MFRED, 10 second interval real and reactive power for groups of 390 US apartments of varying size and vintage

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Building electricity is a major component of global energy use and its environmental impacts. Detailed data on residential electricity use have many interrelated research applications, from energy conservation to non-intrusive load monitoring, energy storage, integration of renewables, and electric vs. fossil-based heating. The dataset presented here, Multifamily Residential Electricity Dataset (MFRED), contains the electricity use of 390 apartments, ranging from studios to four-bedroom units. All apartments are located in the Northeastern United States (IECC-climate-zone 4A), but differ in their heating/cooling system and construction year (early to late 20th century). To adhere to privacy guidelines, data were averaged across 15 apartments each, based on annual electricity use. MFRED includes real and reactive power, at 10-second resolution, for January to December 2019 (246 million data points). The annual average real power per apartment is 343 W (3.27 W/m² of floor area), with strong variation between seasons and apartment size. Considering its large number of apartments, high time resolution, real and reactive power, and 12-month duration, MFRED is currently unique for the multifamily-sector.

Background & Summary

Electricity consumption in buildings is a major component of global energy use and its environmental impacts, including greenhouse gas (GHG) emissions. In the United States, the residential building sector in 2017 consumed 32% of all electricity1, an amount responsible for 9% of all domestic GHG emissions2. Globally, electricity consumption is expected to grow, however with increasing portions generated by renewables sources such as solar and wind3.

Understanding residents’ electricity use has many interrelated research applications, including: (i) determining the potential for energy conservation through resident feedback4–6; (ii) non-intrusive monitoring (NILM) of appliance-level loads via disaggregation7–11; (iii) predicting building electricity use12–14, including with agent-based models15–17; (iv) leveraging a building’s thermal characteristics to optimize its electricity profile used for heating and cooling18,19; (v) switching heating systems from fossil fuels to electricity, e.g., via heat pumps20; (vi) assessing the techno-economic feasibility for distributed electric storage to facilitate integration of intermittent renewables on the grid21–23, including electric vehicles24,25; (vii) quantifying phantom loads, e.g., from electronics in standby mode26; (viii) detecting occupancy patterns27; and (ix) novel market mechanisms and associated technology solutions to enhance the integration from buildings into smart grids27, e.g., for applications in Transactive Energy Networks28.

Here, we present the Multifamily Residential Electricity Dataset, henceforth MFRED (Data Citation 1). MFRED features 10-second resolution real and reactive power in 390 apartments, ranging in size from studios

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to four bedrooms. To place MFRED into context, we note that for US single family homes (detached or attached dwellings) a number of publicly available datasets on electricity use already exist. These typically feature either a large sample size but at low time resolution (e.g., the RBSCA study with 100 homes at the standard 15 minute resolution28 or a small sample size at high time resolution (e.g., the REDD study with 10 homes at 1-second or higher time resolution29). Outside the US, examples include REFIT in the United Kingdom (electricity data of 20 houses, including appliance level, at 8-second time resolution over 2 years)30, AMPds in Canada (1-minute interval electricity loads of a Canadian house, including 21 separate submeter circuits, over 2 years)31, and SustData in Portugal (sub-second interval electricity loads of 6 single family homes and 17 apartments over ~9 months)32. In contrast, for apartments in US multifamily buildings, which are increasingly common, very few datasets have been made public. One example is data of a student housing-style condominium building in Los Angeles, California, with hourly resolution of 118 apartments over 8 months33. With these considerations in mind – diverse multi-family units, sample size, 10-second time resolution, both real and reactive power, and a full year of data – MFRED appears unique.

Methods

Data collection. With authorization from Columbia University's Institutional Review Board, the electric consumption data in MFRED were collected by a standard installation of a Siemens embedded micro metering system34 with SEM3 controllers and 9410 data loggers, running in combination with WinPM data collection software35 (henceforth Real-Time Metering, RTM). The hardware and software installations were carried out by licensed contractors.

The RTM for each apartment (sense, log, communicate) was installed in the buildings’ utility rooms, in proximity to the existing utility meters and apartment circuit breakers in each building (rather than inside each apartment), with fifty-amp split-core current transformers on each pole going to an apartment, to measure real-time currents. Currents are relayed to a controller (firmware version 2.3.7.AE; 1–2 controller(s) per building), which computes real and reactive powers using the voltage probed at the building’s main circuit breaker. Some apartments are wired with only one pole and others with two poles at different phase (“3 Phase Wye” configuration). Each controller transmits the power and energy data (see section Data record glossary) to a data logger (firmware version 001.003.001), which timestamps the data and reports them to a central server via the building’s Ethernet. The data loggers store about 18 hours of data in onboard memory, acting as a buffer in case of temporary Ethernet outages. The server runs the data collection software (version 7.1) on a Microsoft Windows Server 2012R2 virtual machine. The data collection software stores the data in a Microsoft SQL database on the server.

Various test routines were carried out to ensure that the data for each apartment were properly communicated to the SQL database. For example, during installation of the RTM, this included measuring the amperage of every pole with a separate, handheld ampere meter and cross-validating this amperage against the respective data in the controllers. Additional test routines, including for meter accuracy, are described in Technical Validation.

Data de-identification and 15/15 rule. All data in MFRED have been fully de-identified and thus carry no identifiable information such as names of residents, building addresses, or apartment numbers. To further reduce the risk of possible re-identification or privacy breaches, and in consultation with the project management at the US Department of Energy and data privacy and re-identification experts (see Acknowledgements), MFRED follows the data aggregation standard recommended for publishing utility data in the State of New York, commonly referred to as the 15/15 rule36. Briefly, this standard recommends that electricity data not be made public at the level of individual apartments but only as aggregates of 15 (or more) apartments each, with the additional requirement that no individual apartment comprise more than 15% of the respective aggregate (see section Data record/Apartment groups for details).

Data Records

Building types and heating/cooling systems. The 390 apartments in MFRED (dataset available on Harvard Dataverse37) are located across over a dozen buildings in the borough of Manhattan, New York, NY, USA (IECC climate zone 4A38). All 390 apartments are rented, and the vast majority of residents pay for their electricity through their own contract with the local utility (rather than through their rent).

The buildings were chosen to represent typical Manhattan residential building stock: 79% of the buildings in MFRED were constructed prior to 1940, 7% between 1940 and 1980, and 14% post 1980. The average size of apartments in MFRED (which ranged from studios to four-bedroom units) is 105 m² (standard deviation: 48 m²). For comparison, the entire Manhattan residential and mixed-residential building stock is 86% pre-1940, 6% 1940–1980, and 8% post-1980, with an average apartment size of 92 m² (standard deviation: 64 m²)39.

Of the apartments in MFRED, 89% have heating supplied centrally (steam or hot water), but the air conditioning is provided by the residents' own appliances (typically installed in the windows). This means that, with the exception of supplementary personal space heaters or heating blankets, heating in these apartments does not contribute to the electricity data reflected in MFRED, whereas air conditioning does. The remaining 11% of apartments use various types of packaged terminal air conditioning units (PTAC), with the majority such that the bulk of the heating and cooling load is supplied centrally, thus not contributing to an apartment's own electric loads. Consequently, the majority of apartments in MFRED exhibit higher electric power draw during summer months, as a function of weather conditions. In contrast, the power draw during winter months depends only marginally on weather conditions.

Apartment groups. Following the 15/15 rule36 (above), we organized the 390 apartments into 26 groups of 15 apartments each (Table 1). These groups are identified by the prefix “AG01” through “AG26” in the column headers for each data record in MFRED. To simplify the use of MFRED, the data for each apartment group show
In order to obtain AGs with similar electricity use in each group, we first sorted the 390 apartments by their total electricity consumption in 2019. AG01 comprises the 15 apartments with the lowest 2019 consumption, AG02 the next 15 apartments, etc. This approach also ensured that the 15% requirement of the 15/15 rule was not violated: For 23 of the 26 AGs, the highest single-apartment portion is 7%, and for the remaining 3 AGs it is 13%.

Data record glossary. Table 2 lists each data record in MFRED along with its technical explanation. The acronyms kW, kVAR, and kWh follow standard terminology. The kWh data record can be used to interpolate electricity use during the rare times that some apartment meters were offline (see section Technical validation/Data gaps). For an illustration of how to interpret the various metrics, see section Seasonality and end-use types.

MFRED file organization. MFRED is organized into five csv files (Table 3). Four of these contain the data at 10-second time resolution, one file for each quarter of 2019. The number of rows per csv file was kept below 1 million, to allow for immediate analysis in standard spreadsheet software. The 5th file shows the data of all 4 quarters in a single file, but at 15-min time resolution. Note that, for either time resolution, the real and reactive powers show instantaneous readings at each time step, not readings time-averaged for the period in-between time steps. As such, the 15-min file is simply an excerpt of the other 4 files, provided solely for the convenience of a single, smaller file for the entire year.

Benchmarking of annual average consumption. Between 01 January 2019 and 31 December 2019, the time-averaged electricity use (real power) per apartment was 343 ± 14 W, or 8.2 ± 0.3 kWh per day (where 14 W [0.3 kWh] is the standard error of the mean across the 390 apartments, SEM). The time-averaged use varies strongly between apartments, from less than 50 W to ~2,500 W. As seen in Fig. 1, the variation is partly explained by apartment size. However, even among similarly-sized apartments, differences of a factor 3 or more in time-averaged use are common. Note that, based on electricity use patterns, it appears that some of the 390 apartments were unoccupied for part of the year. Since this is common for rental units in multi-family buildings.
Energy Consumption Survey (RECS) data (latest available data are from 2015). According to that survey, apart-

Residential Building Stock Assessment (RBSA)\(^3\), one of the largest databases for single family homes in
the United States, the annual average electricity use is 1,497 W per home, corresponding to an average electricity
use of 8.03 W/m\(^2\). However, 62\% of this use is attributed to electricity used for heating, leaving 3.05 W/m\(^2\) for all
other electricity use. The value of 3.05 W/m\(^2\) is close to the average electricity use intensity in MFRED, which is

**Table 2.** Data record glossary for MFRED. *For each of the 26 apartment groups (AG), electricity metrics are averaged across the 15 apartments in each group. The group that each column refers to is indicated by the prefix “AG01”, “AG02”, …, “AG26” in the column headers. For ease of use, a grand average across all 390 apartments is also provided (indicated by the prefix “AG01To26” in the column headers). Each metric therefore represents the kW, kVAR, or kWh of an average apartment (not the sum across apartments). The total real [reactive] power on the grid can be calculated by multiplying the given average kW [kVAR] value with the respective number of apartments.

**Table 3.** Names and descriptions of MFRED files (Data Citation 1). The “reporting per time step” metric is explained in section Technical validation/Data gaps. * Indicates files with complete coverage (all 390 apartment meters reporting at every 15-min time step). ** All files contain one row for every 15 min [10 sec] time step during the covered time period.

(e.g., in-between previous and new tenants), the data of these apartments were included in the apartment group averages in MFRED.

An average real power of 343 ± 14 W per apartment is consistent with summary statistics from the Residential Energy Consumption Survey (RECS) data (latest available data are from 2015)\(^4\). According to that survey, apartment units in multifamily buildings of 5 or more units in the Northeastern United States had an average electricity use of 340 W (when excluding any electricity used for space or water heating)\(^2\).

Considering another benchmark, the average electricity use intensity (i.e., use per floor area) in the apartments in MFRED is close to that observed for single family homes, once adjusted for types of electricity use. In the United States Residential Building Stock Assessment (RBSA)\(^3\), the majority of the MFRED apartments use electric window air conditioners

**Seasonality and end-use types.** Figure 2(a) shows the electricity use for different times of the year, with each time of year illustrated using a period of 28 days. These periods are in July 2019 (for summer), January 2019 (for winter), and April 2018 (for the shoulder season). The average real power is highest in July (554 W on week-
days, 583 W on weekends) because the majority of the MFRED apartments use electric window air conditioners
rather than centrally supplied cooling. The average real power is lowest in April (285 W on weekdays, 282 W on weekends) when there is little need for either air conditioning or supplementary electric heaters. January has a slightly higher average real power than April (338 W on weekdays, 339 W on weekends), likely because residents use electric lighting for more hours of the day and some use supplementary electric heating. Still, for the majority of MFRED apartments heating is supplied centrally, so it does not have a significant impact on apartment-level electricity use.

Seasonal differences exist in the diurnal profiles as well. Most notably, the typical load increase in the early evening hours (17–20 h) is steeper in January than in April or July. In July, the diurnal profile, while showing higher use overall, also shows less variation of use during the day. This is expected in climate zone 4 A for the month of July, which features hot and humid weather conditions, prompting substantial use of air conditioning throughout the day and night.

A unique feature of MFRED is that it includes both real and reactive power. This allows MFRED users to separately identify three different types of loads: (i) Inductive loads (such as the electric motors in air conditioners), which draw positive reactive power and thus increase the phase angle of the total apartment load; (ii) capacitive loads (including some consumer electronics), which draw negative reactive power and thus decrease the phase angle; and (iii) resistive loads (such as incandescent light bulbs or space heaters), which draw no reactive power and thus reduce the absolute value of the phase angle (i.e., closer to zero)\(^40\). As an example of such an analysis, the phase angle shown in Fig. 2(b) provides insight into which types of appliances are predominantly used at different times of day and how this varies by season: The elevated phase angle in July is consistent with the above interpretation that the additional electricity use in July seen in Fig. 2(a) stems from increased use of air conditioners, which have large inductive loads. The negative phase angle observed at night in January and April indicates that electronics such as WiFi routers, internet modems, computers, and entertainment devices dominate the average apartment's electricity use at these times. When such electronics are not actively being used (such as a television in stand-by mode), they are often referred to as phantom loads\(^11\).

Technical Validation

Apartment wiring, data consistency, and dynamic range. As laid out in more detail in Methods, all electricity data in MFRED were collected by a standard installation of a vendor-provided RTM. To validate that the metering system is running as expected, we carried out several test routines. One test routine, already described in Methods, ensured that each of the ~750 current transformers was wired to the correct RTM micro-meter module. We carried out the following further test routines, with the focus on ensuring that each of the data fields in the SQL database imports the correct data from the respective controller.

Internal consistency of data. While only the kW, kVAR, and kWh data records are included in MFRED, the controllers record additional metrics for every apartment, including amperage, voltage, apparent power, and phase angle. Each controller displays these metrics on a separately accessible interface. The metrics are inter-related in what is commonly referred to as the power triangle\(^40\). For example, the phase angle can be inferred mathematically from kVAR and kW (Table 2). We used these mathematical relationships to cross-validate the metrics displayed by the controllers directly (e.g., phase angle) with the respective values calculated from the SQL database. This gave us very high confidence that all data fields in the SQL database import the correct data from the respective controller.

Dynamic range of metrics. We validated that all metrics fall into their expected ranges, specifically: (i) instantaneous real power is positive, ranging from 0 kW to about 15 kW per apartment (for large apartments, at some times of day); (ii) reactive power is negative or positive, but typically substantially smaller in absolute value than real power (as seen from the phase angles in Fig. 2(b)); (iii) average real power per floor area is consistent with benchmarks (see section Data records/Benchmarking); and (iv) voltage per pole is ~120 V.
Accuracy. The manufacturer-rated relative accuracy of the RTM with split-core current transformers is ±1%\(^{34}\), with lower relative accuracy expected at times of low power draw because the detection threshold is ~3 W per pole. We confirmed this accuracy of the RTM by comparing cumulative kWh readings from the RTM against those by the utility-provided electric meters used to bill residents. The comparison was carried out for a random sample of 78 apartments (20% of all apartments) and across a time period of 2–16 months between September 2017 and February 2019 (varied by building). We then determined the discrepancy in the real power measurements of the two metering systems as the relative difference of the RTM vs. the utility-meter measurement (using the kWh reading at the beginning and the end of the 2–16 months period). As shown in Fig. 3, the majority of discrepancies (49 of 78 apartments) are below ±1%, with only 4 of the discrepancies larger than ±5%, and 1 larger than ±10%. The average of the absolute value of all 78 discrepancies is 1.42%. As seen in Fig. 3, discrepancies higher than about 2% are limited to apartments with small average real powers. For example, the specific apartment with −11% discrepancy draws comparatively low average real power during the observation period (92 W average on the utility meter vs. 81 W average on the RTM). The small average indicates that a material portion of the total accumulated kWh in this apartment was likely incurred at real powers below the ~3 W detection threshold of the RTM, thus leading to the discrepancy. Communication with the superintendent of the respective building confirmed that the apartment in question was indeed unoccupied for a portion of the observation period. The power-weighted average of the absolute value of all 78 discrepancies is 0.92%, and thus consistent with the manufacturer’s rating of ±1% for the RTM\(^{34}\). As shown in Fig. 3, the RTM readings are above those of the utility-meter for some apartments but below for others. The average discrepancy, when observing the sign, is −0.17% (−0.05% when load-weighted). This shows that there is no material systematic error of the RTM when compared to the utility-meters.

Data gaps. MFRED has a high degree of data completeness. MFRED comprises ~3.2 million 10-second time steps. For the vast majority of these (>99.9%), data were recorded for all 390 apartments and reported in MFRED for all 26 apartment groups (AG). In rare cases, meters for some (but never all) of the 390 apartments were offline, typically for one or a few 10-second time steps in a row. There is only one such case that lasted longer, namely on 09-July-2019 from 14:30 to 21:30 UTC. For time steps where any of the 390 meters were offline, the averaging of data into AGs was handled as follows: MFRED shows “NULL” for any time step and AG where fewer than the respective 15 meters were online (but the data of other AGs at the same time stamp is shown). This approach was chosen for three reasons: (i) to adhere to the 15/15 rule (see Methods/Data preprocessing); (ii) to avoid reporting “partial” data that would not have reflected all 15 apartments in a specific AG and whose values therefore would not have been comparable to those at other times for the same AG; and (iii) to leave possible interpolations of missing data to the discretion of MFRED users.

Completeness metrics for each individual csv file of MFRED are listed in Table 3, expressed as the fraction of the 390 meters that were online, averaged across all time steps in the specific file. Note that for the 15-min data,
the only period with incomplete data (i.e., some of the 26 AGs show "NULL") is on 09 July 2019; for all other 15-min time steps the data are complete.

Real power for those time steps and AGs showing "NULL" in MFRED can be interpolated as follows: Whenever meters were offline – and hence did not transmit their data to the SQL database – they nonetheless measured the cumulative electricity use (kWh). As a result, the kWh data record in MFRED immediately after a period of "NULL" for an AG correctly reflects the cumulative electricity that was consumed by the 15 apartments in that AG during the offline period. Therefore, the real power for any period shown as "NULL" in MFRED can be estimated via interpolation from the kWh data record immediately before and after the "NULL" period (or via more complex approaches preferred by MFRED users).

Usage Notes
MFRED (5 csv files; 2.1GB) is publicly available via Harvard Dataverse37. Column headers and data records are explained in Tables 2 and 3. An overview of select possible uses and research applications of MFRED is listed in section Background and summary. Analyses presented here focus only on the characterization, validation, and benchmarking of the underlying data, in order to provide MFRED users with (i) a readily available overview and descriptive statistics of MFRED (Table 1, Figs. 1, 2); (ii) illustrations of seasonal variations and the use of real vs. reactive power for different end use types (Fig. 2); and (iii) the accuracy of the metering system (Fig. 3). Note that the analysis in Fig. 1 cannot be replicated with MFRED because the electricity use, floor area, and number of rooms of individual apartments are withheld in MFRED, in accordance with common data aggregation guidelines for utility data, specifically the 15/15 rule36 (see section Data records/Apartment groups). This aggregation has to be considered when using the dataset for said research applications, in particular for two of them: First, for disaggregation, the aggregate signal comprises on average more appliances (e.g., a refrigerator) and other individual end-uses (e.g., a specific light fixture in a specific room) at any given time than would be common for a typical, single apartment, thus requiring a successful disaggregation scheme to dissect the aggregate signal into more underlying components. To use a simple example, the aggregate signal of each apartment group comprises 15 separate refrigerators, each with its own on/off pattern. Second, for studying reactive power, the reactive power reported in MFRED is the average of the multiple appliances and other end-uses, not only in a single apartment but instead of those in 15 apartments. Because the reactive power of each appliance/end-use can range from negative to positive values, the reported aggregate reactive power can mask a wide range of the reactive powers of the increased number of individual underlying components.

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Author contributions
C.M., V.M, N.R. and P.C. led the overall work, including building selection, hardware & software installation, and data validation. C.M. maintained the SQL database and MFRED, carried out the analyses, and wrote the manuscript. C.H. and T.C. provided custom software to transfer data from the RTM to Azure for temporary backups. V.D. supported SQL queries for data analyses. A.M. and S.A. supported hardware and building selection as well as coordination with Columbia University’s Institutional Review Board. K.McK. provided expertise in data de-identification.

Competing interests
The authors declare no competing interests.

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