Load Modeling in Synthetic Electric Grids

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Abstract— Synthetic electric grids provide full availability of large-scale realistic test cases to power system researchers without confidentiality concerns. As many power system studies require load information, it is important to have bus level variation modeled in these synthetic test cases. This paper presents a methodology for bus level static load modeling in synthetic electric grid test cases. A realistic load composition ratio for residential, commercial and industrial sectors is assigned to each bus according to the real electric grid data. Multiple normalized template load curves for each load type are created and assigned statically to each bus. The load composition ratio and load templates are then combined and scaled to a footprint electric grid to obtain the bus level load curve for the whole year. The methodology is illustrated in 2000-bus test case and validated using public ERCOT data. A unit commitment solution using the synthetic load is also presented as an application.

*Index Terms—*Synthetic networks, load modeling, residential/commercial/industrial load sectors

I. INTRODUCTION

SYNTHETIC electric grid models provide full public access to power system test cases that statistically and functionally match the actual grid without revealing any confidential information [1-3]. Power system models serve as the basis for a wide range of applications including resource planning, production pricing, environmental assessments, reliability, and policy analysis. These applications require proper modeling of location and time-varying behaviors of electricity demands [4].

Various strategies have been developed to model load behavior in the residential sector [5-7], with the purpose of demand response and network impact study at both the household and feeder level. There is also research on mixed residential, commercial, and industrial (RCI) load modeling in the distribution system [8-10], where load consumption behavior is modeled and predicted based on real telemetry and appliance usage patterns mostly for weekly timescales. As such, this paper aims to build hourly transmission bus level load profiles for a year, with consideration of locational and temporal variations in the RCI sectors. Large systems with yearly load variations are built for application to general large power system studies.

To add complexity to the synthetic load profile, a location-dependent ratio of RCI load compositions is assigned to each bus. The electric consumption behavior of the three sectors vary, so load composition ratios will distinguish and identify their load contribution at the bus level. Modeling the time-dependent behavior of the three load sectors is the next step in the creation of realistic load profile curves for the synthetic electric grid. One of multiple template load curves in each RCI sector is statistically assigned to each bus. According to the load composition ratio and template curves of each sector, a yearly load curve for each bus is obtained and scaled to match the peak value in synthetic network base case to determine the load profile of each bus. Load profiles of all buses are aggregated to obtain the system load profile, of which selected metrics are compared with those obtained using the actual load data. In this paper, the ACTIVSg2000 case is used [11] as an illustrative example. In addition, a rolling unit commitment algorithm is developed to provide the hourly generation schedule for the load profile data. Although the test case is built on a Texas footprint, the method is general enough to be applied to other regions.

In this paper four more sections come as follows. In Section II, a process is developed to automatically determine the load composition ratio and template load curves to create a bus level load profile. Data validation is proposed in Section III. Section IV provides a solution methodology to solve the unit commitment problem, and Section V concludes the paper and provides future work direction.

II. HOURLY LOAD MODELING METHOD

A methodology is developed in this section to obtain bus level load profiles and hourly variations. A load composition ratio of RCI sector is assigned at the bus level. Multiple template load curves are created and statistically assigned to each bus. The load composition ratio and load templates are then combined to obtain location-varying bus load curves, and each is scaled to achieve a desired bus peak load level.

A. Determination of Bus Level Load Composition Ratio

The realistic assignment of a load composition ratio needs to represent geographic and demographic dependence. For example, regions with a dense population should have relatively high residential percentages, and rural areas could have high electricity consumption from industrial loads [12].

Electric utility companies' RCI sales values (in megawatt-hour) are used to determine their respective load composition ratios [13]. Given the geographic information of buses and utility companies, each bus is assigned to its closest electric

utility company. All load buses belonging to the same utility adopt the same load composition ratio.

As depicted in Fig. 1, nearly 75% of the buses in the 2000-bus test case are assigned with more than 40% residential load, which matches statistics from the real electric grid [14]. The northwestern and coastal areas in the 2000-bus test case are assigned with high industrial composition ratios, while the urbanized central area is assigned with high residential percentages, reflecting the demographic assumptions in synthetic electric grid base case [2].
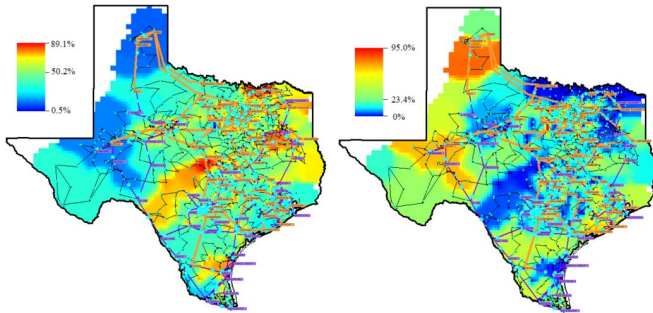

Fig. 1. Residential (left) and industrial (right) load composition ratios in the 2000-bus test case

B. Creation of Template Load Curves

To obtain temporal characteristics of actual electricity consumption behavior, multiple yearly load templates are used for RCI loads. Since all buses assigned to the same utility company share the same load composition ratio, multiple template load curves are considered for each type to add variations to the final load profile.

1) Residential and commercial template load curves

Residential and commercial load curves are expected to represent daily, weekly, and seasonal patterns. Depending on temperature fluctuation, geographic location, and the commercial business type, each load curve will exhibit different behaviors [15].

Simulated data for building energy consumption [16] is used to create the residential and commercial template load curves. The simulated profile data includes multiple residential buildings and 16 commercial building types. It contains hourly energy consumption over a year for cooling, heating, and lighting, etc. All the profiles are tagged with TMY3 numbers, which represent geographic locations with different meteorology.

The electricity consumption profile is extracted from the total energy consumption, among which the electricity used for summer cooling and winter heating is scaled to more realistic statistics based on EIA residential energy consumption survey [17].

Fig. 2 displays the daily and weekly patterns in the residential load templates, where the daily load has a local peak around 8 AM and a maximum peak near 6 PM, and has higher loads during the weekends than on the weekdays. Seasonal behavior is also observed in the templates where cooling generates summer peaks and heating generates winter peaks. It is noticeable that the simulated data uses either electricity or natural gas for winter heating. As a result, for

those residential loads with natural gas heating, the templates have a flat winter load profile; for those with electricity heating, depending on the type of electric heater used and weather responsive behavior, different scales of winter peaks are represented.
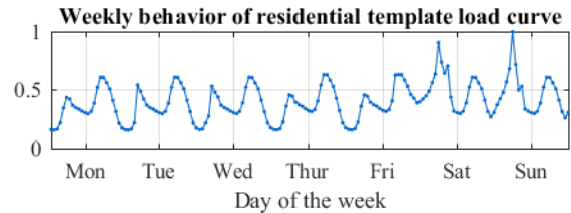

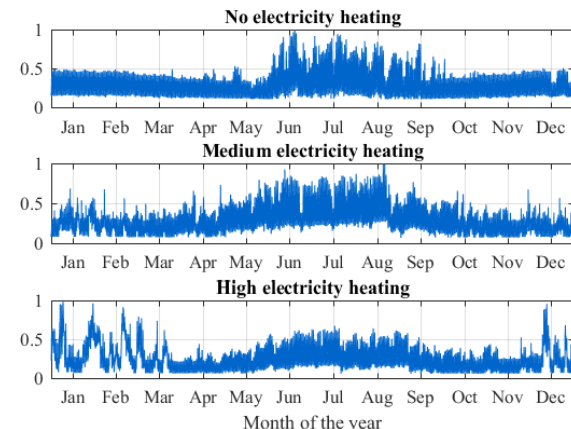Fig. 2. Daily and weekly behavior in residential template load curve

Fig. 3. Templates with different source and scale of winter heating

In the 2000-bus test case, 16 commercial template load curves are created. Each template represents one type of commercial business profile over a year. Fig. 4 displays the daily and weekly behaviors of three commercial load templates. The curves share similar daily trend of an increase in load during the daytime and a decrease in load during the evening, but have different load factors and daily curve shapes. The weekly trend is also represented in the commercial templates where load behaves differently on weekdays and weekends.
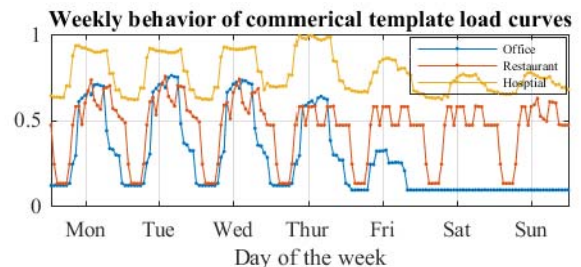

Fig. 4. Weekly and daily behaviors in commercial template load curves

2) Industrial template load curves

Industrial template load curves are created based on Oak Ridge National Laboratory's industrial load assessment [18], where industrial load with high and medium load factors are distinguished. Industrial template load curves exhibit less variation compared to the other load types resulting in higher

load factors. The daily profiles demonstrate stable load over a 24-hour period and are emulated over the course of a year to create the industrial profiles.
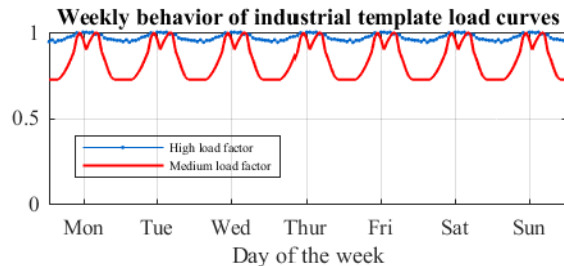

Fig. 5. Weekly and daily behaviors in industrial template load curves

C. Load Templates Assignment

Similar to the load composition ratio assignment, the residential load templates are assigned to each bus based on their geographic distances. The remaining types of template load curves are assigned statistically from pools for added variation.

D. Bus and System Level Load Profile

For the creation of bus level load profiles, the load composition ratio and template load curves assigned to each bus are combined. The bus load composition ratios provide base scale for each load type and normalized load templates introduce temporal variations around the base. It is important to note that load composition ratios are derived from MWh data, representing the ratio of energy consumption instead of a power ratio for the three load types. The three chosen profiles for each bus are scaled so their yearly energy ratios match their load composition ratios. The scaled profiles are then summed to obtain bus level load profile.

To create time series hourly load curve representative of the synthetic network bus case, each load curve is scaled to match the bus peak in the 2000-bus base test case as shown in Fig. 6.
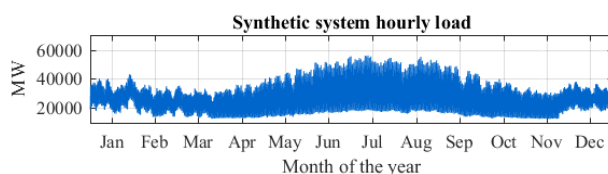

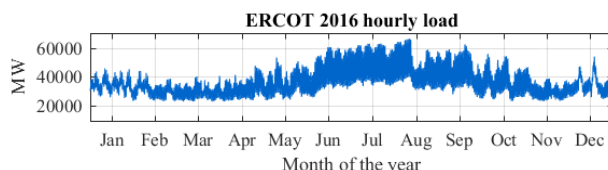Fig. 6. Synthetic hourly load in system level

Fig. 7. ERCOT hourly load in 2016

III. RESULT AND MODEL VALIDATION

The metrics of synthetic hourly load data are compared against historical hourly data from ERCOT for validation from the system and area point of view. The Coast area is chosen to represent the data's area statistics because of its size and geographic characteristics. The statisctical characteristics of the system level synthetic load is compared with ERCOT historical data for years 2016, 2015 and 2014 [19].

In Fig. 6 and Fig. 7 the 28000 MW average for the synthetic year is on the same load scale with ERCOT's 40000 MW year average for 2016. The mean and ranges are normalized to each system's peak in order to capture and compare their trends. The seasonal mean for synthetic load is at a higher percentage of its peak during warm seasons and lower during cool seasons, reflective of ERCOT trends. Both the synthetic and ERCOT data sets experience their load maximums during the summer and load minimums during the spring. Also, the range exhibited in the synthetic data is similar to ERCOT data where warmer seasons exhibit ranges larger than the cooler seasons. As the trend of synthetic load matches with real load for every season, the synthetic seasonal mean is 4 to 16% lower than ERCOT's data and the simulated data has a 20% higher range than ERCOT's data. However, since the purpose of this method is to obtain similar characteristics and not a replication of the real electric grid, it is not necessary to have features such as the average exactly matching ERCOT data.

To better compare the synthetic and ERCOT load, the standard deviation is normalized with respect to the mean. In Fig. 8 the normalized deviation in the synthetic data adheres to the trends of ERCOT data by increasing during warmer months and decreasing during cooler months. The synthetic load shows a slightly higher normalized deviation, signifying that the synthetic data's disturbances resemble real system data.
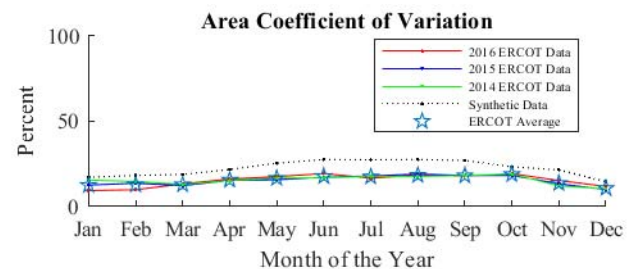

Fig. 8. Area coefficient of variation

A. Time series frequency analysis

Fig. 9 displays a fast Fourier transformation (FFT) on both the synthetic and ERCOT load data to compare the synthetic data's periodic characteristics with real electric grid data. The synthetic load and 2016 ERCOT data both peak at all major frequencies. Frequencies include those of daily, weekly, and twelve-hour periods, which validate that these patterns are present in the simulated data. The ERCOT data contains more noise and a higher base load, so the simulated data consistently has higher magnitudes at major frequencies and lower magnitudes at minor frequencies in comparison.
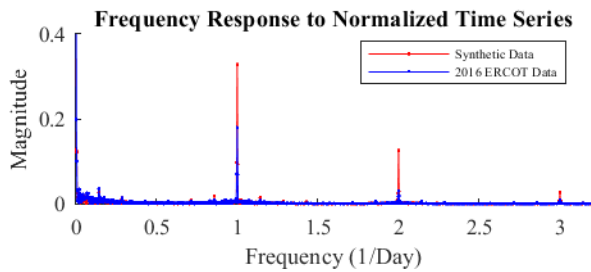
Fig. 9. Normalized by dividing total load at each time point by yearly peak.
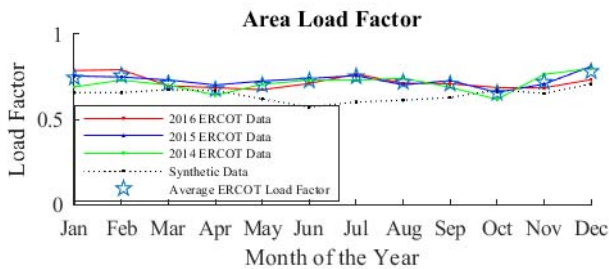
B. Load Factor

Fig. 10. Area load factor

The comparison of load factors over a year in Fig. 10 highlight that the synthetic data follows the average ERCOT trend for the cool months but decrease rather than increase during warm months. The synthetic load factor adheres within 13% of the ERCOT data during cool months and diverges up to 21% in warm months, indicative of a low average present in the synthetic data's summer data. The simulated data's load factors vary between 1 and 21% of the average ERCOT load factors for each month, which verify the load factors are similar to that of a real system.

C. Synthetic Load Profile Time Behavior

Fig. 12 displays the seasonal patterns for the yearly synthetic data. In comparison to the ERCOT seasonal trends in Fig. 11, the synthetic winter daily pattern looks typical with a peak in the morning and a peak in the evening; the summer daily pattern has a typical peak during the evening. The spring and fall daily patterns in Fig. 12 both share similar base loads, similar load oscillation ranges, and contain elements present in the summer and winter daily curves as seen in Fig. 11. Similar to the ERCOT data, the synthetic data has daily loads that vary in response to weather patterns, has weekends with smaller peak loads, and has base loads during the summer and winter that are higher than during the spring and fall.
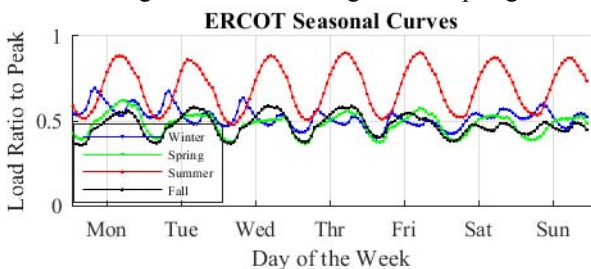

Fig. 11. 2016 ERCOT data normalized by dividing total load at each time point by yearly peak.
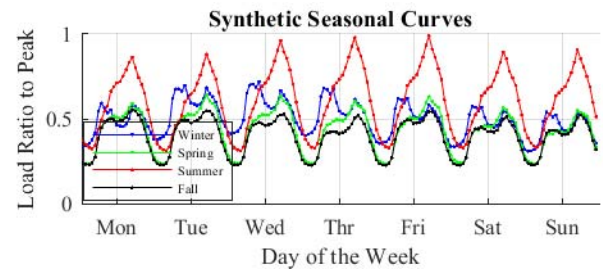

Fig. 12. Normalized by dividing total load at each time point by yearly peak
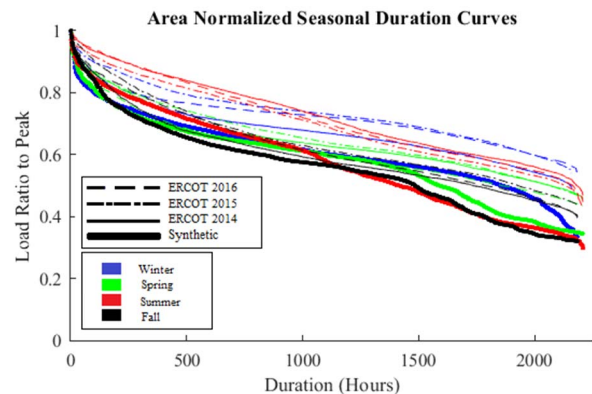

Fig. 13. Duration curves for Synthetic and ERCOT data normalized by dividing total load at each time point to their seasons' respective peaks.

The load duration curves in Fig. 13 are used to display how load behavior changes throughout the seasons. The ERCOT data depicts load duration gradually increases as the system load decreases and that longer durations of high load are present in the winter and summer than in the spring and fall. The synthetic data generally follows these ERCOT load duration trends, except lower load values are present for shorter periods of time due to a low base load in the system.

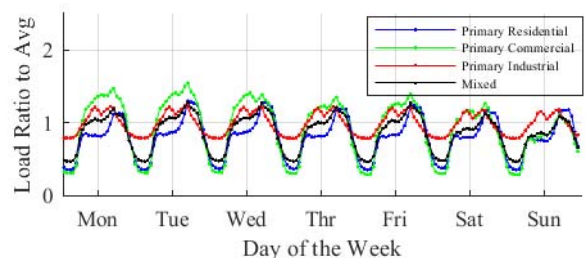### D. Synthetic Hourly Schedule by Load Type

Fig. 14. Mixed and RCI Bus types are added and normalized by dividing total load at each time point by their respective yearly averages. Buses are categorized as either primarily commercial, industrial, or residential buses if its respective RCI percentage is greater than 65%, else the bus is considered to have a mixed load. The time period displayed is during the spring.

In Fig. 14, the buses display expected qualities for primarily residential, commercial, and industrial loads. Both the residential and commercial buses experience typical peaks at 6 PM (5 PM Standard Time) while the residential bus also experiences an expected relative peak at 8 AM (7 AM Standard Time). The average industrial bus has a base load and minor daily variation near its yearly average while in comparison the average residential bus has a much smaller

base load than its yearly average with larger variations for the same period. The commercial load bus should have intermediate values between industrial and residential loads but the base load is relatively low in comparison due to a dominating presence of low frequency sinusoids with large amplitudes in the commercial load profile.

In general, the metrics of the load model for the synthetic case match that of load from the actual electric grid, with one manifested problem that the variation in synthetic load is higher than realistic. As each bus in synthetic test case is representative of major population clusters instead of distribution level feeders, and RCI load is modeled by a single small population profile, the resolution of the case's bus loads are decreased and prevent a better representation of real electric grid load. This problem will be addressed as part of future work.

IV. Unit Commitment Solution Methodology

This paper adopts a rolling unit commitment solution method to solve a security-constrained ACOPF for each hour, in consideration of generators' operational and physical constraints [20]. Additional constraints include minimum durations, ramping limits, and so forth.

A. Solution Methodology

Fig. 15 summarizes the solution methodology used to solve the unit commitment prolem and provides hourly generation schedule on a rolling basis. Generation states and outputs in previous hours are used to determine whether a generator is allowed to change status and how much each generator is allowed to change its output at hour t. Then, an security-constrained ACOPF is performed for current hour t.
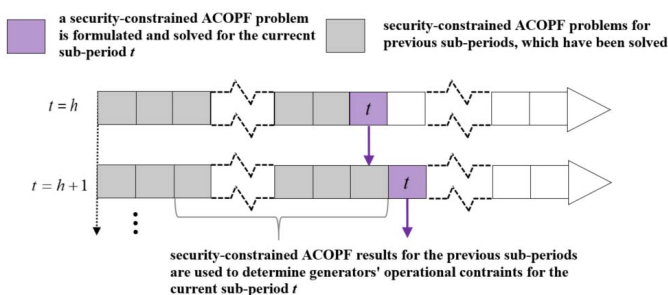

Fig. 15. Rolling unit commitment illustration

Specifically, suppose one unit has a minimum on duration of h1 hours, a minimum off duration of h2 hours, and a ramping rate of dP. At time t, if this unit has always been online for the previous h1 hours or always off for the previous h2 hours, then either the minimum on or off duration is satisfied, and this unit can change status. If this unit is online at hour t-1 but not always online in the previous h1 hours, this unit can change outputs by an amount no more than dP at time t to satisfy the ramping constraint. As such, a security-constrainted ACOPF can iteratively be solved to obtain a feasible yearly generation plan.

B. Simulation Results

The rolling unit commitment famework is applied to obtain the electricity production schedule for the ACTIVSg2000 case with time-varying load levels. Fig. 16 displays the total eltreicity demand, the net load (total electricity demand – dispatched renewable energy production), and the average electricty cost for a summer day. The simulation results verify the capability of large-scale test cases with bus-level load profiles to successfully run unique frameworks solving a unit commitment problem.
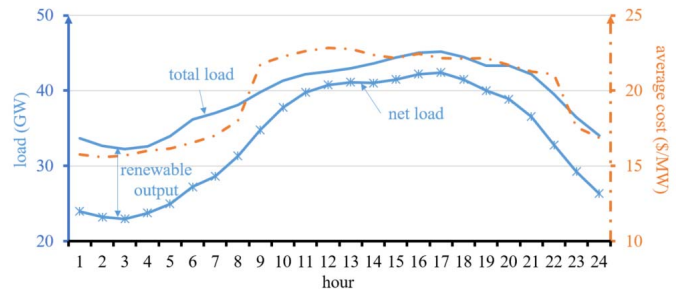

Fig. 16. Simulation results for a summer day

V. Conclusion and Future Work

This paper presents a methodology to create bus level synthetic load profile and hourly schedule based on statistics summarized from actual power systems. The method is general enough to be applied in any synthetic case. A model validation process is introduced where the metrics of synthetic load is compared against that of a footprint electric grid. The load model adds complexity to the current synthetic electric grid test case, and could be used for many applications such as power system planning, reliability analysis, and market operation studies.

The expansion of the synthetic network case and improvement of the synthetic load resolution to better represent the real electric grid are the two major parts for future work.

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