers made minimum contributions of 45 GW•s and nuclear plants consistently contributed 18 GW•s [23].

2.3.3. Weather Conditions

Ambient operating conditions can subtly impact the capacity and efficiency of thermoelectric generating units, influencing their competitiveness within the merit order. While the inertial contribution of an online synchronous generator does not change with ambient conditions, the propensity of the plant to be allocated or idled, and therefore its contribution to system inertia, evolves over time with the competitiveness of the facility's market offerings.

Improvements in the quality and availability of reanalysis data make it possible to recreate a data set of the ambient conditions in which electric generating units operate. We obtain hourly 2-meter temperature data from the 0.25° grid of the ERA5 data set produced by the ECMWF. For the initial version of GFCM, the integration of reanalysis data was limited to temperature, but future work could readily expand this integration to include measures of atmospheric pressure, humidity, wind speeds, radiation, and even cloud cover.

While an API exists for interfacing with the ECMWF data, the current version of the GFCM uses static inputs downloaded and cleaned in advance of the MATLAB model runs. ERA5 reanalysis data is downloaded as a NetCDF file, converted to .csv using a python script, and then imported into MATLAB for model integration.

2.4. Process Modules

The GFCM is composed of a series of modules that combine user parameters and electric grid input data to model a scenario. An accounting of the MATLAB functions employed to implement the GFCM is in Table 3 in Appendix B. The dependency of these functions on each other is presented in Fig. 9. This section describes the components of the model in conceptual form. The first function uses the input described in Section 2.2.3 to specify the scenarios to be run with the GFCM and orchestrates the calling of all other functions to produce the standard model outputs.

2.4.1. Fleet Selection

After ingesting specifications, the next component of the model involves tracking the fleet of operable generating units at the monthly level. Generating fleet data is obtained from Form EIA-860M. A series of data sets is created containing all reporting generators in U.S. BAs and changing monthly according to retirements and new installations. These data sets provide the pools of generating resources from which the model will draw to meet load and estimate inertia. Fleet selection is handled in the *gfcm_v1_scenario_main.m* function.

2.4.2. Marginal Cost Determination

For a given BA, we obtain an hourly rank order of generating units by mapping in data on marginal cost structures. The function *gfcm_v1_scenario_main.m* handles most of the data wrangling tasks while *gfcm_v1_scenario_snapshot.m* determines marginal costs and generator allocation. Marginal costs of production include outlays for fuel and variable operating and maintenance (VOM) costs. In conjunction with generator efficiency data (heat rates), it is possible to estimate the marginal cost of serving load. Fuel cost data is obtained through an API call, and it varies at the monthly level. The generator efficiency data employed in the model is the average tested heat rates by prime mover and energy source data, which is reported in Table 8.2 of the EIA EPA. VOM costs are likely to vary somewhat at the generator level. However, in keeping with a parsimonious approach to modeling, we obtain average values for specific generating technologies from two cost studies available through the EIA [24, 25].

Operations and maintenance expenditures are rising for many synchronous generation facilities as the need for unit cycling – operating generating units at varying levels of load – can increase with the penetration of variable generation [26]. Future iterations of the GFCM may seek greater modeling fidelity through explicit treatment of cost variability due to generating unit cycling, but the present model ignores these effects.

A generator's geographic location and thus position within the network structure of the electric grid may effect its rank in the generator fleet merit order. To allow for this variation the GFCM includes a network cost adder that by default is a draw from a normal distribution with mean zero and standard deveiation of one. The distribution of network related costs associated with electricity delivery may be altered by the analyst to reflect regionally specific network structures.

Optionally, the GFCM can utilize spatial differences in temperature to introduce subtle hourly variation in the rank order of generating units that would otherwise be tied with respect to their marginal cost. The sensitivity of individual generating units to temperature varies with the technology group and specific design parameters of the facilities. Rather than conduct an exhaustive and data-intensive adjustment of each plant's efficiency and capacity to the constantly varying weather conditions, the GFCM assumes the merit order of production (generator competitiveness) to be decreasing with temperature while not imposing specific changes to the assumed marginal cost.

The GFCM incorporates many of the data resources necessary to model generator-level heterogeneity with respect to local ambient conditions, positioning the model for further augmentation. A summary of literature investigating the condition-adjusted efficiency and output of thermal generating plants can be found in [27]. As natural gas turbine power plants increasingly account for the marginal generating technologies serving load, understanding how operating conditions such as ambient temperature affect their allocation and thus contribute to system inertia is crucial to planning for system resilience.

The density of air fed into gas turbines decreases with ambient temperature, requiring greater fuel inputs to compress the same mass of air for combustion. Increased fuel inputs for the same level of output results in higher heat rates and lower net efficiency of generation for gas turbine plants, both simple cycle and combined cycle [28]. For additional references on the sensitivity of power plant operations to ambient conditions, see [29–39].

2.4.3. Generator Allocation

Several heuristics are used to simplify the modeling of generator allocation. Data on BA load, net generation by energy source, and total interchange with adjacent BAs are all obtained using the EIA API. Within a BA, demand is equal to net generation minus total net interchange.[4] Some generation serves base load while other generating units modulate their offerings commensurate with variable demand. We assume that nuclear power plants always serve base load in the BA where they are located. Nuclear fuel costs are treated differently than the fossil fuel costs of other thermal generation, as power output does not scale directly with fuel consumption in nuclear plants. We allocate the hourly net generation from nuclear power among the fewest possible reactors in a given BA. Next, we allocate net generation from each of the three variable renewable generation groups: hydroelectric, solar, and wind power. The fewest hydroelectric plants necessary to supply the observed level of net generation are modeled as online and providing inertia. Net generation

[4]Positive values of total net interchange for a BA indicate exports, and negative values indicate the BA is importing power from adjacent BAs.

from wind and solar generating units is allocated uniformly across all generators.[5]

The remaining net load is met with thermal generating units. The net generation from each of the thermal generating energy source groups is allocated among the relevant generating units by merit of their marginal costs. In this manner, out of merit order (as determined by marginal cost) generation that serves load for reliability or security reasons is automatically allocated in the model. While we do not see which specific thermal generating units are committed to serve load or how they are dispatched, we can make the simple assumption that in the limiting case the fewest, lowest marginal cost resources for each energy source group are used. The results sketch an envelope within which actual grid operations, constrained by dynamic operating and congestion constraints, will occur.

The heuristic approach to generator allocation can be modified to evaluate the model's sensitivity to assumed input values and market rules. In its simplest form, the model focuses on some of the least mutable components of the electric grid, the physical generating units, which are designed for multi-decade service lives. Transmission and distribution network topology continues to evolve through discrete changes associated with new installations and configurations. Furthermore, the high levels of anticipated investment in electricity delivery infrastructure over the coming years suggests that the current experience with operating constraints may change substantially. Individual segments of the transmission and distribution grid may change slowly, but the full network model evolves with each new node and edge.

2.4.4. Market Snapshot

By modeling an allocation of generating resources sufficient to meet observed levels of net generation and system load, we produce a snapshot of the resources that could supply inertial contributions to the electric grid. Figure 2 presents the supply curve or industry marginal cost curve of generators allocated to serve load at a local minimum in system inertia observed on April 22, 2019 at 8:00 UTC. We map in inertia constant values for each generator and aggregate contributions within the BA to estimate the value of system inertia that would be obtained in the absence of binding constraints on operating dynamics and congestion.

[5]In reality, especially in a BA as geographically large as ERCOT, the generation profile of solar resources in the west will lag that of the those in the east due to the sun's passage overhead. For simplicity, this operational diversity is not modeled.

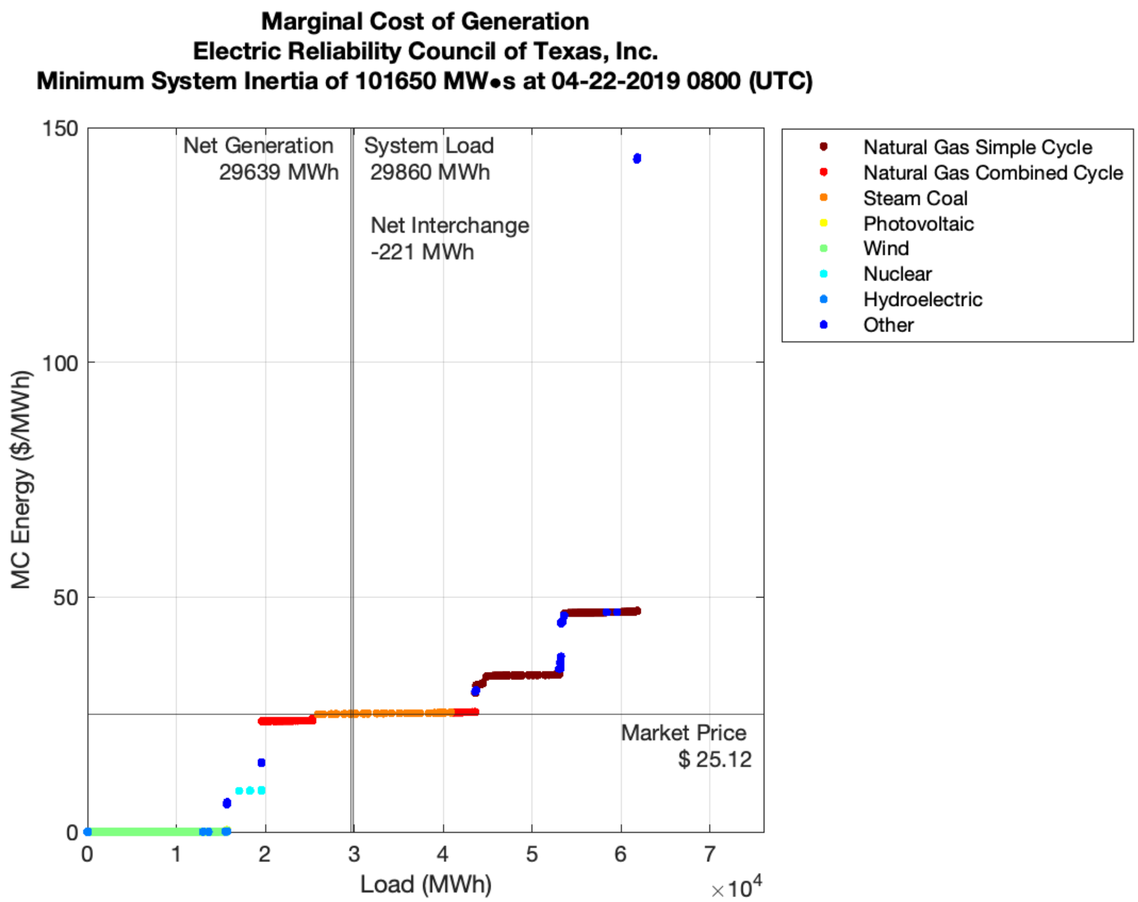


Fig. 2. Marginal Cost Curve for Generating Units Serving Load

For each of the 8760 hours in the focal year of 2019, the $gfcm\_v1\_scenario\_snapshot.m$ function produces a static merit order of generating units, assorted summary statistics, and generating-level operating logs. The outputs from the snapshot function include the estimates of system inertia and average generator H value as well as system cost and revenue estimates. The generator-level operating logs make it possible to recreate plausible allocations of generating units. A series of market snapshots is collated to construct longitudinal data on system inertia levels and the associated market conditions.

2.4.5. Auxiliary Sources of Inertial Contributions

Inertial contributions from additional sources are modeled as percent shares of the system inertia inclusive of generator fleet inertia and are defined by a pair of sine waves that are parameterized as shown in Eq. 1.

$$I_x^{\%} = \bar{I}_x^{\%} + \alpha_x \sin\left(\left(\frac{h+\theta_x}{24}\right)(2\pi)\right) \tag{1}$$

The percent of total system inertia derived from source $x \in \{PUN, Load\}$ is denoted $I_x^{\%}$. The time average percent of system inertia from source x is denoted $\bar{I}_x^{\%}$. The amplitude of the sine wave is modulated with the parameter α_x, the variable h is the hour of the day in UTC time as an integer, and $\theta_x \in [-23, -22, \cdots, 0, \cdots, 22, 23]$ is a temporal offset parameter for adjusting the phase of the diurnal cycle. Any defensible choice of offset parameter may be input through the scenario specification spreadsheet. However, changes to the offset parameter may have substantial impacts on model outputs if the imputed diurnal cycle of inertia from load and PUN resources aligns or counterbalances the prevailing diurnal cycle in load.

2.4.6. Function Descriptions

This section briefly describes each of the MATLAB functions that together form the GFCM. See Appendix B for a tabular summary of the functions and graphical representation of the relationships between them.

2.4.6.1. gfcm_v1_scenario_specifier.m

The scenario specifier is generally the first function run by the analyst. It imports parameters describing the simulation to be run and makes calls to all the other functions that together model electric grid operations and techno-economic outcomes of interest. The specifier function also initiates the validation process to determine the quality of model outputs.

2.4.6.2. gfcm_v1_scenario_main.m

The scenario main function conducts most of the data handling process for data inputs not obtained through the EIA API. In a typical GFCM run, the scenario main function is called 12 times, once for each month in a given year. While individual hours are modeled though calls from the scenario main to the scenario snapshot function, the scenario main function collects these hourly model outputs into generator logs for comprehensive analysis.

2.4.6.3. gfcm_v1_scenario_snapshot.m

The scenario snapshot function takes data from the scenario specifier and scenario main functions to determine the marginal cost of generation for each member of the generator fleet and constructs an hourly-varying merit order along which to allocate observed net generation by energy source. While the precise identity of generators serving load in any given hour is unknown, the GFCM scenario snapshot produces a plausible allocation of generators absent the spatiotemporal operating constraints.

2.4.6.4. gfcm_v1_validation.m

The validation function compares model outputs to historically observed data not employed elsewhere by the GFCM to determine the validity of the model as applied. The validation process includes the production of both tabular and graphical outputs for review by the analyst. The validation function is intended to provide the analyst with a replicable process for evaluating the GFCM's fitness for purpose that can be used with a wide variety of potential applications, favoring a multifaceted approach over the production of a single binary indicator of validity.

2.4.6.5. gfcm_v1_event_focus_graphics.m

The event focus graphics function allows the analyst to zoom in to a shorter segment of time around an event like the minimum system inertia, or an observed disruption in grid operations. The event focus graphics include time series plots and temporal heat maps for variables of interest like inertia, load, net generation, and net interchange with neighboring balancing authorities.

2.4.6.6. gfcm_v1_dir_parent.m

This function provides a simple stand alone means for the analyst to specify the local parent directly from which the GFCM is run. This function supports the portability of the GFCM MATLAB code.

2.4.6.7. gfcm_v1_eia_api_call.m

This function makes the API call to EIA servers and contains a simple procedure for error handling.

2.4.6.8. gfcm_v1_api_url_constructor.m

The API URL constructor function assembles the URL strings that indicate where GFCM data inputs can be found on the EIA website. This function follows the format for version two of the EIA API.

2.4.6.9. gfcm_v1_api_v2_data_handler.m

The API data handler function takes the URLs created by the API URL constructor and makes a call for data to EIA servers using the EIA API call function. Then the handler function takes the data returned from the EIA and formats it for use by the rest of the GFCM. This function is designed to work with version two of the EIA API.

2.4.6.10. gfcm_v1_recursive.m

The recursive function makes the specified number of calls to the scenario specifier function and enables the systematic adjustment of model parameters to iteratively improve model fit to a specific year and balancing authority pair. The recursive function is not necessary in most simple runs of the GFCM. The recursive variable must be set equal to 1 in line 100 of the specifier function and line 32 of snapshot before starting the GFCM from the recursive function.

2.4.6.11. gfcm_v1_eia_api_key.m

The EIA API key function is where the user should specify their API key for automated data acquisition. The analyst must obtain a key from https://www.eia.gov/opendata/register.php and specify the value in this function before attempting to run the GFCM.

2.5. Model Outputs

When the analyst runs the *gfcm_v1_scenario_specifier.m* function, an analysis of the 8760 hours in a year is conducted in roughly 1.5 hours. The model will take a little longer if it is the first time running and all EIA API data resources must be acquired. First, a directory for the specific BA under evaluation is made if it does not already exist. Next, a scenario batch (SB) directory is made and labeled according to the timestamp at which the SB was initiated. Within this timestamped directory, hourly model outputs are collected into monthly subdirectories, and grouped by the primary data products of interest located in the "GenLogs" and "Validation" subdirectories. An additional *ValidationLog.mat* file is created and updated if the recursive model fitting options are employed by the analyst. The "GenLogs" directory contains monthly panel data detailing the hourly status of each generator in the BA. Most of the model visualizations are collected into the "Validation" directory.

Figure 3 presents a temporal heat map for total inertial contributions on the ERCOT system over the course of 2019. Diurnal fluctuations in the prevalence of system inertia are found throughout the year, but the largest swings in system inertia echo the largest swings in system load. For ERCOT, system inertia is at its peak in the summer months and obtains its minimum levels during the shoulder seasons of spring and fall, when heating and cooling loads are relatively diminished.

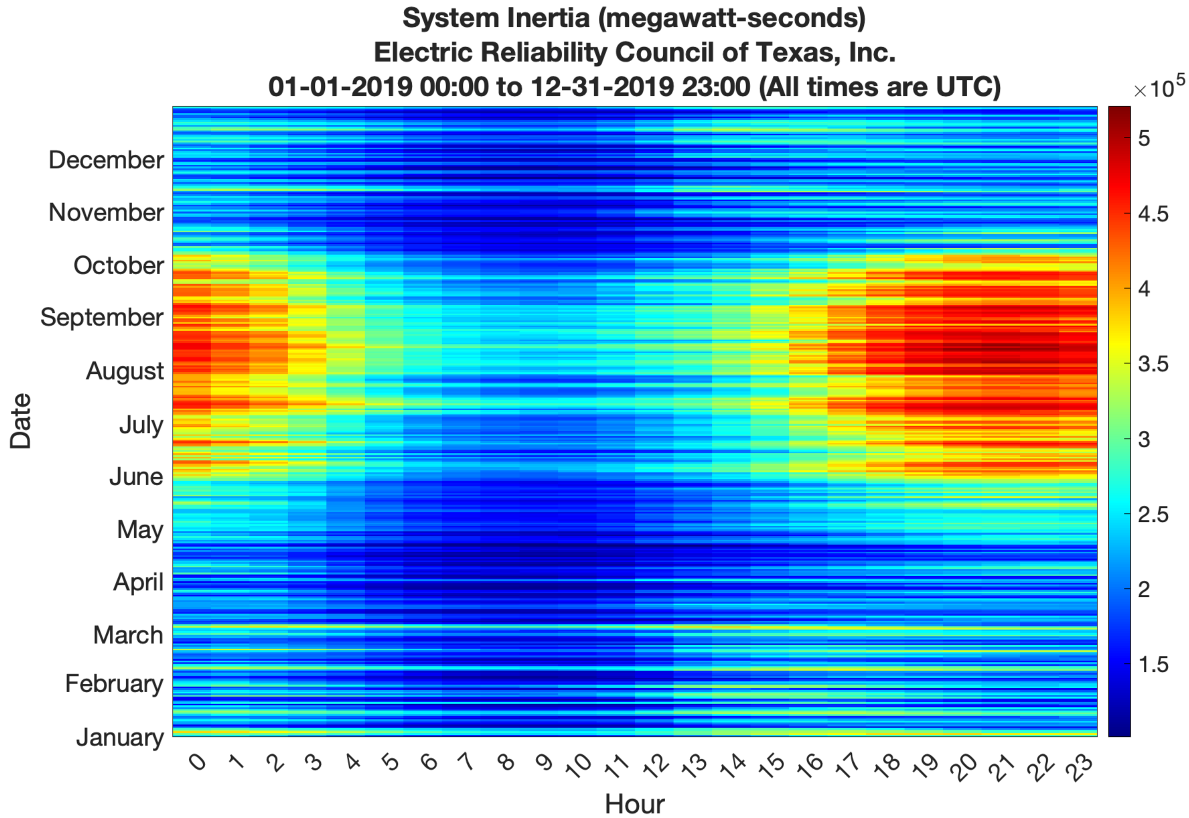
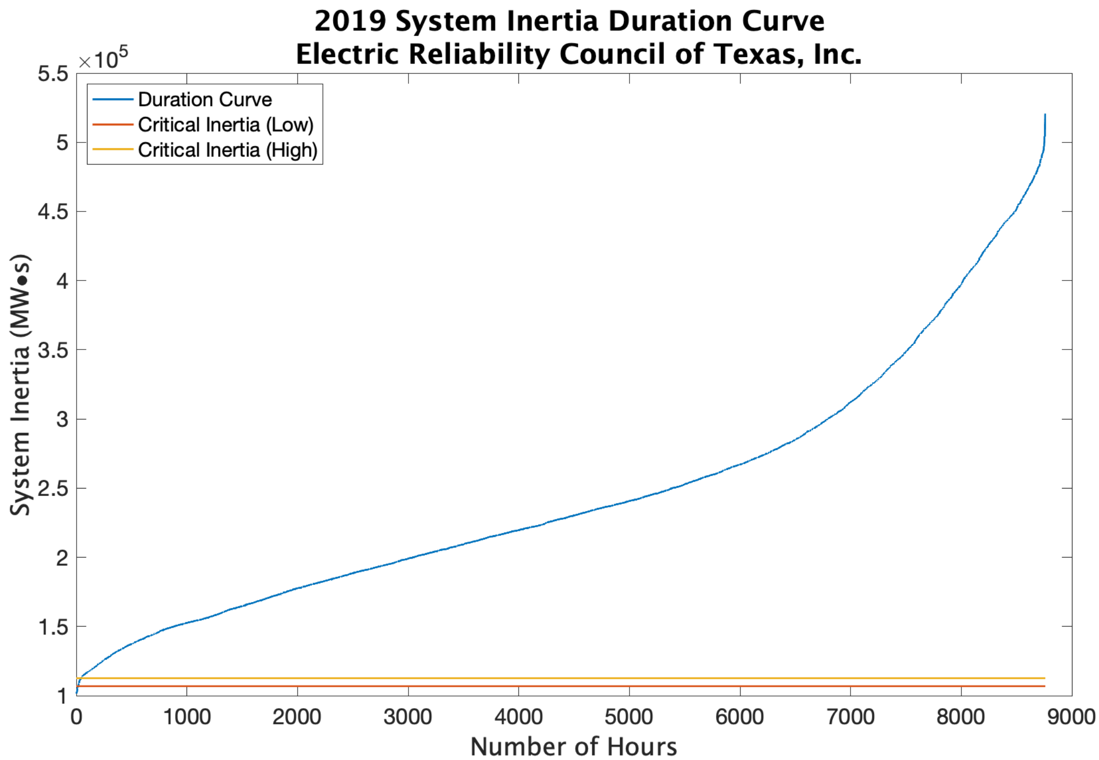


Fig. 3. Temporal Heat Map

Figure 4 presents a duration curve for system inertia as estimated by the GFCM for ERCOT in 2019. The duration curve displays the number of hours for which system inertia is at or below a given level. The model run presented in Fig. 4 indicates that system inertia falls below a critical value in only 15 out of 8760 hours. The critical inertia level is estimated following the approach discussed in [3]. The critical inertia value for any given hour will change with the size of the largest contingency (the generating capacity of the two largest online generators, which in Texas, are usually nuclear reactors). The high and low critical inertia values presented in Fig. 4 are the highest and lowest hourly values estimated in the course of the year. The GFCM achieves a high level of agreement with ERCOT's own published estimates for the distribution of system inertia values [40]. While ERCOT has not reported system inertia dropping below the critical level, the estimate of the critical inertia level produced by the GFCM is slightly higher than that reported by ERCOT. This small difference in critical inertia level may account for the difference in estimates of sub-critical system inertia levels.

The assumption that inertia from load and PUN scales proportionally with load achieves good fidelity between modeled and observed values at the low end of the distribution, but overstates the amount of inertia under high load conditions. As system inertia is only a problem when inadequate, model fidelity at the low end of the distribution is more important than at peak load.



Case	Critical Inertia Estimate	Hours Below Critical	Percent of Hours
Low	106805.8	15	0.0017
High	112596.5	43	0.0049

Fig. 4. Inertia Duration Curve

Figure 5 shows a spatial representation of inertia and net generation at the generator level for the hours in which system inertia is estimated to obtain its minimum value. Similar graphics can be produced with the GFCM for the hour in which wind generation is estimated to reach its highest share of net generation. In this case, natural gas plants account for a large amount of the inertial contributions made to the ERCOT grid. Careful observers of Fig. 5 may notice the peculiar presence of an ERCOT plant located in Oklahoma. This is the Tenaska Kiamichi Generating Station, which is capable of selling power to either ERCOT or the Southwest Power Pool (SPP) [41, 42].

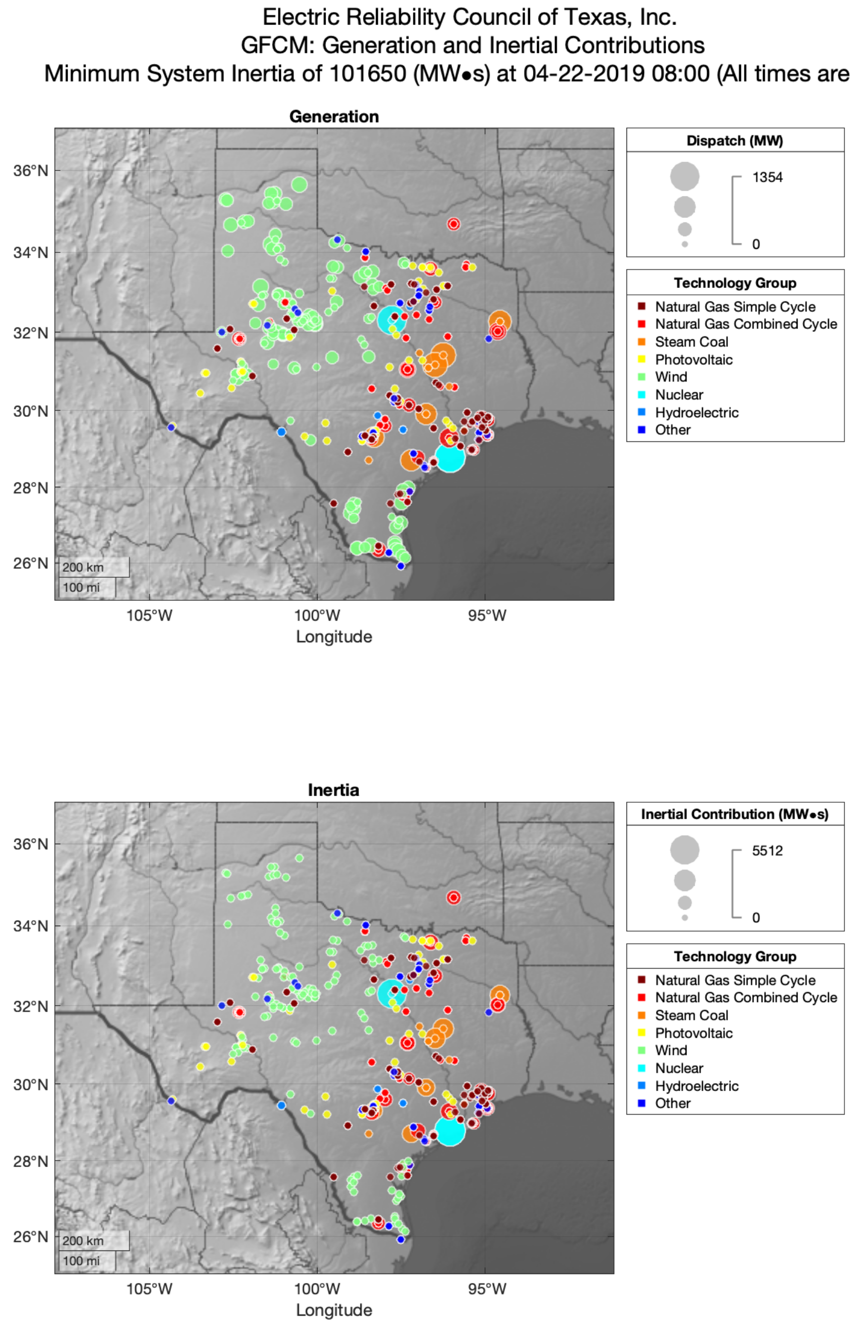
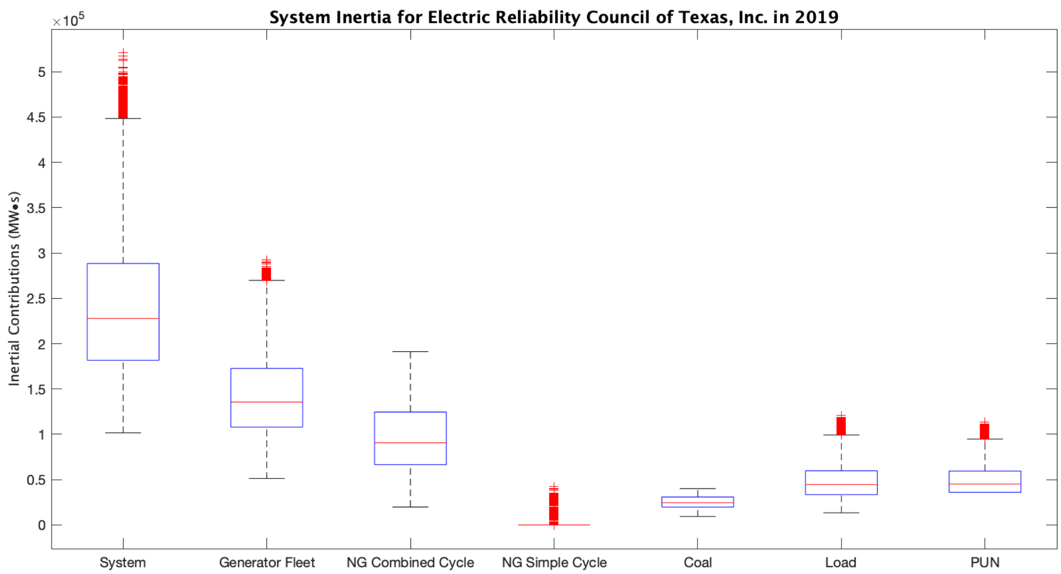


Fig. 5. Balancing Authority Map at Annual Minimum Inertia

Figure 6 presents a box plot of the total system inertia values estimated for ERCOT in 2019 using the GFCM. The distribution of hourly inertial contribution values attributable to combined cycle natural gas plants, simple cycle natural gas plants, coal generation, load, and private use networks is also displayed. Combined cycle plants are among the largest contributors to system inertia, both individually and as a group. Contributions to system inertia from conventional coal plants appear smaller than those from load and private use networks, both of which are assumed to scale with load. This finding suggests that system operators may need to treat inertia from load and private use networks commensurate with the fact that these sources account for a non-negligible share of system inertia. The table included in Fig. 6 allows comparison of the GFCM estimate of minimum system inertia, 101650 MW•s, with the target value of 134500 MW•s [40]. Note that for the purpose of GFCM reporting, generator counts record wind farms with multiple turbines as a single generator. The distribution of GFCM values for inertia from natural gas simple cycle generation is a result of the model determining that such generators have higher marginal costs than their combined cycle counterparts and are therefore allocated only when demand exceeds levels which can be met by combined cycle generation alone. Heterogeneity in generator design or grid conditions, if modeled with greater levels of granularity, could create a smoother transition between technology groups along the merit order.



Model Outputs	Values	Targets
Time of Minimum System Inertia (UTC)	04-22-2019 08:00	03-27-2019 06
Inertial Contributions (MW•s)	101650	134500
System Load (MWh)	29860	29883
Marginal Cost of Generation ($)	25.12	-
Generator Count	162	-
Wind Generation Share (%)	0.53	0.5

Fig. 6. Inertia Estimates Box Plot

While system inertia and the minimum inertia event date differ between observed and modeled values, the GFCM value for demand in that hour, 29860 MWh, is within 0.1 percent of the target value of 29883 MWh. The remaining discrepancy between model and observed system inertia may be driven by assumed patterns in PUN and load-based inertial contributions, neither of which are directly observable by the analyst.

Table 2 presents summary statistics for hourly system inertia values estimated by the GFCM for ERCOT from 2019 through 2021. The maximum, minimum, mean, and median system inertia values decline over the three years. The standard deviation of hourly system inertia values decreased in 2020 before rising in 2021. The onset of the COVID-19 pandemic and the effects of policy responses to the public health crisis cannot be eliminated as potential drivers of the observed change in system inertia. The inertial contributions of demand-side and PUN resources remain a source of model uncertainty, especially during a period of study for which significant changes to economic organization occur. Additionally, rising input price volatility or increasing penetration of intermittent resources may be sufficient to explain the rising standard deviation of system inertia values in 2021.

Table 2. System Inertia Estimates: Summary Statistics for ERCOT 2019-2021

Year	2019	2020	2021
Maximum	520 942	508 819	499 569
Minimum	101 650	100 944	89 350
Mean	245 959	232 801	228 481
Median	227 755	216 049	207 692
Standard Deviation	87 662	82 069	90 014

System inertia summary statistics are valued in MW•s.

2.6. Model Validation

Validation of the GFCM is a process of obtaining and evaluating visualizations and metrics of model performance. Ultimately, it is up to the analyst to determine whether the GFCM is performing sufficiently well to justify its application to a given scenario. This section discusses several of the model outputs produced to aid the analyst with model validation.

As a first step, net generation is aggregated to the monthly generator level to harmonize the model output with the variables presented in EIA Form 923. EIA Form 923 is not used at any other point in the GFCM and is thus suited for model validation exercises. For a subset of generating units, we obtain actual net generation values against which to validate model performance. We use monthly aggregates because hourly generator level output data is proprietary. We are mainly interested in determining whether the distributions of modeled net generation reflect patterns observed in the actual data. Because we do not differentiate assumed inertial constants within a given technology group, matching a specific generator value is less important than capturing the distribution of values with satisfactory fidelity.

Figure 7 presents a scatter plot of the observed (EIA Form 923) and modeled monthly data broken out by a third variable indicating technology. Both axes are in log scale. The GFCM validation function produces similar scatter plots coded by other tertiary variables, including the decade when the generator began operating, the energy source code, the month of the year, industry classification code, prime mover codes, and industrial sector. Proximity to the 45 degree line indicates a higher degree of model agreement with reality at the generator level, though complete agreement at this level of analysis is not necessary for the GFCM to capture system dynamics in synchronous inertial contributions. These scatter plots are intended as a diagnostic tool for the analyst to identify and understand any systematic departures of the model outcomes from the values reported in EIA Form 923.

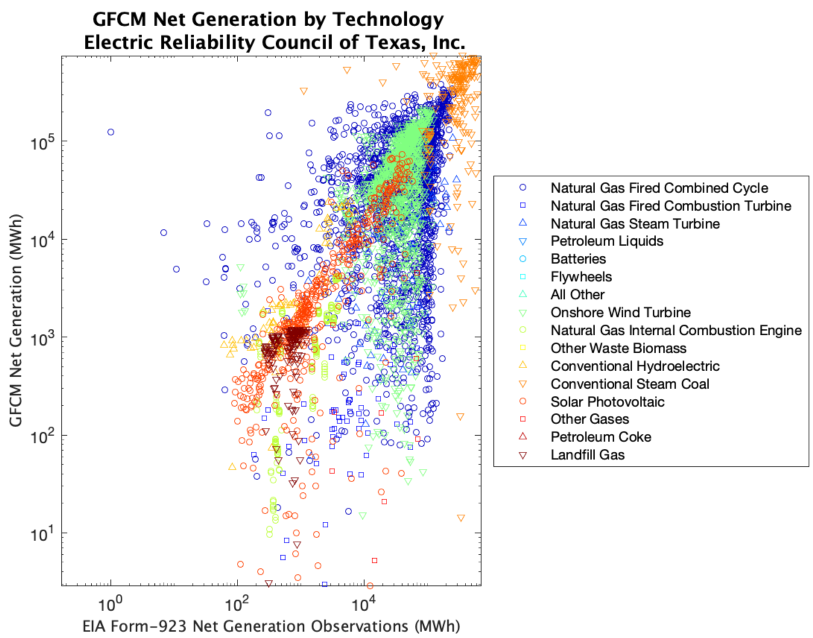


Fig. 7. Observed and Modeled Monthly Net Generation by Technology

The scatter plots are useful for diagnosing potential model bias, but they mask the degree to which the GFCM is able to recreate observed distributions of generating unit output. Figure 8 compares the distribution of monthly net generation produced by the GFCM with that from EIA Form 923.

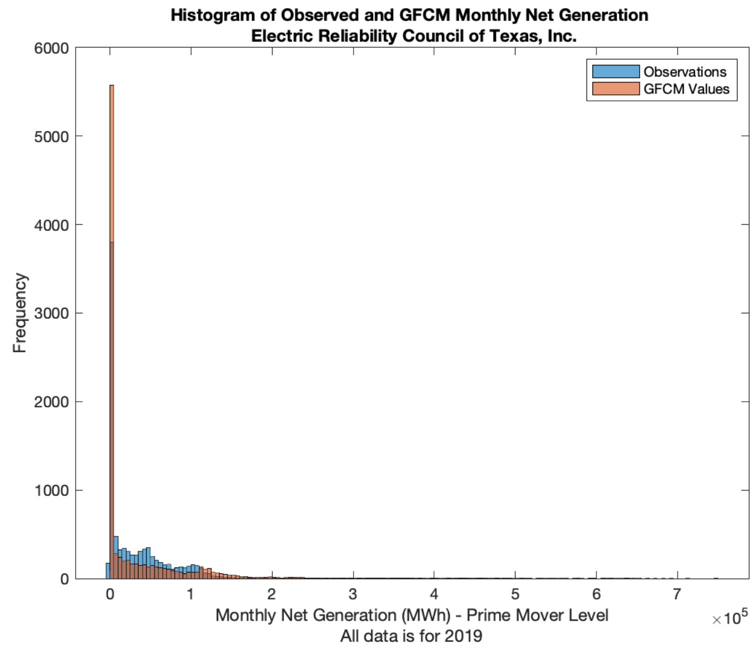


Fig. 8. Observed and Modeled Monthly Net Generation

While scatter plots and histograms provide intuitive visual evidence concerning model fit, quantitative measures of model fit are needed to evaluate the validity of the GFCM. Furthermore, a method is needed for determining the sensitivity of core model findings to improvements in fit. If the distribution and summary statistics of system inertia change little as the model is adjusted to improve fit with EIA Form 923 data, the findings' small sensitivity is an indication that the model is adequate for the purpose of understanding patterns of change in system inertia.

Once a measure of model fit is obtained, it can be used to recommend a course of action to improve model fidelity and evaluate the sensitivity of model outputs to changes in inputs. A version of the log accuracy ratio (LAR), described in [43], is calculated to evaluate model fit further and produce adjustments to generator marginal costs that may be employed in subsequent iterations of the scenario runs. The LAR can be simply expressed as $LAR = -ln(observed/predicted)$, where "observed" and "predicted" refer to the generating unit level monthly net generation values by prime mover code. Perfect agreement between observed and predicted values would lead to a quotient (observed/predicted) of one and a LAR of zero. Such a finding would lead to the recommendation that no changes be made to the assumed marginal cost values for generating units employing that kind of prime mover. A quotient above unity indicates that observed net generation values are larger than those produced by the GFCM. If the quotient is 1.1 the corresponding *LAR* value is -0.0953 and if the quotient is 0.9, indicating observed values are below the GFCM values, the *LAR* value is 0.1054. Effectively the *LAR* provides us with an indicator of how to adjust the assumed marginal cost of generating technologies by prime mover codes, enabling a recursive model fitting effort. When the GFCM overallocates generation employing a specific prime mover, the *LAR* offers a percent increase in marginal cost that should reduce the relative competitiveness of the prime mover in subsequent scenario batches and lead the model to obtain more accurate allocations. When the GFCM underallocates generation employing a given prime mover, the *LAR* proposes a decrement to the assumed marginal costs that should increase the competitiveness of that group of generators in the following model iterations.

After the initial scenario batch is run, a series of additional scenario batches are run recursively using the *LAR* values to tweak the assumed cost structures of different generating technologies. The $gfcm\_v1\_recursive.m$ MATLAB function can be used to recursively fit the GFCM to the data, taking the LAR values into consideration. Recursive modeling efforts also require the analyst to ensure that the variable "recursive" is set to one at the beginning of both the scenario specifier and snapshot functions. By default the value of the "recursive" variable is set to zero.

The "ValidationLog.mat" file, which is updated with each iteration of the recursive fitting algorithm, shows that the distribution of hourly system inertia estimates is insensitive to the implemented changes in the assumed relative costs of generation disaggregated by prime mover code. That is, the summary statistics presented in Table 2 do not change appreciably as we modulate marginal cost assumptions from iteration to iteration. Changes in relative costs of generation at the margin have the potential to rearrange the merit order of generating units, leading to different amounts of inertia on the system. If all the rearrangements to the merit order are sub-marginal – that is, they only affect generation allocated below the market clearing quantity and price – the total amounts of system inertia are unlikely to change. This is one possible explanation for the robustness of the estimated inertia distributions to changes in marginal costs.

Simple use of the GFCM produces 8760 hourly snapshots of a given BA to understand how the inertial contributions of the generating fleet evolve over the course of a year. While the processing time is limited by not employing a fully security-constrained optimization problem, a single annual scenario run generally takes upwards of 80 minutes. Using the recursive model-fitting function will necessarily scale processing times in roughly linear fashion according to the number of iterations specified by the analyst. BAs with larger generator fleets will tend to take longer for the model process.

3. Tutorial

This section is intended to help you get started using the GFCM. In addition to downloading data inputs, you will need MATLAB, the signal processing toolbox, and the statistics toolbox to run the GFCM.

3.1. GFCM Download and Setup

The GFCM can be found using the following digital object identifier: https://doi.org/10.18434/mds2-2835. To install the model, download the GFCM V1 directory to your machine. This initial download contains all the necessary data inputs and original functions to run the GFCM. Next, populate the parent directory function (`gfcm_v1_dir_parent.m`) located in the `Matlab Code` subdirectory as well as the API key in `gfcm_v1_eia_api_key.m`.

The user will need an EIA API key, which may be obtained for free from the EIA by following this link to https://www.eia.gov/opendata/. The reliance on API calls allows the code to be lightweight and portable, and the user may decide how often to refresh the downloaded data through new calls to EIA. If the user desires, run time may be reduced in subsequent scenario runs for a given BA by not updating the EIA data. The parameter `data_fresh_thresh`, found in `gfcm_v1_scenario_main.m`, controls the threshold number of days since last download past which a fresh download is conducted.

The scenario specification and all other input data not acquired from the EIA API is located in the subdirectory, `Input Data`. By default, `gfcm_v1_scenario_specifier.m` is preset to run scenarios for the ERCOT BA using `ScenarioSpecifications2019ERCO.xlsx`, but any of the scenario specification files included in the `Input Data/Scenario Specifications` directory will work after updating the input file names in `gfcm_v1_scenario_specifier.m`. The user should review all entries in the specification input to ensure they are consistent with the scenario they wish to simulate. One note of caution: if you change the number of scenarios (rows in the .xlsx file), be sure to update the appropriate data ingestion parameters, `opts.DataRange`, in `gfcm_v1_scenario_specifier.m`.

3.2. Running the GFCM

The entire model can be run from the initial function, `gfcm_v1_scenario_specifier.m`, which loads parameters from the specification input file and then calls on `gfcm_v1_scenario_main.m` to build data sets of monthly operable generator fleets before calling `gfcm_v1_scenario_snapshot.m` to create hourly models of the conditions on the BA's system. Finally, `gfcm_v1_validation.m` is called to produce a report of the model run consisting of data and figures. To run the GFCM, load `gfcm_v1_scenario_specifier.m` in MATLAB and click "Run" in the toolbar at the top of your screen. The function will automatically create a timestamped scenario batch directory in a BA-specific subdirectory of the `Output Data` folder. All model outputs, both data and figures are catalogued by scenario.

3.3. Note on Hardware and Runtimes

GFCM code was originally developed in MATLAB R2022a on a MacBook Pro laptop running macOS 11.6.8 Big Sur with an Intel Core i9 processor and 16 GB of DDR4 memory. The GFCM code was further tested for cross-platform compatibility on a laptop running Windows 10 with an Intel i5 processor and 32 GB of memory. Run times were comparable between the two test systems. Run times are increasing in the duration of scenarios tested as well as the number of generators in a given BA. Initial (8760 hour) runs of the GFCM for ERCOT took less than 90 minutes. Subsequent runs generally took less than 60 minutes.

4. Conclusion

This manuscript has described the basic structure of the GFCM and how it has been used to produce hourly estimates of system inertia for the ERCOT BA. The GFCM may be used to produce similar analyses for other BAs in the contiguous U.S. even with the messy, imperfect nature of the public data resources harnessed. Furthermore, the GFCM can now be employed to understand the provision of other non-market services associated with the characteristics of the electric generating fleet. While the first model application concerned system inertia, the GFCM is now positioned as a general-purpose tool for understanding how change in the characteristics of the electric generating fleet will interact with market forces and impact the provision of grid services. Future work with the GFCM should consider the development of additional MATLAB functions as standardized tools for building and comparing case studies and counterfactuals.

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Appendix A. List of Symbols, Abbreviations, and Acronyms

API Application Programming Interface

BA Balancing Authority

CDS Climate Data Store

ECMWF European Centre for Medium-Range Weather Forecasts

EIA Energy Information Administration

EPA Electric Power Annual

EPM Electric Power Monthly

ERA5 ECMWF Reanalysis v5

ERCOT Electric Reliability Council of Texas

GFCM Generator Fleet Characteristics Model

LAR Log Accuracy Ratio

NIST National Institute of Standards and Technology

PUN Private Use Network

SB Scenario Batch

SPP Southwest Power Pool

TN Technical Note

VFD Variable Frequency Drive

VOM Variable Operating and Maintenance

Appendix B. Data and Code Manifest

Figure 9 presents dependencies between the MATLAB functions that constitute the GFCM. Table 3 lists and describes these functions. Table 4, the input data manifest, contains data handles, the identity of the source organization, the date accessed, the file name, and url of each data input.

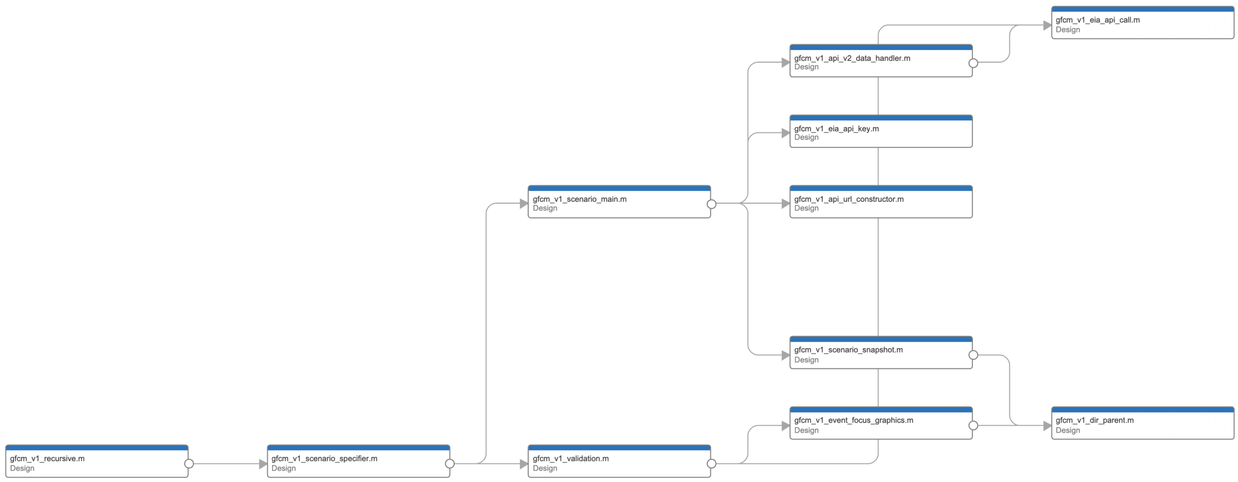

Fig. 9. Code Dependency Diagram

Table 3. MATLAB Code

ID	Function Name	Lines	Description
M01	gfcm_v1_scenario_specifier.m	292	Orchestrate scenario runs
M02	gfcm_v1_scenario_main.m	2072	Conduct primary data handling
M03	gfcm_v1_scenario_snapshot.m	1149	Create hourly picture of market operations
M04	gfcm_v1_validation.m	1885	Visualize and validate model results
M05	gfcm_v1_event_focus_graphics.m	307	Produce additional visualizations
M06	gfcm_v1_dir_parent.m	16	Specify parent directory
M07	gfcm_v1_eia_api_call.m	58	Make call to EIA API
M08	gfcm_v1_api_url_constructor.m	106	Assemble url strings for EIA API call
M09	gfcm_v1_api_v2_data_handler.m	186	Process data obtained through EIA API call
M10	gfcm_v1_recursive.m	31	Iterate calls to scenario specifier for recursive model fitting
M11	gfcm_v1_eia_api_key.m	18	Specify user EIA API key

Table 4. Input Data Manifest

	Handle	Source	Date Accessed
	Average power plant operating expenses for major U.S. investor-owned electric utilities	**EIA**	**12.3.2020**
File Name: URL:	epa_08_04_1020.xlsx https://www.eia.gov/electricity/annual/		
	Average tested heat rates by prime mover and energy source	**EIA**	**12.3.2020**
File Name: URL:	epa_08_02_1020.xlsx https://www.eia.gov/electricity/annual/		
	Content and Layout of the Annual Electric Generator Report (EIA-860) Data Files for 2018	**EIA**	**12.11.2019**
File Name: URL:	LayoutY2018.xlsx https://www.eia.gov/electricity/data/eia860/		
	Data from Sargent and Lundy - Capital Cost Study - Cost and Performance Estimates for New Utility-Scale Electric Power Generating Technologies	**EIA**	**12.11.2019**
File Name: URL:	Sargent_Lundy_FOM_VOM.xlsx https://www.eia.gov/analysis/studies/powerplants/capitalcost/pdf/capital_cost_AEO2020.pdf		
	EIA 923 Detailed Data	**EIA**	**10.22.2021**
File Name: File Name: File Name: URL:	EIA923_Schedules_2_3_4_5_M_12_2019_Final_Revision.xlsx EIA923_Schedules_2_3_4_5_M_12_2020_Final_Revision.xlsx EIA923_Schedules_2_3_4_5_M_12_2021_18FEB2022.xlsx https://www.eia.gov/electricity/data/eia923/		
	EIA 930 Reference Tables	**EIA**	**10.22.2021**
File Name: URL:	EIA930_Reference_Tables.xlsx https://www.eia.gov/electricity/930-content/EIA930_Reference_Tables.xlsx		
	Generator Set	**EIA**	**10.29.2019**
File Name: URL:	august_generator2019.xlsx https://www.eia.gov/electricity/data/eia860m/		
	Reanalysis ERA5 Single Levels	**CDS**	**10.22.2021**
File Name: File Name: File Name: URL:	CDS_201901_t2m.csv ··· CDS_202112_t2m.csv https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview		
	Scenario Specification Data	**USER**	**10.29.2020**
File Name:	ScenarioSpecifications2019ERCO.xlsx		