# HOURLY WIND AND SOLAR GENERATION PROFILES (1980-2020)

PREPARED FOR:
**ELECTRIC RELIABILITY COUNCIL OF TEXAS (ERCOT)**

*Ref. No.: 21-03-036658*

ERCOT Region

22 September 2021

CLASSIFICATION
CLIENT'S DISCRETION

ISSUE
B

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## DOCUMENT HISTORY

| ISSUE | DATE | SUMMARY |
|---|---|---|
| A | 08/31/2021 | Draft Report |
| B | 09/22/2021 | Final Report |

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# 1. EXECUTIVE SUMMARY

UL Services Group, LLC.[1.1] was retained by the Electric Reliability Council of Texas ("ERCOT" or the "Client") to generate hourly power profiles for approximately 25.4 gigawatts (GW) of operational wind, 31.0 GW of hypothetical wind, 7.0 GW of operational and planned utility-scale solar, 7.0 GW of hypothetical utility-scale solar, and 30.1 GW of distributed PV generation (rural and urban) for the period of January 1, 1980 through December 31, 2020. The purpose of this work is to support ERCOT's various modeling and analysis efforts. The current study was predated by similar works, most recently UL (2020).[1.2]

Historical meteorological conditions were simulated on a 9-kilometer grid over the state of Texas using the Weather Research and Forecasting (WRF) model to obtain the necessary variables used for power conversion. Model data were adjusted with surface measurements to ensure the annual, seasonal, and diurnal mean wind speed and irradiance patterns, including ramping characteristics, are accurately represented. Results show that the adjusted model time series capture the dynamic behavior of annual, monthly, and diurnal wind speeds and solar irradiance. The average wind speed bias is -0.6%. The average global horizontal irradiance (GHI) bias is -2%.[1.3] Other meteorological variables such as temperature, air density, relative humidity, precipitation, and turbulence intensity were also used to create the power profiles.

Wind and solar plant specifications were compiled from data provided by ERCOT, along with numerous other sources. The plant layouts and other static details of operational plants were used to model each plant as accurately as possible. Measured generation data was supplied for both wind and solar plants, as well as the plant's estimate of potential generation (without curtailment). The data was filtered, and periods of high-quality, uncurtailed generation data were used to validate and adjust the modeled time series at operational wind and solar plants.

Future technology and scenario assumptions were retained from UL (2020). Hypothetical wind plants were modeled using a 90-meter hub height and wind turbine characteristics anticipated in the 2-to-6-year time horizon. Hypothetical utility-scale solar PV (single and dual-axis plants), as well as distributed PV, were modeled using a PV composite technology representing near-current potential PV generation (i.e., for projects built in the years 2020 – 2025). The capacity assumptions for all hypothetical wind and PV profiles remain the same as in UL (2020).

Hourly wind power profiles were generated at 155 operational and 148 hypothetical sites with Openwind, UL's plant design and optimization software used for energy production estimates. The adjusted WRF time series, operational plant characteristics, and next-generation wind technology at hypothetical plants were used to simulate hourly, net wind power generation for four scenarios: operational or hypothetical plants with standard availability losses or with adjusted availability losses that included only planned maintenance (thus omitting unplanned or random outages). Operational and planned plants were modeled collectively, so as to include the effect of additional, upstream wake losses anticipated from nearby plants (the hypothetical plants were omitted from these scenarios). Hypothetical plant scenarios were run including all operational and planned plants in the Openwind simulations, thus accounting for the any wake losses induced by those plants.

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[1.1] Formerly known as AWS Truepower (AWST).

[1.2] Rojowsky, K, Gothandaraman, A, Beaucage, P. 2020. Hourly Wind and Solar Generation Profiles. Prepared for the Electric Reliability Council of Texas. Technical Report prepared for ERCOT by UL. Reference number 19-08-027944

[1.3] GHI is defined as the total solar radiation received on a surface horizontal to the ground.

The modeled wind generation at operational plants was adjusted to account for non-standard and site-specific plant losses, such as turbine availability or power curve derating behavior that were not explicitly modeled in Openwind. At each operational plant, an adjustment was developed using concurrent observed and modeled generation data. For operational or planned plants with an insufficient data record, a composite adjustment was developed and applied. The plant-specific adjustments were developed using the standard availability modeled generation data, and applied to both sets of modeled time series, i.e., both the standard availability and the adjusted availability time series. No adjustment was made to the hypothetical profiles.

The final wind power generation results were evaluated for reasonableness and compared to historical wind generation. The net capacity factor (NCF) of the modeled generation time series with standard availability range from 21.7% to 52.6% for the operational plants, and 23.7% to 54.9% for hypothetical plants. The final dataset has a bias of less than 1.0% and an hourly coefficient of determination ($R^2$) of 0.89 for the aggregate generation. The modeled wind generation time series are shown to well capture the seasonal and diurnal cycle of observed generation, as well as the ramping behavior.

The hourly averaged irradiance was converted to solar generation using UL's latest power conversion software at 53 utility-scale operational, 139 hypothetical plants (single and dual), and aggregate sites of distributed rooftop generation (representing the four greater metro areas and six rural aggregates by ERCOT's Capacity, Demand, and Reserves or CDR zones). The profiles of hypothetical, operational, or planned utility-scale solar plants that did not have sufficient generation data for custom adjustment were adjusted using a composite adjustment developed from all operational solar plants. For the distributed rooftop generation profiles, a composite matrix was developed using recent historical rooftop generation data from zip codes in each of the metro areas.

Results show that the overall PV generation values align well with expectations on a monthly, diurnal, and overall annual basis, and that ramping statistics appear to reasonably depict fluctuations in power generation. The operational plants have mean NCFs ranging from 18.6% to 31.3%, with an aggregate bias of 0.0% on generation and an hourly coefficient of determination ($R^2$) of 0.92. Generally, the distributed PV profiles exhibit lower NCFs than the utility-scale PV plants. Even when accounting for local irradiance resource, generation varies between centralized, utility-scale and distributed rooftop generation due to plant characteristics. The net capacity factor of distributed rooftop generation in the urban areas varies little across the different land use classes (15.2 to 15.4%), while the rural profiles exhibit a wider range of NCFs spanning 14.9 to 19.6%. The distributed generation profiles for the greater urban and rural areas have a bias of 0.1% on generation and an hourly coefficient of determination ($R^2$) of 0.95.

## 2. INTRODUCTION AND BACKGROUND

UL has collaborated with ERCOT since 2012 to simulate hourly generation profiles for both operational and hypothetical wind capacity across its service territory. Modeling wind and solar generation fleets is a challenging task that seeks to balance the required model inputs with an efficient process to reproduce plant behavior that aligns with historic weather patterns. This requires the use of state-of-the-art modeling techniques that are updated continuously as industry knowledge expands and rapidly evolves. Over the past nine years, new methods have been applied in the development of ERCOT's hourly generation profiles including updated or new atmospheric models, initialization data, resource assessment methods, power conversion software tools, and adjustment processes. Understanding the similarities and differences between methods used to create each version of profiles is important to its application, and therefore references to previous work are provided throughout this report.

The first series of wind profiles simulated historical wind power for the period of 1997 – 2012, with annual updates provided through 2016, using consistent power conversion methods and composite power curves. In 2015, UL began using the Weather Research and Forecast Model (WRF) to simulate the hourly atmospheric variables, and previous wind profiles were recreated (1997-2014) using the variables from WRF as input to UL's power conversion method. All other wind resource assessment and power conversion processes and specifications remained static. This dataset was updated annually until 2017 using the same methods and input parameters by appending new model data and converting it to power. In 2018, a set of hourly wind profiles was provided using operational plant specifications, as available, and the then-current (2017) fleet configuration as applied to an extended historical weather record (1980-2017). Operational and hypothetical utility-scale solar PV plants, and distributed generation profiles based on land use classes in four major urban areas (Austin, Dallas, Houston, and San Antonio) were also modeled in 2017. In 2020, additional operational utility-scale (wind and solar) plants were included, in addition to distributed generation profiles representative of the potential rooftop generation in the rural areas of ERCOT's six Capacity, Demand, and Reserves (CDR) zones.

Current methods were applied to convert the meteorological conditions into hourly power for 25.4 GW of operational wind, 31.0 GW of hypothetical wind, 7.0 GW of operational and planned solar, 7.0 GW of hypothetical utility-scale solar, and 30.1 GW of distributed PV generation for the period of January 1, 1980, through December 31, 2020. This report summarizes the methods and results and is divided into eight main sections:

Section 3 describes the methods used to develop the modeled atmospheric time series using a state-of-the-art Numerical Weather Prediction model for each operational and hypothetical location. Resource validation and adjustment are described, as well as new initialization data and the application of a microscale model for wind.

Section 4 describes the wind power conversion process using Openwind, a state-of-the-art wind resource assessment and optimization software, including the plant specifications used as input for operation and hypothetical plants, operational data available for validation, and the results.

Section 5 describes the specifications used for utility-scale operational and hypothetical (single and dual-axis tracking) solar PV plants, the composite technology applied, and the operational data available for validation.

Section 6 describes the method used to identify the potential rooftop generation across metro and rural areas.

Section 7 summarizes the validation and results for the utility-scale operational and hypothetical utility-scale solar PV plants, as well as the distributed PV urban and rural aggregate profiles.

Section 8 provides end-users with a summary of assumptions and potential sources of bias in the hourly profiles to help guide their future use and application.

# 3. ATMOSPHERIC MODELING, VALIDATION, AND ADJUSTMENT

## 3.1 Mesoscale Modeling

Historical meteorological conditions were simulated over the state of Texas using the Weather Research and Forecasting (WRF) model,[3.4] a leading open-source numerical weather prediction (NWP) model. The WRF model was initialized with ERA5, the fifth-generation reanalysis dataset provided by the European Center for Medium Range Weather Forecasting.[3.5]

WRF simulations were carried out to model the atmospheric circulation for the 1980 to 2020 study period to obtain the variables necessary for estimating wind and solar power production at each site. WRF was set up to run two nested grids simultaneously over the project area with horizontal grid spacings of 27 and 9 kilometers (km). Further details of the WRF model setup can be found in UL (2020). The final model simulation includes both the ERCOT service area and nearby adjacent land areas to provide a complete dataset for the period of January 1, 1980 to December 31, 2020. Simulated meteorological values required for solar PV and wind power production models were retained on an hourly basis.

## 3.2 Resource Adjustment and Validation

Before converting the modeled meteorological time series to plant production, it is first necessary to correct for biases to ensure that the modeled wind and solar resource used in the conversion to power is accurate. This is done by scaling the WRF meteorological variables to match the expected resource average and resource variability at each site. The adjustment and validation of model data require a sufficiently large sample of observed data to tune the modeled variables to observed values.

UL did not make any substantial updates to the resource adjustment process and closely followed the process outlined in 2020. The atmospheric variables for wind were adjusted using tall tower data from 39 towers. For solar, the model irradiance was adjusted using solar irradiance measurements from 13 reference locations.

The tall tower data were used to adjust diurnal mean patterns in the modeled hub-height wind speed time series. Results show that the adjusted model time series capture the dynamic behavior of annual, monthly, and diurnal wind speeds, with an average bias of -0.6%. The adjusted WRF wind speed and other meteorological variables such as temperature, air density, relative humidity, precipitation, and turbulence intensity served as inputs to the Openwind software used to create the power profiles.

High-quality solar irradiance measurements (both GHI and components, when available) were used to validate and adjust the modeled irradiance time series. Data from 13 reference stations were compiled and used to adjust the modeled irradiance resource. The frequency distribution of the modeled irradiance time series was adjusted to better reflect the distribution of observed values. This process adjusts both the means and the extremes of modeled irradiance data and results in a more accurate representation of clear, partly cloudy, and cloudy days. The adjustment reduced the annual irradiance bias at all thirteen validation stations to well within reasonable limits (and measurement uncertainty), resulting in an average bias of -2.0 % for GHI. The root-mean-squared error (RMSE) after adjustment is 3.4% for GHI.

[3.4] Skamarock, W. C., Klemp J.B., Dudhia J., Gill D.O., Barker D.M., Duda M.G., Huang X-Y., Wang W. and Powers J.G. A Description of the Advanced Research WRF Version 3. Boulder: NCAR Technical Note NCAR/TN-475+STR, 2008.

[3.5] Available at: https://www.ecmwf.int/en/forecasts/datasets/reanalysid-datasets/era5

### 3.3 Mesoscale-Microscale Wind Modeling

The accurate prediction of a wind plant's energy production is dependent upon a detailed understanding of the spatial distribution of the wind resource across the project area. UL independently pioneered a method to couple a mesoscale model and a microscale model to characterize the wind resource at spatial resolutions on the order of 10 to 100 meters.[3.6] UL's modeling system, known as SiteWind, relies on a mesoscale model to properly simulate the atmospheric flow up to the meso-gamma scales (~1 km). The mean wind flow modeled by the mesoscale model is downscaled to a 200-m grid spacing using a diagnostic mass-conserving model called WindMap. The WindMap model is a mass conserving model that ingests mesoscale NWP model outputs and computes the three-dimensional wind field. WindMap attempts to retain as much information as possible from the mesoscale NWP model while accounting for the high-resolution terrain elevation and land cover data. The WindMap model outputs are stored in binary wind resource grid (WRB) files, which are later used by the Openwind software to extrapolate the adjusted WRF meteorological time series to the turbine sites and estimate wind power generation.

# 4. WIND GENERATION PROFILES

### 4.1 Operational Wind Plants

Wind plant details for previously modeled sites were re-used from UL (2020), and all sites were rerun except for Sites 35, 62 and 122 (these three sites were retired). New wind plants added in 2021 are represented by Sites 4000-4007. Details for these plants were compiled and processed in the manner as described in UL (2020). These new plants achieved commercial operation between 2019 and 2020. A summary of all operational plants modeled can be found in Appendix A, and the counties represented by the 155 operational units are highlighted in Figure 4.1 (the nine counties which contain the 8 new plants are shaded dark red). For each new wind plant, the layouts were compared to static plant details and aerial imagery, when possible. Plant capacity assumptions were compared to historical generation data and outside sources of information, e.g., ERCOT Seasonal Assessment of Resource Adequacy (SARA) reports and Resource Asset Registration Form (RARF) data.

Each plant's turbine model and the manufacturer's power curve were used to simulate the operational unit at the installed hub heights. Plant-specific power curves were not available. For some units, the RARF turbine megawatt (MW) ratings were slightly higher than the manufacturer's standard power curve ratings (representing a particular power mode variant). For these unit codes, generic performance settings were developed to best approximate the expected behavior of the variant or a site-specific power curve. UL applied high and low temperature thresholds by plant as provided by the client. The modeled plant profiles were validated and adjusted using the highest granularity of historical generation possible, which varied amongst operational plants based on the amount of measured data available.

[3.6] Brower, M.C. (1999). Validation of the WindMap Program and Development of MesoMap. Proceedings from AWEA's WindPower conference. Washington, DC, USA.

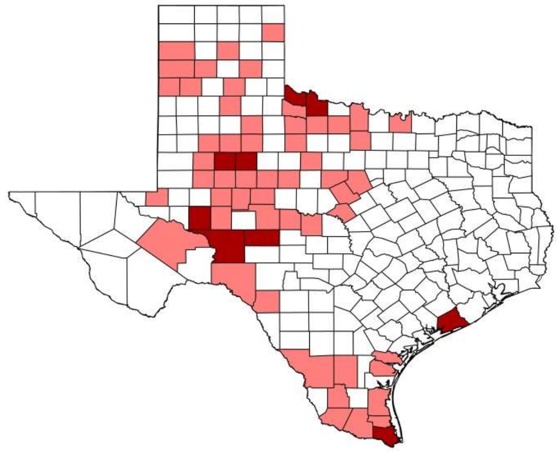

**Figure 4.1: Counties with Operational & Planned Wind Plants Modeled**

### 4.1.1 Operational Data Review

Operational wind plant production data was reviewed to determine the period of valid data for each individual plant that was subsequently used for modeled time series adjustment. The valid period is defined as the period of generation following each plant's "break-in" period, once it has achieved its "fully-waked" condition.

UL assumes a typical break-in period of four months (minimum) before plants are running at peak efficiency. Only those with at least one year of operational data past the break-in period were adjusted and validated using their plant-specific generation data.

Historical, hourly generation data from operational plants were used to adjust the modeled plant profiles to account for turbine and plant underperformance, plant availability, power curve variants, generator heating or cooling packages, and other plant-specific losses that cannot be explicitly modeled. The historical generation data includes the actual, measured power generation (including curtailment), and the high sustainable limit (HSL) for each hourly record.[4.7] The HSL refers to the limit established by the plant owner/operator (qualified scheduling entities) that describes the maximum sustained energy production capability of the plant at that time. In essence, the HSL reflects the expected, uncurtailed power generation at actual plant availability. UL used the greater of the observed power and the HSL to help define the valid "historical" period to be used in the adjustment process.

The historical plant data was screened, filtered, and truncated as necessary before being used in the modeling process. The plant's break-in period was filtered out of the historical period, and the remaining data from each plant was quality controlled as in UL (2020). The dataset was then truncated to include only the period of data after which all upstream wind farms were built and operational (the "fully waked period"). The date of the most recently installed upstream wind farm was used as the start of the fully waked period for plants that were identified as "waked". The remaining data available for each plant was considered the "valid" period for use in adjustment and validation processes. Of the 155 operational plants, 151 wind plants were considered by UL as being past their break-in period.[4.8] Four plants were

[4.7] New measured data was incorporated only for plants which had < 1 year of data prior to 2020.

[4.8] A visual inspection of the generation data was carried out for each plant to determine the break-in period. At some plants, up to six months of initial generation data were discarded because of data discontinuity with the remainder of the record, e.g., no data, low data recovery, or unusual fluctuations in power generation.

not mature enough to provide meaningful actual power generation for the modeling process. The four operational wind farms within their break-in period were: Sites 4000, 4001, 4004, and 4007.

## 4.2 Hypothetical Wind Plants

UL retained the same hypothetical plants modeled in UL (2020). This consisted of 148 plants at 100-400 MW each, totaling 31.0 GW (Appendix B) and the composite technology power curves from UL (2020) were applied.

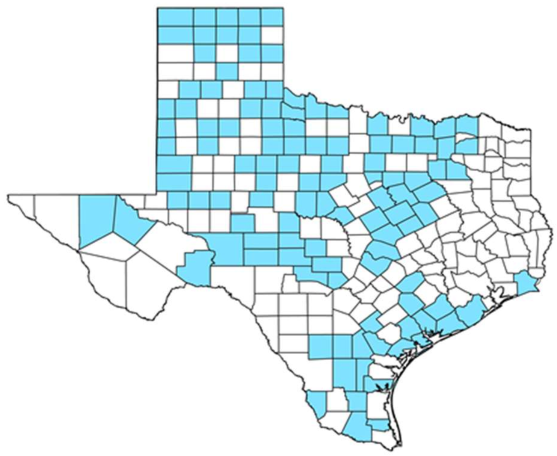

**Figure 4.2: Counties with Hypothetical Wind Plants Modeled**

## 4.3 Wind Power Generation

Hourly wind power profiles were generated at 155 operational and 148 hypothetical sites. The adjusted WRF time series (Section 3.2) served as input to Openwind, UL's plant design and optimization software used for energy production estimates. Operational plant characteristics (Section 4.1) and next-generation wind technology at hypothetical plants (Section 4.2) were used to simulate hourly wind power generation across all sites. The following section describes the Openwind setup and configuration used to simulate gross and net energy production, as well as plant losses.

### 4.3.1 Openwind Configuration

The Openwind model simulations were set up according to UL (2020). The spatial distribution of the wind resource was obtained from binary wind resource grids (WRBs), generated by UL's Windmap (the coupled mesoscale-microscale modeling system described in Section 3.3). Terrain elevation and surface roughness maps were imported from the WindMap simulations. Adjusted WRF meteorological time series (Section 3.2) from each wind plant was also imported into Openwind as "virtual meteorological masts" to adjust the resource grid, extrapolating the wind resource and ancillary variables to each turbine location. Turbine characteristic files were created (or obtained from the previous study) for each of the operational and next-generation turbines; these files include parameters for the hub height and rotor diameter, power and thrust curves, cut-in, cut-out, and cut-back-in wind speeds, and extreme temperature shutdown.

The Openwind time series energy capture module runs the meteorological time series at each turbine through the respective power curve and estimates gross wind power generation, adjusting for the effects of turbulence intensity and air density on the power curve. Data from adjacent heights are used within Openwind for extrapolating to any turbine-specific hub heights that are between these mesoscale model levels. Details of the energy loss calculations to estimate net power are given in the following section.

The time series energy capture module was run for four scenarios. The first two scenarios included only operational and planned wind farms, so that the operational and planned plant profiles did not include wake effects of hypothetical sites. The second two scenarios included operational, planned, and hypothetical wind farms; this allowed hypothetical plant profiles to include wake losses from nearby operational and planned sites. Both sets of profiles (operational or planned, and hypothetical) were simulated using standard availability losses, and then using adjusted availability losses (as described in the following section) that reflect removal of unplanned maintenance or forced outages.

### 4.3.2 Openwind Plant Losses and Availability

The net energy production for a wind farm is derived by subtracting all the wind plant losses from the gross energy by turbine and represents the total power at the electrical connection point of the wind farm to the grid (typically a substation). UL estimated gross and net energy production, including losses, for the following categories: wake, availability, environmental, and electrical. Losses not included in this simulation were: blade degradation, curtailment, and turbine performance. Blade degradation is marginal and difficult to estimate accurately and therefore omitted. All profiles were modeled with no grid curtailment losses. UL did not have a clear indication of turbine performance issues in the ERCOT territory or specific turbine de-rating behavior and therefore assumed that the power generation of all turbines followed their advertised power curve or a known variant. However, the final, adjusted model profiles at operational plants account for plant-specific turbine performance losses because of their adjustment to historical HSL data (which reflects the theoretical, uncurtailed power generation). No force majeure was considered.

UL uses the Deep Array Wake Model (DAWM) inside Openwind to calculate wake losses.[4.9] The DAWM is comprised of two separate wake models operating independently: (1) the Eddy Viscosity model (based on the Navier-Stokes equations rate of wake dissipation)[4.10] and (2) a model designed to better capture wake losses in deep (multi-row) arrays of wind turbines.[4.11] In combining the two models, the DAWM implicitly defines “shallow” and “deep” zones within a turbine array. In the shallow zone, the direct wake effects of individual turbines dominate, and the unmodified Eddy Viscosity (EV) model is used to calculate wake deficits; in the deep zone, the deep-array effect is more prominent, and a surface roughness-based model is employed.

In addition to wake effects from turbines within the same wind farm (i.e., internal wakes), the turbine-induced wakes from neighboring wind farms located upstream can impact the energy production at any particular plant. Openwind is able to capture these plant-on-plant wake losses (i.e., the “wind farm shadowing effect”).

Time-varying wind plant availability was modeled in the Openwind software using a Markov chain method.[4.12] The availability model simulates the change in the number of turbines that are available to generate power from one time step to the next. Availability losses occur when some turbines in a project, or the entire project, are unavailable for some reason when they could be generating power. This can occur due to turbine faults or a failure of one or more turbine components. It can also be caused by a failure or shutdown of the power grid or substation. Plant start-up problems, repair delays, fleet-wide turbine retrofits, or systemic operational issues can cause extended periods of downtime that reduce

[4.9] Brower, M. C. and N. M. Robinson, (2012) The Openwind Deep Array Wake Model – Development and Validation, Technical report from AWS Truepower, Albany (NY), USA. 16 pp.

[4.10] “Openwind Theoretical Basis and Validation. Technical report from AWS Truepower. Albany (NY), USA. 26 pp.

[4.11] Loosely based on Frandsen, S.T. (2007). "Turbulence and Turbulence-Generated Structural Loading in Wind Turbine Clusters". Technical report from the DTU Wind Energy (Risø-R-1188), Roskilde, Denmark. 130 pp.

[4.12] Plant availability includes planned and unplanned turbine outages, grid or substation shutdowns, and any repair or restart times.

the long-term average availability. An average availability loss of 2-10% is typically encountered in operations[4.13] and can vary widely amongst plants.

The main component of the Markov chain is a transition matrix, which indicates the probability of transitioning from any given current state to any other state in the next time step. In Openwind, for a given availability state, specific turbines are selected at random to be switched off. This allows the effect of availability on wake losses, for example, to be correctly modeled. From one time step to the next, only the minimum number of turbines that need to be switched on or off to arrive at the next availability state is selected in order to model the persistence of turbine downtime patterns. To prevent wind turbines from going on and off constantly in an unrealistic way, once a turbine is shut down due to maintenance or an outage, the model keeps it down until the availability rises enough that it must be turned back on.

Various environmental losses are calculated in Openwind using the WRB-adjusted resource time series at each turbine location. These losses include low and high-temperature shutdowns, and high wind hysteresis. Openwind models the low- and high-temperature shutdown or power curve derating behavior for each turbine type using several wind turbine control set points such as the minimum and maximum threshold, if available and applicable. High wind hysteresis is accounted for using the waked wind speeds and the appropriate cut-in and cut-out speeds, as well as power curve derating, for each turbine type.

Electrical losses are experienced by all electrical components of a wind farm, including those from the padmount and substation transformers, electrical collection system, as well as turbine power consumption, including any hot or cold weather packages. The electrical efficiency of a wind farm is primarily driven by losses associated with the transformers and the collector system. The Openwind software includes an electrical efficiency model derived from operational data that simulates this behavior. Turbine power consumption consists of electricity used to run equipment such as yaw mechanisms, blade-pitch controls, aircraft warning lights, oil heaters, pumps, etc. The sum of these sources of turbine power consumption is typically much less than 1%.[4.14] The Openwind software includes a turbine consumption model derived from operational data to account for these losses.

Two sets of profiles were provided for the modeled wind plants. One set includes UL's standard availability assumptions (planned & unplanned outages). The other set is the "adjusted-availability" profiles, which only include planned availability losses (i.e., no unplanned maintenance or forced outages). In modeling these profiles, the unplanned availability loss is randomized, and planned outages or maintenance follows a schedule (varying on a per-turbine basis). Thus, the wind profiles are modeled with partial plant outages. The availability rates and maintenance schedule are gleaned from UL's experience across North America.

## 4.4 Adjustment and Validation

The model generation time series were adjusted using the valid historical generation data from operational plants[4.15] to more accurately reflect real power generation patterns. The main purpose of this adjustment is to account for non-standard and site-specific plant losses, such as turbine availability or power curve derating behavior that were not explicitly modeled in Openwind. For the final adjustment process, correction matrices were developed based on concurrent historical and modeled power generation at each plant. The modeled data with standard availability was used for this purpose. The

[4.13] Brower, M.C. et al. (2012). "Wind Resource Assessment: A Practical Guide to Developing a Wind Project". Wiley, 296 pp.

[4.14] UL did not explicitly model the power consumption of hot or cold weather packages as no information was available regarding their installation.

[4.15] The valid historical generation data is described in Section 4.1.1.

plant-specific matrices were used to adjust the power generation time series at each operational plant with at least one year of valid data. For the four operational plants with an insufficient data record (see Section 4.1.1), a composite adjustment was developed from data at the other 151 plants. No post-processing adjustment was applied to the hypothetical wind plant profiles.

The plant-specific (or aggregate) adjustments described above were applied to both sets of modeled time series, i.e., the standard availability profiles and the adjusted availability profiles. The final generation profiles were examined for reasonableness by plant and as an aggregate. These results are shown below in Figure 4.3 and Figure 4.4 for a comparison of observed data and modeled profiles with standard availability. The modeled generation time series capture the diurnal cycle and ramp distribution of observed generation reasonably well. The final dataset has a bias of less than 1% and an hourly coefficient of determination ($R^2$) of 0.89 for the aggregate generation. Figure 4.4 includes the histogram and the frequency duration curve of concurrent, modeled and observed power generation data for the operational wind plants with one year of validation data or more. As shown, the wind profiles capture the dynamic behavior of generation at the operational wind plants.

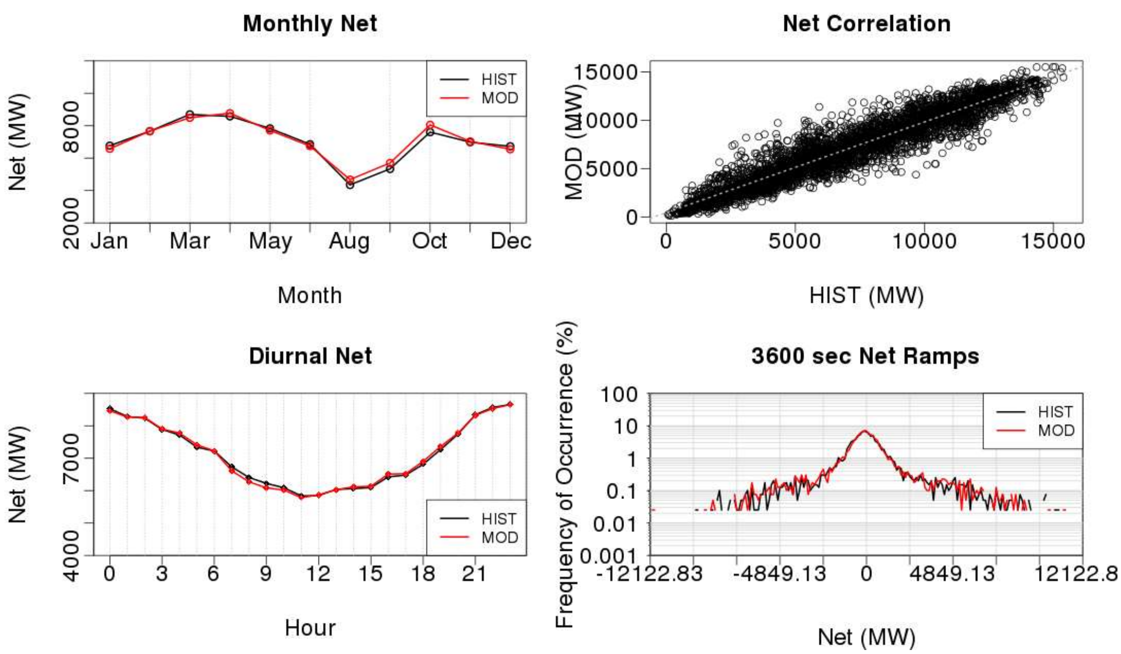


**Figure 4.3: Monthly, Hourly and 1-Hour Ramp Distribution of Aggregated Operational Wind Plant Time Series for Concurrent Observed (black) and Modeled (red) Net Power with Correlation Plot (local standard time). Standard availability profiles shown.**

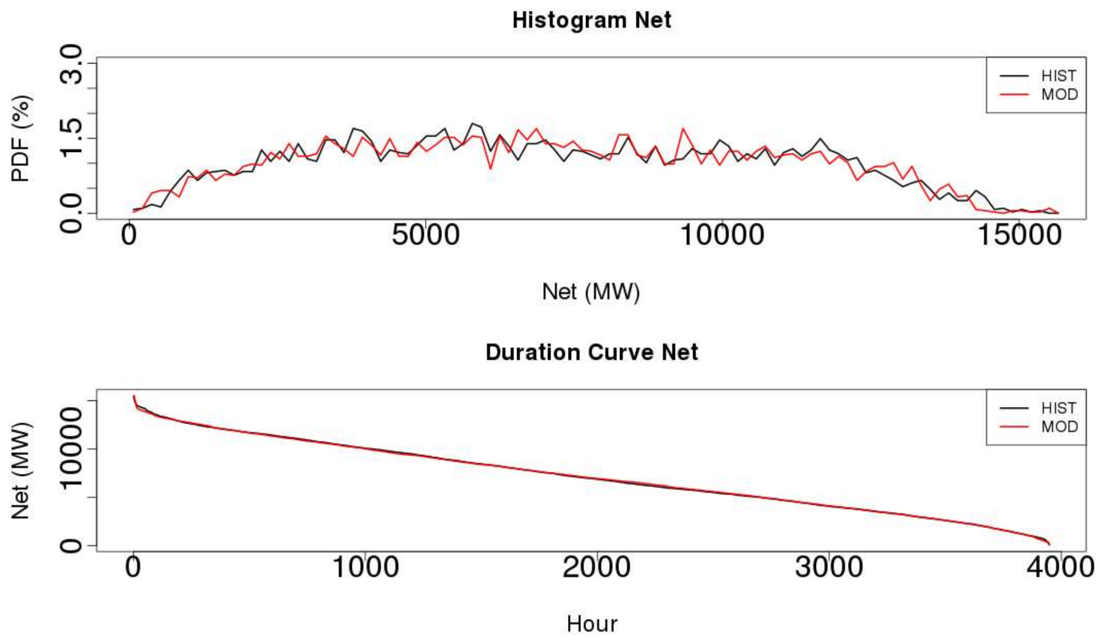


**Figure 4.4: Probability Distribution Function and Duration Curve of Aggregate Operational Wind Plant Time Series for Concurrent Observed (black) and Modeled (red) Net Power. Standard availability profiles shown.**

## 4.5 Wind Power Generation Results

Hourly net generation profiles were simulated for the period 1980-2020 across 155 operational plants and 148 hypothetical plants within the ERCOT domain (Figure 4.5). The net capacity factor (NCF) of the standard-availability modeled generation time series range from 21.7% to 52.6% for the operational plants, and 23.7% to 54.9% for hypothetical plants (Table 4.1). These results are also presented for the adjusted availability time series in Table 4.2. The average net capacity factor across the region (for operational and hypothetical profiles) increases from 42.2% to 43.9% when removing forced outages (i.e., for the adjusted availability profiles).

The power generation across the ERCOT domain shows a peak in the overall generation during the spring months and a lull in late summer; the diurnal pattern exhibits a peak in the generation during the overnight hours (Figure 4.6). This diurnal pattern in domain-wide generation is dominated by the climatic conditions in the West CDR zone (which encompasses much of the operational and hypothetical capacity). An in-depth discussion of weather conditions in the ERCOT territory was provided in UL (2020).

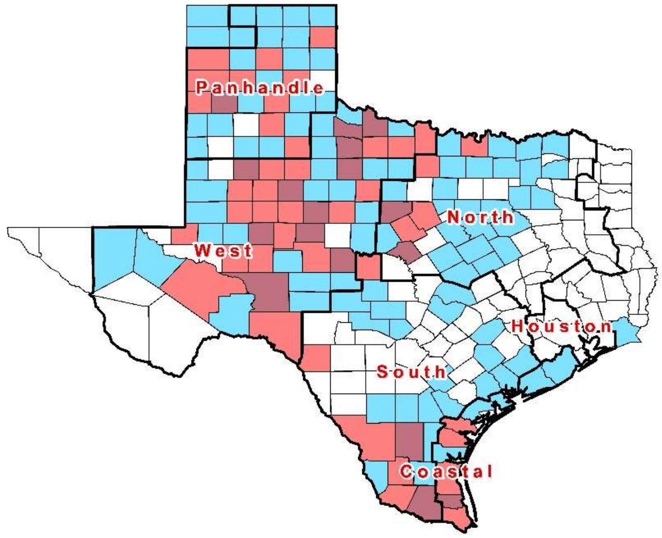


**Figure 4.5: Counties Intersecting Hypothetical (blue) or Operational (red) Wind Plants with CDR Zones Outlined**

**Table 4.1: Generation Summary by CDR Zone for Operational and Hypothetical Wind Plants (Standard Availability)**

| Zone | Hypothetical | | | Operational | | |
|---|---|---|---|---|---|---|
| | Cap (GW) | Avg NCF | Range NCF | Cap (GW) | Avg NCF | Range NCF |
| Coastal | 1.6 | 41.4% | 34.2% - 46.3% | 3.6 | 32.8% | 25.4% - 37.8% |
| North | 7.1 | 43.7% | 37.4% - 53.8% | 1.3 | 40.1% | 30.4% - 48.4% |
| Panhandle | 7.0 | 48.7% | 42.5% - 53.1% | 4.4 | 44.4% | 36.1% - 52.6% |
| South | 5.6 | 41.8% | 31.4% - 50.3% | 2.3 | 40.1% | 31.3% - 45.1% |
| West | 9.4 | 48.8% | 35.9% - 54.9% | 13.7 | 36.5% | 21.7% - 52.6% |
| Total[4.16] | 31.0 | 45.8% | 23.7% - 54.9% | 25.4 | 37.8% | 21.7% - 52.6% |

**Table 4.2: Generation Summary by CDR Zone for Operational and Hypothetical Wind Plants (Adjusted Availability)**

| Zone | Hypothetical | | | Operational | | |
|---|---|---|---|---|---|---|
| | Cap (GW) | Avg NCF | Range NCF | Cap (GW) | Avg NCF | Range NCF |
| Coastal | 1.6 | 42.8% | 35.3% - 47.8% | 3.6 | 34.1% | 27.1% - 39.2% |
| North | 7.1 | 45.1% | 38.5% - 55.6% | 1.3 | 41.9% | 31.4% - 51.0% |
| Panhandle | 7.0 | 50.4% | 43.9% - 55.0% | 4.4 | 46.3% | 37.5% - 54.7% |

[4.16] The totals for the hypothetical plants include two sites that are not within any ERCOT CDR zone (Site 730 and Site 750 both in Jefferson county); and one site outside of the ERCOT territory (Site 996 in El Paso county).

**Table 4.2: Generation Summary by CDR Zone for Operational and Hypothetical Wind Plants (Adjusted Availability)**

| Zone | Hypothetical | | | Operational | | |
|---|---|---|---|---|---|---|
| | Cap (GW) | Avg NCF | Range NCF | Cap (GW) | Avg NCF | Range NCF |
| South | 5.6 | 43.2% | 32.3% - 51.9% | 2.3 | 41.8% | 32.6% - 47.3% |
| West | 9.4 | 50.4% | 36.9% - 56.7% | 13.7 | 38.6% | 22.5% - 54.4% |
| Total[4.19] | 31.0 | 47.3% | 32.3% - 56.7% | 25.4 | 39.7% | 22.5% - 54.7% |

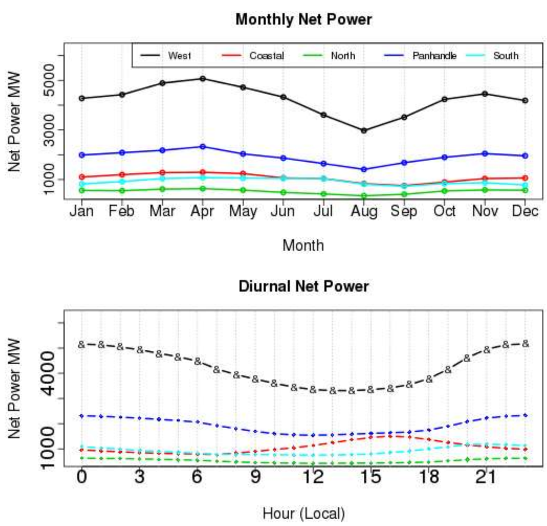


**Figure 4.6: Monthly & Diurnal Modeled Net Power (Standard Availability) for Operational Wind Plants by CDR Zone (local standard time)**

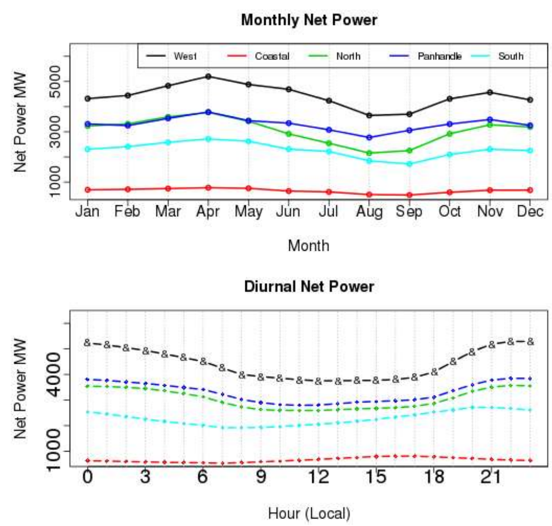


**Figure 4.7: Monthly and Diurnal Modeled Net Power (Standard Availbility) for Hypothetical Wind Plants by CDR Zone (local standard time)**

# 5. UTILITY-SCALE SOLAR PLANTS

## 5.1 Operational and Planned Solar PV Plants

### 5.1.1 Plant Characteristics

The solar plant details for all previously modeled operational or planned plants were retained from UL (2020) and updated to include new plants using details provided by ERCOT and other public sources. Each plant was classified as operational or planned (non-operational) based on the availability of generation data and client-provided information. RARF unit codes were aggregated for multi-phase projects if the phases were geographically aligned such that no obvious distinction could be made between their layouts. A total of 53 utility-scale PV plants were modeled representing all the RARF unit codes provided by ERCOT (Appendix C). This information was reviewed for consistency and compared to information from public sources, as applicable.

### 5.1.2 Operational Plant Data

Observed generation data concurrent with the modeling period was received from ERCOT and subsequently screened for reasonableness. Data from individual plants start on the date that ERCOT approved commercial operations, and therefore did not require truncating for a break-in period. The historical generation data for all plants consisted of the hourly high sustainable limit (HSL) for each record. The HSL refers to the limit established by the plant owner/operator (i.e., qualified scheduling entities) that describes the maximum sustained energy production capability of the plant at that time. In essence, the HSL reflects the expected, uncurtailed power generation at actual plant availability.

New generation data was processed only for those plants that received a composite adjustment in the previous study or was included as a new operational plant. The same quality control procedures outlined in UL (2020) were applied. Of the 53 utility-scale plants modeled, 26 plants had greater than 1 year of valid data and 27 plants had less than 6 months of valid data or no data at all. The utility-scale plants modeled were categorized as below based on their operational status, the availability of generation data, and knowledge of static plant details.

- operational plants: generation data sufficient for adjustment tuning to operational data; and
- planned plants: generation data insufficient or unavailable; composite adjustment from operational tuning.

## 5.2 Hypothetical Solar PV Plants

The hypothetical, utility-scale PV sites from UL (2020) which consisted of 139 hypothetical utility-scale sites of 50 $MW_{AC}$ each (totaling 6.95 GW) were modeled and are shown in Figure 5.1. These sites had been previously selected based on their resource potential and proximity to key operational or planned utility-scale solar PV plants, and distance to transmission. UL applied the same technology specifications as in UL (2020). For an in-depth discussion of how these composite specifications were made, and for the module specifications, see UL (2020).

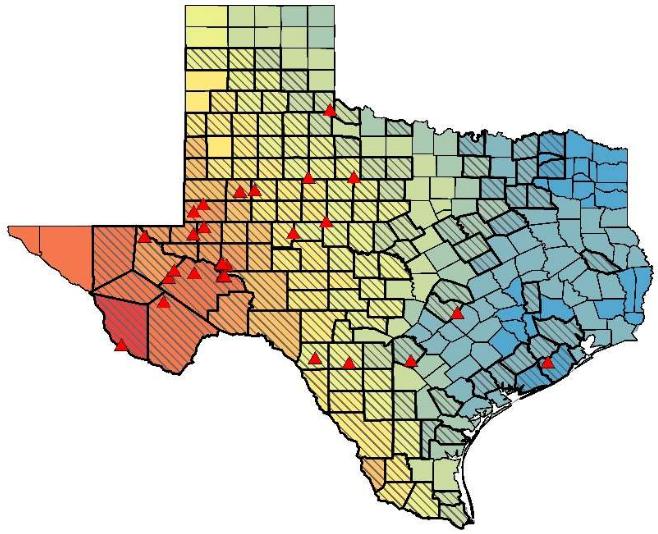

**Figure 5.1: Counties with Hypothetical PV Plants (shaded) and Operational or Planned PV Plants (triangles), with GHI Resource as Background**

# 6. DISTRIBUTED SOLAR GENERATION SITES

## 6.1 Simulated Rooftop Generation for Greater Metro Areas

In previous studies by UL, the greater metro areas of Austin, Dallas, Houston, and San Antonio were evaluated for potential distributed rooftop generation PV (DGPV) by estimating the rooftop area available for solar panels. A total of 12 DGPV aggregate sites were identified within these four metro regions, and each was defined according to their intensity of development (high, medium, or low). In UL (2020), the capacity estimates for each of these aggregate sites was revised (Table 6.1) and these capacities were reused in the present study.

**Table 6.1: Capacity ($MW_{AC}$) by Metro Area and Intensity of Development**

| Metro Area | Low | Medium | High | Total |
|---|---|---|---|---|
| Austin | 374 | 411 | 1,405 | 2,190 |
| Dallas | 1,557 | 1,611 | 6,552 | 9,720 |
| Houston | 1,211 | 1,779 | 6,677 | 9,667 |
| San Antonio | 420 | 431 | 1,672 | 2,523 |
| *Total (GW)* | | | | *24.1* |

## 6.2 Simulated Rooftop Generation for Rural Regions

In 2020, UL worked with ERCOT to develop a methodology to estimate the potential distributed rooftop PV generation across rural counties within ERCOT. A total of 221 counties that had rural development areas were identified for PV profile modeling (grey counties in Figure 6.1). The potential capacity of rural development areas was retained from UL (2020) and is provided by CDR zone in Table 6.2. The final modeled profiles of rural DGPV were aggregated by CDR zone.

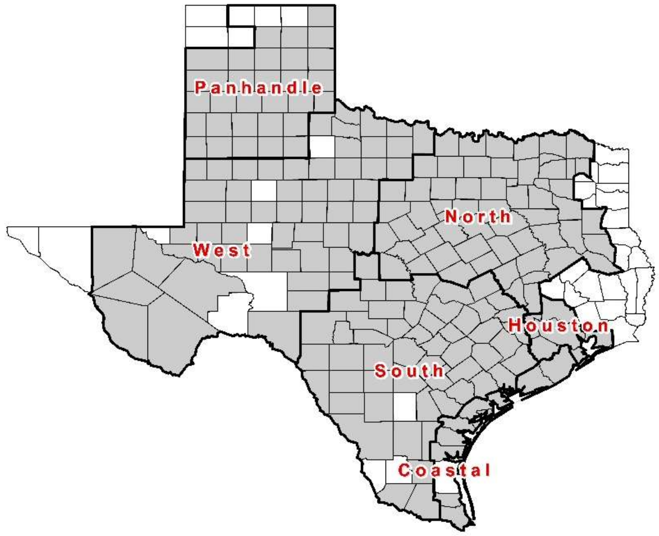


**Figure 6.1: Counties Represented by Rural Profiles**

**Table 6.2: Rural Distributed PV Capacity by CDR Zone**

| Zone | Cap ($MW_{AC}$) |
|---|---|
| Coastal | 835.98 |
| Houston | 249.32 |
| North | 1965.63 |
| Panhandle | 564.31 |
| South | 1497.02 |
| West | 863.70 |
| *Total* | *5975.96* |

# 7. SOLAR GENERATION PROFILES

## 7.1 Solar Power Generation

UL simulated hourly generation using the adjusted WRF modeled time series at the utility-scale and DGPV rooftop sites. Atmospheric variables that impact module performance and power conversion were extracted from the WRF numerical data output. The WRF modeled irradiance was converted to hourly averaged irradiance using an interval averaging method. A new version of UL's power conversion software, TS2Solar Version 5.0 was developed to convert the hourly averaged modeled irradiance to solar PV output.[7.17] Operational sites were modeled with plant-specific parameters as agreed upon by ERCOT and UL. The static plant details for hypothetical and distributed PV sites were retained from UL (2020).

[7.17] A new method was incorporated to better capture the irradiance, and ensuing solar PV generation, observed in the first and last hours of daylight. This method relied on using solar geometry to calculate sub-hourly (1-minute) clear sky irradiance for the entire modeling period (1980-2020), on which the hourly WRF cloudiness factor is applied. This yields a high frequency irradiance dataset which is then averaged to an hourly interval (hour-ending values). In this way, non-zero values of solar resource are captured at the beginning and end of days. The hourly averaged irradiance is then used in lieu of the instantaneous WRF modeled irradiance in the solar power conversion process.

The power conversion process follows the methodology in AWST (2017)[7.18] and UL (2020). The static loss assumptions used for power conversion can be found in UL (2020).

## 7.2 Adjustment and Validation

The modeled solar generation data were adjusted using quality-controlled, hourly-ending historical generation data to more accurately reflect real-world power generation patterns. The main purpose of this adjustment is to account for discrepancies in static plant details (e.g., layout, equipment, tilt, tracking characteristics), loss assumptions, and any other deficiencies in the modeling process. The final adjustment process applied a correction matrix specific based on concurrent observed and modeled power generation.

### 7.2.1 Utility-Scale Solar PV

Historical generation data from operational utility-scale plants were used to adjust the modeled profiles at all utility-scale PV plants (operational or planned, and hypothetical). No new data from operational plants with greater than 1 year of observed generation in UL (2020) was incorporated. Observed generation was obtained and processed for any previously-modeled operational plant that had less than 1 year of data in UL (2020)—and these plants received site-specific adjustments. No new operational plants included in this study had a sufficient data record to be utilized in a custom adjustment. All site-specific adjustment matrices were (re)calculated for the present study to account for updates in the power conversion methodology. A composite adjustment was applied to the profiles of the operational or planned utility-scale solar plants with less than 1 year of valid data, and to the hypothetical plant profiles.[7.19]

After adjustment to monthly and diurnal expected values, the overall generation time series were scaled to the observed maximum value at each plant. Therefore, modeled generation will reach 100% of the nameplate MWAC capacity at the operational sites if the historical data reaches 100% capacity. For hypothetical sites, the modeled generation reaches 100% of the $MW_{AC}$ capacity (50 $MW_{AC}$ per site).

The final generation profiles were examined for reasonableness at the plant level and as an aggregate for the operational plants with at least one year of available historical generation data. The adjusted modeled generation time series match the observed monthly and diurnal patterns (as expected with an adjustment based on month and hour) and also captures the observed hourly ramp frequency distribution well (Figure 7.1). The final dataset has a bias of 0.0% on generation and an hourly coefficient of determination ($R^2$) of 0.92. Depicted in Figure 7.2 is the frequency duration curve for all concurrent, hourly historical and adjusted model data for plants that had at least one year of historical generation data. This analysis shows that the final dataset accurately captures the dynamic behavior of utility-scale solar plants.

[7.18] Rojowsky, K. (2017). Solar Site Screening and Hourly Generation Profiles. Technical report prepared for ERCOT by AWS Truepower. Reference number: 03-16-014484

[7.19] The use of operational data to adjust the hypothetical profiles assumes that the hypothetical sites will operate like the existing operational sites, including availability issues inherent in the observed generation data. Also, deficiencies in the static plant details of operational plants and subsequent modeling process will be reflected in this adjustment. Therefore, the adjusted profiles may represent a conservative lower bound for the generation at future hypothetical sites given historical availability patterns and the static assumptions provided for the operational sites. High-quality operational plant metadata (static data) may benefit future work when adjusting to operational data.

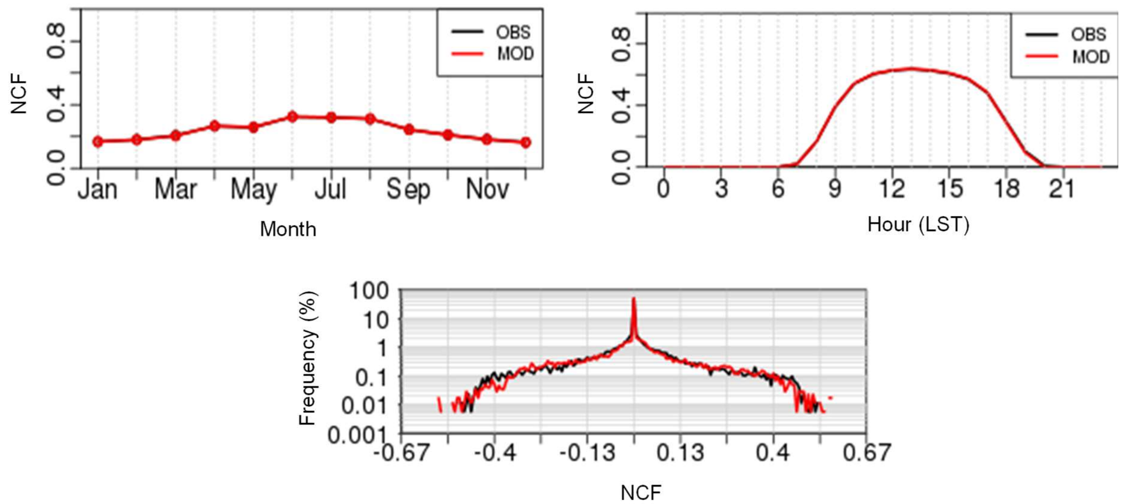


**Figure 7.1: Hourly Mean Monthly (top left), Diurnal (top right) and Ramp Frequency Distribution (bottom) NCF for an Aggregate of Operational Solar Plants (local standard time)**

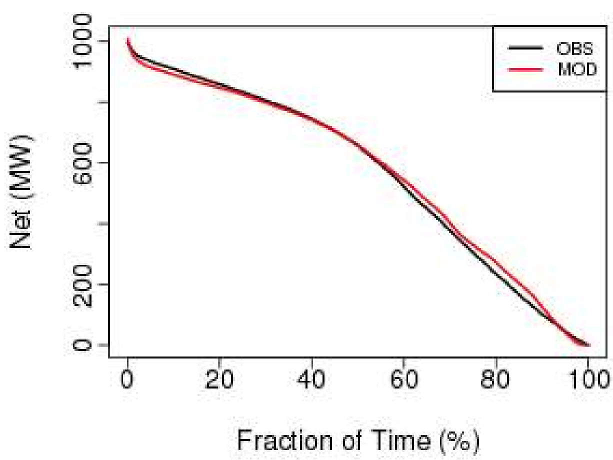


**Figure 7.2: Frequency Duration Curve for Operational Solar Plants**

## 7.2.2 Distributed Rooftop Sites

For the distributed rooftop generation profiles, a composite matrix adjustment was developed using the historical rooftop generation data obtained previously for UL (2020). Observed and updated modeled generation from zip codes in each metro area were used to recalculate this adjustment for the present study and account for updates in the power conversion methodology. All DGPV metro areas and rural sites were adjusted using this composite matrix. The resulting modeled profiles were scaled to the maximum observed over the period; therefore, DGPV metro and rural profiles reach 97.5% of the assumed $MW^{AC}$ capacity.

The final generation profiles were examined for reasonableness at the site level and as an aggregate of all the zip codes for which rooftop generation data was obtained (Figure 7.3). As with the modeled utility-scale generation time series, these modeled DGPV generation time series accurately depict the diurnal and monthly mean patterns of observed generation data. The model overestimates the largest ramps, which provides a conservative estimate of the hourly ramping potential of DGPV across these metro areas. The final dataset has a bias of 0.1% on generation and an hourly coefficient of determination ($R^2$) of 0.95. Depicted in Figure 7.4 is the frequency duration curve for all concurrent, hourly historical and adjusted model data for generation data across the four metro areas. This analysis shows that final dataset accurately captures the dynamic behavior of distributed rooftop generation.

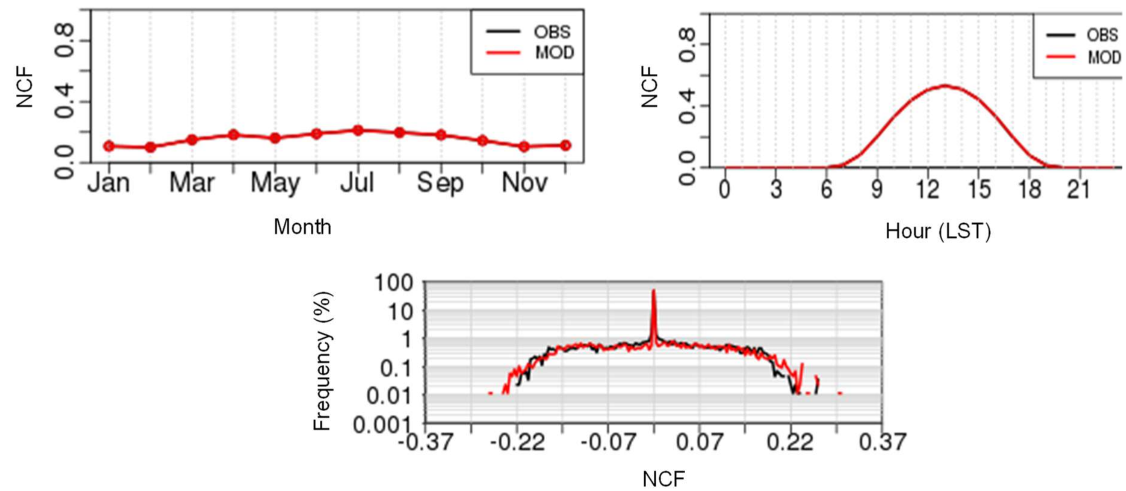


**Figure 7.3: Hourly Mean Monthly (top left), Diurnal (top right) and Ramp Frequency Distribution (bottom) NCF for Aggregated Rooftop Data (local standard time)**

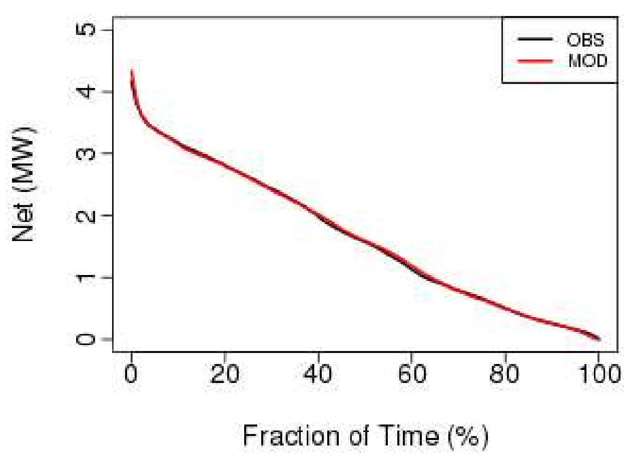


**Figure 7.4: Frequency Duration Curve for Aggregated Rooftop Data**

## 7.3 Solar Power Generation Results

Hour-ending time series of PV generation profiles were developed for 139 hypothetical utility-scale sites, 53 operational or planned utility-scale plants, 12 DGPV sites across four metro areas, and six CDR zone DGPV rural profiles for the years 1980-2020 (Figure 7.5).

The range of net capacity factors (NCF) for each site type can be found in Table 7.3. The operational plants have mean NCFs ranging from 18.6% to 31.3%. As expected, the hypothetical plant profiles modeled with near-current technology show higher values of min and max NCF than the operational plants (24.1 to 32.6 % depending on tracking scenario). The use of operational data to adjust the hypothetical profiles assumes that the hypothetical sites would operate like the existing operational sites (i.e., with equivalent availability). Generally, the DGPV profiles exhibit lower NCFs than the utility-scale PV plants. Even when accounting for local irradiance resource, generation varies between centralized, utility-scale and distributed rooftop generation due to plant characteristics. These differences are largely due to: tracking (fixed rooftop PV compared vs. tracking utility-scale systems); module technology; and modeling assumptions (rooftop systems were assumed to have wind-driven cooling only on one face of the panels and thus experienced higher temperature losses).

The monthly and diurnal mean net power at a sample hypothetical site modeled is shown in Figure 7.6. As expected, the dual-axis profiles exhibit higher power than the single-axis counterparts during midday and in the winter, when dual-axis trackers are better able to maximize production during the sun's low wintertime altitude compared to the single-axis trackers, which are flat midday.[7.20] This difference is more pronounced with increasing latitude (not shown).

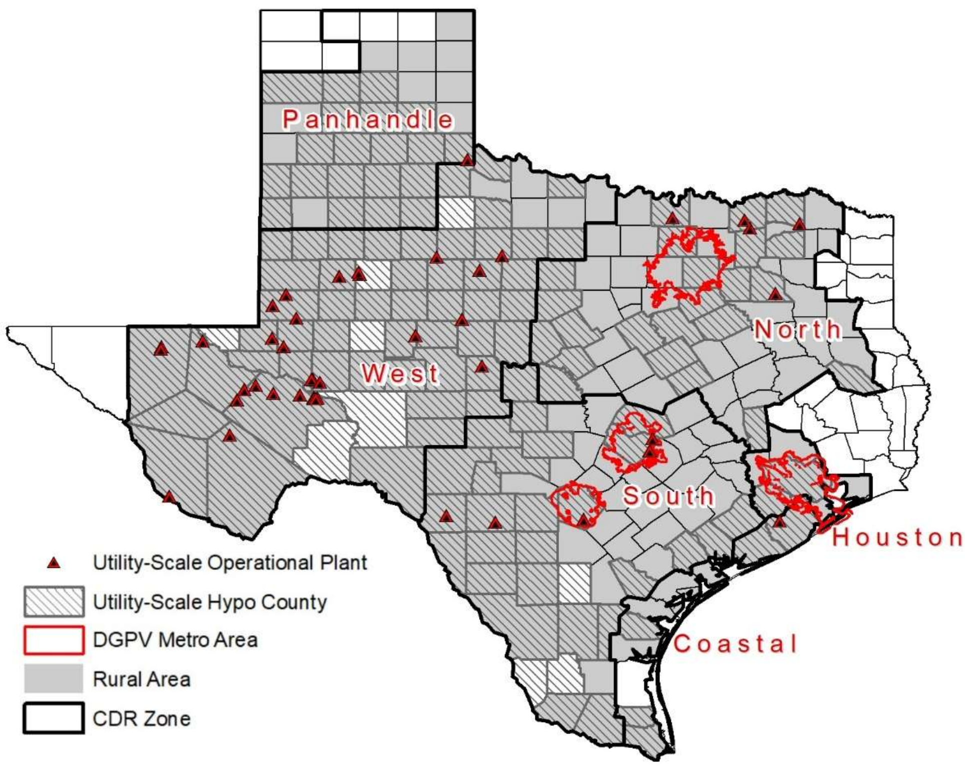


**Figure 7.5: Areas Represented by Modeled PV Profiles**

[7.20] The final generation profiles for the dual-axis trackers exhibit slightly lower NCF during the summertime than their single-axis counterparts, primarily due to the adjustment to observed generation data where this is seen.

**Table 7.1: Range of Net Capacity Factors (NCFs) for Modeled Solar PV Time Series**

| PV Generator Type | Range NCF (%) |
|---|---|
| Operational and Planned Utility-Scale | 18.6 – 31.3 |
| Utility-Scale Hypothetical (Single-Axis) | 24.7 – 32.6 |
| Utility-Scale Hypothetical (Dual-Axis) | 24.1 – 31.6 |
| Distributed Rooftop (Metro) | 15.2 – 15.4 |
| Distributed Rooftop (Rural) | 14.9 – 19.6 |

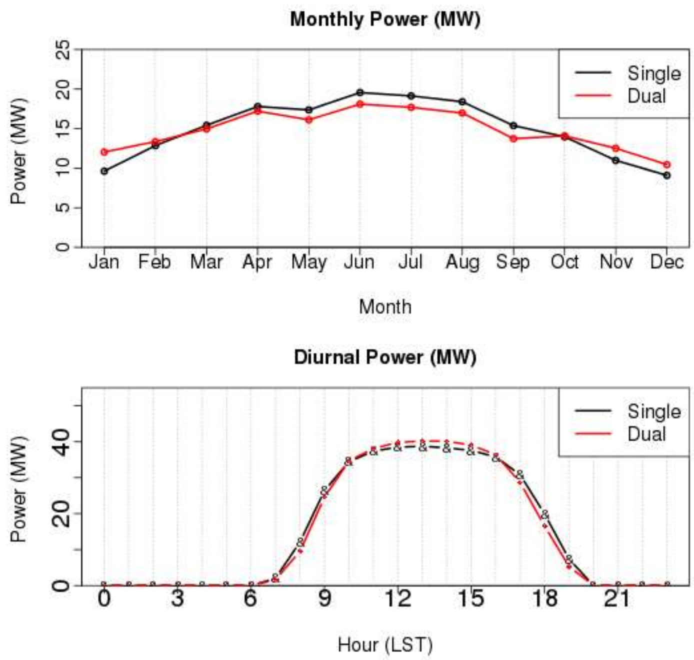


**Figure 7.6: Monthly and Diurnal Mean Net Power at a Sample Hypothetical Site modeled as Single-axis (black) and Dual-axis (red) Tracking (local standard time)**

The distributed rooftop generation profiles were evaluated for differences in the potential generation across the metro areas. As seen in previous work, the overall net capacity factor varies little across the different land use classes within individual metro areas, but the normalized generation does vary across the four metro areas, due to differences in local climates. Further analysis also shows a difference in the timing of generation across these four metro areas, as shown by the average diurnal NCF calculated as a sum of all three land class sites per metro area (Figure 7.7). All profiles achieve non-zero generation at the same hours (06:00 and 19:00) and peak generation at the same hour (13:00). However, the effect of longitude on the relative solar position can be seen in the mean diurnal NCF, with Houston power generation reaching higher generation earlier in the morning, followed by Dallas, Austin, and San Antonio, from east to west. The opposite pattern, although less well pronounced, is seen in the afternoon. Similar to the DGPV metro profiles, analysis of the DGPV rural profiles show a difference in the timing of generation across the CDR zones, as shown by the average diurnal NCF profile calculated for each zone (Figure 7.8). An in-depth discussion of the weather conditions in the ERCOT territory and how this impacts the timing of the generation at the DGPV metro and rural locations was provided in UL (2020).

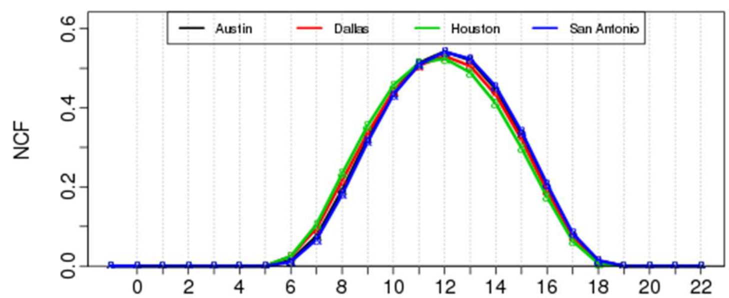


**Figure 7.7: Diurnal Net Capacity Factor for DGPV metro areas (local standard time)**

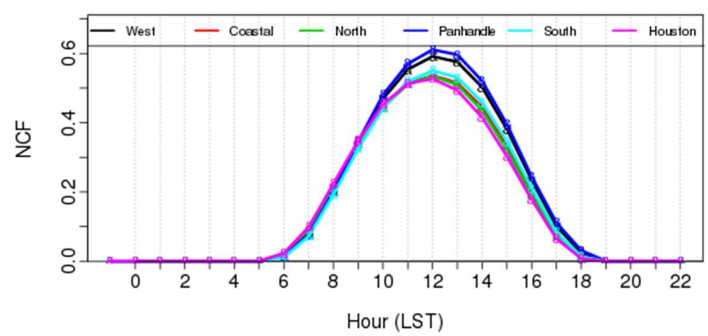


**Figure 7.8: Diurnal Net Capacity Factor for DGPV Rural Zones (local standard time)**

# 8. DATASET USAGE

The goal of this work was to provide high fidelity power generation profiles for operational and hypothetical installations to support resource adequacy and regional planning studies. Therefore, it is important to understand the modeling assumptions and methods applied to guide their future use and application.

UL simulated ERCOT's wind power profiles using Openwind, a state-of-the-art resource assessment, and power optimization modeling tool used across the wind industry during all phases of project development. Openwind calculates plant-level and turbine level losses at each time step including wake, availability, environmental, turbine performance, and electrical losses. Plant-specific characteristics such as plant layout, turbine model, and power curve heavily influence the power generation and wind plant losses on various time scales.

UL adapted the Openwind software allowing for fleet modeling with a high degree of success across large project areas where plant specifications are well documented and supplied as input for modeling. These characteristics were defined for ERCOT's operational wind plants to the best of UL's ability through public and proprietary sources of information. However, in the absence of measured plant-specific losses for this work, UL applied assumptions in the Openwind model based on UL's methods derived from operational plants across North America. These wind profiles reflect a significant change in the methods used to simulate wind power profiles in ERCOT prior to 2020, and therefore a record-to-record comparison with earlier works may not be appropriate.

It is important to note that simulated profiles may not match historical plant generation at a given time for several reasons:

- All plants were modeled for the period 1980-2020 using assumed plant specifications (for previously modeled plants) or the 2020 fleet configuration (for new plants), regardless of the actual commissioning date or any change in plant specifications over time. Information regarding changes in plant configuration or the repowering of operational plants either via a physical change to plant layout, software configuration, or modification to operational settings, power curve etc., were not available.
- Plant details did not always align with expectations based on data reviews. UL and the client discussed deviations and assumptions employed to mimic unknown static details at these plants. Plant layouts were not modified and therefore some plants may not reach full generation capacity.
- Validation and adjustment of wind and solar profiles from previously modeled sites with >1 year of operational data relied heavily on post-processing adjustment using operational data. For plants these plants, UL relied on data from UL (2020) and did not incorporate additional, more recent operational data. Wind and solar plants with <1 year of operational data were adjusted using a composite adjustment developed from those with sufficient data, and therefore would not align with plant operations (as these vary from site to site).
- The modeled wind data were scaled to historical generation to account for site-specific losses not captured in the model output. The scaling required indicates that input data for the plants may be lacking (e.g. a derating of power curves), or that atmospheric variables contain a bias that affects the Openwind simulation of time-varying losses.
- UL did not model all operational wind plants in the ERCOT fleet. It is likely that non-modeled plants are contributing to plant-on-plant waking at modeled sites resulting in artificially high generation.
- An attempt was made to remove the effects of grid curtailment from the historical generation data by using the HSL data for the model adjustment. Therefore, the modeled data are not reflective of curtailment that may have been experienced at a wind or solar plant, as is present in the actual generation measurements.
- UL did not have an hourly historical record of the actual turbine availability indicating downtime due to events such as preventive or unscheduled maintenance, and plant or grid outages. Instead, the turbine availability was modeled in Openwind with a Markov Chain to best represent the statistical behavior of turbine availability based on a large number of operational plants in the US. Because plant or turbine-level availability was not explicitly given for any plant, it is possible that the modeled availability does not align with the actual availability at each operational plant.
- Standard methods were applied for cold temperature conditions at wind plants, which seek to optimize related losses (e.g., icing, accretion, melting) over the long term, not for a specific event or duration. An advanced icing model is available for wind plants that may more accurately capture these time-varying losses.
- Some of the operational wind plants modeled for this effort did not have one year of valid data for the final adjustment process (4 of 155 plants). Therefore, an alternative method for modeled data adjustment were developed that may not reflect plant performance at these locations. It is highly recommended that these sites be re-adjusted when a year or more of actual plant generation data is available.

- Solar plant details at some locations were lacking, and assumptions regarding the AC/DC ratio, plant phases, inverter losses etc. were applied after consultation with ERCOT.

The hypothetical PV sites modeled in this study were identified via a high-level identification of allowable land remaining after exclusions and additional assumptions were applied. A detailed analysis below 200-m resolution was not performed, and therefore some sites may not be commercially viable. Factors such as the total area of contiguous land available to build, construct, and operate a solar PV plant with a reasonable cost of energy have not been considered, neither have policy or regulatory constraints.

Distributed generation rooftop PV (DGPV) is rapidly expanding. While its penetration varies across the landscape, it is highly correlated to land use and population, which are the drivers used to define DGPV sites for ERCOT in both the metro and rural areas. While the location and potential capacity of DGPV in metro and rural can be assessed assuming current development, future land use changes may affect the location, capacity, and/or modeled characteristics of rooftop installations (e.g., transition of single family homes to multi-unit buildings, commercial real estate development, or an expansion of suburban development). The rooftop PV capacity modeled in this study assumes static land use characteristics in NLCD (2016). Additionally, the distributed solar generation profiles assume all modeled capacity consists of future installations deployed with near-current technology. These profiles do not account for aged technology in-place at existing rooftop installations.

The wind and solar resource were modeled at a 9-km horizontal resolution. While this resolution captures much of the spatial variability in wind and solar resource across the state of Texas, assumptions need to be made about details in the weather patterns. For example, a mesoscale model such as WRF with grid spacing coarser than 4 or 5 km cannot explicitly resolve cumulus clouds, and thus it must rely on a convective parameterization scheme. Rather than physically simulating the lifecycle of individual cloud elements, these parameterizations characterize the bulk effects of various cloud types and their lifecycles based on the environmental conditions present at the grid cell level. Because of this parameterization, the 9-km resolution is generally considered sufficient for hourly solar generation studies by striking a balance between computational time and the need to resolve localized terrain and roughness effects. For both wind and solar power generation studies, accurate environmental resource characterization is fundamental to replicating real-world power generation. UL incorporated observed wind speed and solar radiation data to ground-truth these specific parameters. However, a bias in any ancillary variables such as temperature, turbulence intensity, relative humidity, or precipitation can adversely affect the modeled wind or solar generation.

This dataset was developed specifically for use in modeling and analysis efforts related to the high penetration of wind and solar and its long-term variability. It has been shown that the final modeled dataset accurately represents the historical generation patterns at individual plants and on an aggregate basis. Additional bias correction for atmospheric variables and updated plant specifications may improve the alignment with the operational data, reducing the need for manual adjustment in the future. Finally, it should be noted that modeled data provided by this study is not a replacement for onsite measurements.

# APPENDIX A – OPERATIONAL WIND PLANTS

**Table A.1: Operational Wind Plants in Counties A - Fl**

| SITE # | County | Modeled Capacity (MW) | Data Review |
|---|---|---|---|
| 140 | Archer | 64.4 | |
| 5 | Archer | 162 | |
| 133 | Archer | 198 | |
| 3006 | Baylor | 30.24 | |
| 45 | Baylor | 150 | |
| 11 | Borden | 61 | |
| 102 | Borden | 84 | |
| 4002 | Borden | 158 | |
| 18 | Borden | 180 | |
| 118 | Borden | 211.22 | |
| 12 | Briscoe | 149.85 | |
| 109 | Cameron | 93 | |
| 4003 | Cameron | 144.9 | |
| 20 | Cameron | 165 | |
| 104 | Carson | 150 | |
| 100 | Carson | 181.7 | |
| 46 | Carson | 200.48 | |
| 47 | Carson | 211.22 | |
| 99 | Carson | 218.3 | |
| 55 | Castro | 299.7 | |
| 114 | Clay | 204.085 | |
| 43 | Coke | 69.6 | |
| 44 | Coke | 80 | |
| 68 | Comanche | 200.1 | |
| 25 | Concho | 148.35 | |
| 139 | Cooke | 112.5 | |
| 135 | Cooke | 119.6 | |
| 4005 | Crockett | 302.4 | |
| 4007 | Crockett | 502.135 | < 1yr |
| 82 | Dawson | 211.22 | |
| 56 | Deaf Smith | 99.9 | |
| 57 | Deaf Smith | 100 | |
| 87 | Dickens | 150 | |
| 107 | Donley | 174 | |
| 40 | Erath | 60 | |
| 2014 | Erath | 100.05 | |
| 27 | Floyd | 50.4 | |
| 28 | Floyd | 151.2 | |

**Table A.2: Operational Wind Plants in Counties Fl - Mi**

| SITE # | County | Modeled Capacity (MW) | Data Review |
|---|---|---|---|
| 69 | Floyd | 200 | |
| 115 | Floyd | 200 | |
| 137 | Floyd | 257.25 | |
| 116 | Floyd | 300.3 | |
| 138 | Floyd | 59.8 | |
| 3001 | Foard | 350.28 | |
| 81 | Glasscock | 90 | |
| 95 | Glasscock | 115.5 | |
| 94 | Glasscock | 142.5 | |
| 88 | Glasscock | 196.65 | |
| 2105 | Glasscock | 206.345 | |
| 54 | Haskell | 230 | |
| 108 | Haskell | 250 | |
| 83 | Hemphill | 288.6 | |
| 85 | Hidalgo | 100 | |
| 84 | Hidalgo | 150 | |
| 2112 | Howard | 34.32 | |
| 91 | Howard | 58.8 | |
| 48 | Howard | 119.93 | |
| 34 | Howard | 121.9 | |
| 61 | Jack | 110 | |
| 13 | Jack | 120 | |
| 111 | Jack | 150 | |
| 36 | Jim Hogg | 78 | |
| 3007 | Kenedy | 201 | |
| 3 | Kenedy | 202 | |
| 130 | Kenedy | 283.2 | |
| 97 | Kenedy | 403.2 | |
| 86 | Kent | 30 | |
| 1 | Kinney | 99.825 | |
| 136 | Knox | 150 | |
| 117 | Lynn | 164.68 | |
| 3008 | Lynn | 302.4 | |
| 123 | Martin | 120 | |
| 4004 | Matagorda | 151.2 | < 1yr |
| 106 | McCulloch | 160 | |
| 2049 | Mills | 156.16 | |
| 42 | Mills | 200 | |
| 73 | Mitchell | 49.5 | |
| 72 | Mitchell | 100.5 | |

**Table A.3: Operational Wind Plants in Counties Mi - Sh**

| SITE # | County | Modeled Capacity (MW) | Data Review |
|---|---|---|---|
| 131 | Mitchell | 209 | |
| 26 | Nolan | 126.5 | |
| 17 | Nolan | 170.2 | |
| 52 | Nolan | 223.5 | |
| 16 | Nolan | 232.5 | |
| 129 | Nolan | 37.5 | |
| 128 | Nolan | 80.5 | |
| 124 | Nolan | 98.82 | |
| 121 | Nolan | 101.2 | |
| 127 | Nolan | 105.8 | |
| 125 | Nolan | 135 | |
| 126 | Nolan | 135 | |
| 132 | Nolan | 150 | |
| 134 | Nolan | 169.5 | |
| 59 | Nolan | 197 | |
| 110 | Nueces | 243 | |
| 120 | Oldham | 160.95 | |
| 119 | Oldham | 194 | |
| 3000 | Oldham | 210.105 | |
| 79 | Parmer | 230.4 | |
| 141 | Pecos | 77.22 | |
| 92 | Pecos | 82.5 | |
| 142 | Pecos | 82.5 | |
| 63 | Pecos | 132 | |
| 60 | Pecos | 160.5 | |
| 2 | Randall | 163.2 | |
| 53 | Reagan | 300 | |
| 3004 | San Patricio | 162.855 | |
| 93 | San Patricio | 179.85 | |
| 29 | San Patricio | 200.1 | |
| 3002 | San Patricio | 307.06 | |
| 4006 | Schleicher | 199.5 | |
| 10 | Scurry | 99 | |
| 31 | Scurry | 120 | |
| 30 | Scurry | 130.5 | |
| 41 | Scurry | 155.4 | |
| 101 | Scurry | 249 | |
| 32 | Scurry | 253 | |
| 58 | Shackelford | 165.6 | |

**Table A.4: Operational Wind Plants in Counties Sh - Wi**

| SITE # | County | Modeled Capacity (MW) | Data Review |
|---|---|---|---|
| 71 | Shackelford | 200 | |
| 2070 | Shackelford | 200 | |
| 78 | Starr | 110 | |
| 76 | Starr | 200 | |
| 77 | Starr | 200 | |
| 3005 | Starr | 237.6 | |
| 80 | Sterling | 124.2 | |
| 22 | Sterling | 149.5 | |
| 96 | Sterling | 199.5 | |
| 21 | Sterling | 214.5 | |
| 23 | Sterling | 298.5 | |
| 19 | Taylor | 114 | |
| 15 | Taylor | 120.6 | |
| 50 | Taylor | 213 | |
| 51 | Taylor | 299 | |
| 67 | Tom Green | 150 | |
| 66 | Upton | 40.3 | |
| 64 | Upton | 78 | |
| 65 | Upton | 159.9 | |
| 39 | Val Verde | 27.44 | |
| 38 | Val Verde | 121.9 | |
| 7 | Webb | 19.69 | |
| 37 | Webb | 92.34 | |
| 24 | Webb | 150 | |
| 2009 | Webb | 200 | |
| 8 | Webb | 230 | |
| 3009 | Webb | 300.5 | |
| 4001 | Wilbarger | 99.36 | < 1yr |
| 2006 | Wilbarger | 137.7 | |
| 3003 | Wilbarger | 183.75 | |
| 4000 | Wilbarger | 200.2 | < 1yr |
| 33 | Wilbarger | 230 | |
| 74 | Willacy | 200.1 | |
| 75 | Willacy | 201.6 | |
| 103 | Willacy | 203.28 | |
| 4 | Willacy | 228 | |
| 90 | Winkler | 60 | |
| 2089 | Winkler | 92.565 | |

# APPENDIX B – HYPOTHETICAL WIND PLANTS BY COUNTY

**Table B.1: Count of Sites and Total Capacity by County**

| County | # | Cap (MW) | County | # | Cap (MW) | County | # | Cap (MW) |
|---|---|---|---|---|---|---|---|---|
| Andrews | 2 | 345.7 | Grayson | 1 | 191.8 | McMullen | 2 | 350.4 |
| Armstrong | 1 | 383.9 | Hall | 2 | 542.2 | Menard | 2 | 362.2 |
| Bailey | 1 | 245.3 | Hansford | 1 | 400 | Midland | 2 | 328.6 |
| Bee | 2 | 323.8 | Hardeman | 2 | 311.9 | Mills | 1 | 140.2 |
| Bell | 1 | 122.5 | Hartley | 1 | 352.1 | Montague | 2 | 326.7 |
| Bosque | 2 | 292.5 | Haskell | 2 | 434.1 | Moore | 1 | 400 |
| Brazoria | 1 | 130.8 | Hidalgo | 2 | 454.9 | Motley | 2 | 341.2 |
| Brooks | 1 | 154.1 | Hill | 1 | 375.1 | Navarro | 2 | 414.5 |
| Brown | 2 | 452.1 | Hood | 1 | 162.4 | Nolan | 1 | 338.6 |
| Calhoun | 1 | 199.8 | Hopkins | 1 | 143.1 | Ochiltree | 1 | 130.3 |
| Callahan | 1 | 103.5 | Hunt | 1 | 237.3 | Parker | 1 | 230.6 |
| Castro | 1 | 357.8 | Hutchinson | 1 | 271.5 | Potter | 2 | 749.1 |
| Childress | 1 | 310.4 | Irion | 1 | 208.9 | Reeves | 1 | 102.7 |
| Cochran | 1 | 130.8 | Jackson | 3 | 617.5 | Refugio | 1 | 169.9 |
| Coke | 1 | 212.6 | Jefferson | 2 | 247.5 | Roberts | 2 | 329.5 |
| Coleman | 2 | 498.8 | Jim Wells | 1 | 171.4 | Schleicher | 1 | 241 |
| Collin | 1 | 223 | Johnson | 2 | 350.3 | Scurry | 1 | 311.8 |
| Concho | 1 | 252.2 | Jones | 1 | 210.6 | Sherman | 1 | 148.9 |
| Coryell | 2 | 409 | Karnes | 1 | 158.1 | Stephens | 2 | 349.7 |
| Cottle | 2 | 428.1 | Kaufman | 1 | 103.9 | Stonewall | 1 | 343.2 |
| Crockett | 1 | 254.4 | Kendall | 1 | 305.1 | Sutton | 2 | 275.3 |
| Crosby | 1 | 400 | Kerr | 1 | 126 | Swisher | 1 | 176.1 |
| Culberson | 1 | 160 | Kimble | 1 | 115.4 | Terrell | 1 | 155.4 |
| Dallam | 1 | 222.3 | King | 2 | 405.8 | Throckmorton | 2 | 422.6 |
| Denton | 1 | 351.4 | Kleberg | 1 | 254.9 | Travis | 1 | 121.1 |
| Duval | 2 | 455.7 | Knox | 1 | 117 | Van Zandt | 1 | 183 |
| Eastland | 1 | 105.7 | Lamar | 1 | 213.3 | Victoria | 1 | 106.5 |
| Ector | 1 | 400 | Lamb | 1 | 105.6 | Wharton | 1 | 194.2 |
| Ellis | 2 | 560 | LaSalle | 1 | 252 | Wheeler | 2 | 318.1 |
| Falls | 1 | 167.2 | Lavaca | 1 | 185.6 | Wichita | 1 | 151.6 |
| Fannin | 1 | 335.6 | Limestone | 1 | 229.8 | Wilbarger | 2 | 391.2 |
| Fayette | 1 | 151.3 | Lipscomb | 1 | 281 | Willacy | 2 | 636.9 |
| Fisher | 1 | 130.6 | Live Oak | 1 | 187.6 | Williamson | 1 | 262.5 |
| Foard | 1 | 308.9 | Lubbock | 1 | 150.8 | Wise | 1 | 152.9 |
| Gaines | 1 | 108.2 | Lynn | 1 | 145.9 | Yoakum | 1 | 259.7 |
| Gillespie | 1 | 400 | Mason | 1 | 148 | Young | 1 | 332.9 |
| Glasscock | 2 | 299.6 | Matagorda | 1 | 210 | Zapata | 2 | 337 |
| Gray | 1 | 271.2 | McLennan | 1 | 246.6 | *Total (GW)* | 148 | 30.9 |

# APPENDIX C – OPERATIONAL AND PLANNED UTILITY-SCALE PV PLANTS

**Table C.1: Operational and Planned Utility-Scale PV Plants in Counties A - N**

| Site # | County | MWAC | Data Review |
|---|---|---|---|
| 29 | Andrews | 100.7 | |
| 39 | Andrews | 153.6 | < 1 year valid |
| 45 | Andrews | 426.7 | < 1 year valid |
| 54 | Andrews | 150 | < 1 year valid |
| 14 | Bexar | 39.18 | |
| 37 | Borden | 101.4 | < 1 year valid |
| 38 | Borden | 125.3 | < 1 year valid |
| 50 | Borden | 305.6 | < 1 year valid |
| 36 | Brazoria | 120 | < 1 year valid |
| 9 | Brewster | 50 | |
| 12 | Childress | 121.4 | < 1 year valid |
| 46 | Concho | 256.96 | < 1 year valid |
| 56 | Cooke | 59.8 | < 1 year valid |
| 27 | Crane | 152.5 | < 1 year valid |
| 41 | Culberson | 187.2 | < 1 year valid |
| 58 | Culberson | 267.9 | < 1 year valid |
| 10 | Dawson | 50 | |
| 11 | Dawson | 101.6 | |
| 52 | Ector | 180 | < 1 year valid |
| 43 | Fannin | 125.7 | < 1 year valid |
| 53 | Fannin | 83.9 | < 1 year valid |
| 22 | Haskell | 106.4 | |
| 40 | Jones | 201.5 | < 1 year valid |
| 13 | Kent | 118.6 | < 1 year valid |
| 5 | Kinney | 37.62 | |
| 49 | Lamar | 198.5 | < 1 year valid |
| 28 | Nolan | 102.2 | < 1 year valid |
| 48 | Nolan | 102.3 | < 1 year valid |

**Table C.2: Operational and Planned Utility-Scale PV Plants in Counties P - W**

| Site # | County | MWAC | Data Review |
|---|---|---|---|
| 8 | Pecos | 7.41 | |
| 7 | Pecos | 22 | |
| 21 | Pecos | 50 | |
| 20 | Pecos | 110.2 | |
| 47 | Pecos | 258.5 | |
| 55 | Pecos | 250 | < 1 year valid |
| 57 | Pecos | 254.8 | < 1 year valid |
| 2 | Pecos | 126 | |
| 19 | Pecos | 155.44 | |
| 24 | Pecos | 182 | |
| 1 | Presidio | 10 | |
| 17 | Reeves | 78.75 | |
| 18 | Reeves | 78.75 | |
| 35 | Reeves | 101.01 | |
| 3 | Sterling | 30 | |
| 42 | Sterling | 115 | < 1 year valid |
| 25 | Travis | 26.7 | |
| 44 | Travis | 144 | < 1 year valid |
| 23 | Upton | 157.5 | |
| 4 | Upton | 180 | |
| 32 | Upton | 205 | |
| 6 | Uvalde | 95 | |
| 51 | Van Zandt | 59.8 | < 1 year valid |
| 15 | Winkler | 125.04 | |
| 16 | Winkler | 127.95 | |

# APPENDIX D - HYPOTHETICAL PV PLANTS BY COUNTY

**Table D.1: Net Capacity Factor for Hypothetical & Queued Sites in Counties A - La**

| SITE ID | County | NCF Single | NCF Dual |
|---|---|---|---|
| 745 | Andrews | 30.3% | 29.7% |
| 5726 | Angelina | 24.7% | 24.1% |
| 2804 | Armstrong | 28.7% | 28.5% |
| 1115 | Bailey | 30.1% | 29.6% |
| 4753 | Bee | 25.6% | 24.7% |
| 4433 | Bexar | 25.2% | 24.4% |
| 1403 | Borden | 29.0% | 28.5% |
| 4051 | Bosque | 26.2% | 25.7% |
| 5922 | Brazoria | 25.0% | 24.2% |
| 30 | Brewster | 32.6% | 31.4% |
| 2695 | Briscoe | 28.9% | 28.6% |
| 3202 | Brown | 27.3% | 26.7% |
| 2864 | Callahan | 27.8% | 27.3% |
| 2740 | Cameron | 26.6% | 25.6% |
| 2946 | Carson | 28.6% | 28.4% |
| 1908 | Castro | 29.5% | 29.2% |
| 3846 | Childress | 27.6% | 27.4% |
| 945 | Cochran | 30.1% | 29.6% |
| 2326 | Coke | 28.2% | 27.6% |
| 2925 | Coleman | 27.5% | 26.9% |
| 3511 | Comanche | 27.3% | 26.7% |
| 2168 | Concho | 27.7% | 27.0% |
| 4971 | Cooke | 25.8% | 25.3% |
| 3415 | Cottle | 28.0% | 27.7% |
| 577 | Crane | 30.2% | 29.5% |
| 805 | Crockett | 29.1% | 28.5% |
| 2101 | Crosby | 29.1% | 28.7% |
| 176 | Culberson | 32.6% | 31.6% |
| 5018 | Dallas | 25.3% | 24.8% |
| 1136 | Dawson | 29.3% | 28.8% |
| 1348 | Deaf Smith | 29.8% | 29.5% |
| 4831 | Denton | 26.0% | 25.5% |
| 2759 | Dickens | 28.5% | 28.1% |
| 1713 | Dimmit | 26.2% | 25.2% |
| 3405 | Donley | 28.3% | 28.1% |
| 2436 | Duval | 25.6% | 24.7% |
| 3116 | Eastland | 27.3% | 26.8% |
| 651 | Ector | 30.3% | 29.6% |
| 1720 | Edwards | 27.1% | 26.3% |
| 4779 | Ellis | 25.4% | 24.9% |
| 4963 | Falls | 25.3% | 24.7% |
| 5516 | Fannin | 25.2% | 24.7% |
| 2173 | Fisher | 28.2% | 27.7% |
| 2560 | Floyd | 29.0% | 28.6% |
| 5961 | Fort Bend | 25.0% | 24.3% |
| 2688 | Frio | 25.5% | 24.7% |
| 831 | Gaines | 30.1% | 29.5% |
| 1980 | Garza | 29.0% | 28.6% |
| 2437 | Gillespie | 26.9% | 26.1% |
| 1008 | Glasscock | 29.0% | 28.4% |
| 5597 | Grimes | 25.1% | 24.5% |
| 2062 | Hale | 29.2% | 28.8% |
| 3399 | Hall | 28.1% | 27.8% |
| 4156 | Hardeman | 27.2% | 26.9% |
| 5718 | Harris | 25.5% | 24.8% |
| 3061 | Haskell | 27.6% | 27.2% |
| 1545 | Hidalgo | 26.6% | 25.7% |
| 4458 | Hill | 25.6% | 25.1% |
| 1238 | Hockley | 29.7% | 29.2% |
| 6003 | Hopkins | 25.0% | 24.5% |
| 1217 | Howard | 28.9% | 28.3% |
| 5790 | Hunt | 25.0% | 24.5% |
| 1117 | Irion | 28.3% | 27.6% |
| 5417 | Jackson | 25.2% | 24.4% |
| 105 | Jeff Davis | 32.6% | 31.6% |
| 1309 | Jim Hogg | 26.6% | 25.6% |
| 4553 | Jim Wells | 25.7% | 24.7% |
| 2638 | Jones | 27.9% | 27.5% |
| 5366 | Kaufman | 25.1% | 24.6% |
| 2154 | Kent | 28.6% | 28.2% |
| 2405 | Kerr | 26.6% | 25.8% |
| 2134 | Kimble | 27.0% | 26.2% |
| 3022 | King | 27.9% | 27.6% |
| 1923 | Kinney | 26.2% | 25.3% |
| 3443 | Knox | 27.5% | 27.1% |
| 2351 | La Salle | 25.8% | 24.9% |
| 6025 | Lamar | 24.9% | 24.4% |
| 1336 | Lamb | 29.6% | 29.2% |

**Table D.2: Net Capacity Factor for Hypothetical & Queued Sites in Counties Lo - Z**

| SITE ID | County | NCF Single | NCF Dual |
|---|---|---|---|
| 672 | Loving | 30.6% | 29.9% |
| 1992 | Lubbock | 29.1% | 28.7% |
| 1475 | Lynn | 29.3% | 28.8% |
| 1047 | Martin | 29.1% | 28.6% |
| 2346 | Mason | 27.2% | 26.5% |
| 5892 | Matagorda | 25.2% | 24.3% |
| 1715 | Maverick | 26.4% | 25.5% |
| 2279 | McCulloch | 27.5% | 26.8% |
| 4657 | McLennan | 25.6% | 25.0% |
| 2870 | McMullen | 25.6% | 24.7% |
| 3480 | Medina | 25.4% | 24.6% |
| 1999 | Menard | 27.5% | 26.8% |
| 896 | Midland | 29.4% | 28.7% |
| 3397 | Mills | 26.9% | 26.3% |
| 1618 | Mitchell | 28.5% | 28.0% |
| 3062 | Motley | 28.7% | 28.4% |
| 4946 | Navarro | 25.4% | 24.8% |
| 1957 | Nolan | 28.6% | 28.0% |
| 4515 | Nueces | 25.6% | 24.7% |
| 2338 | Oldham | 29.7% | 29.4% |
| 1233 | Parmer | 29.9% | 29.5% |
| 136 | Pecos | 31.5% | 30.5% |
| 3188 | Potter | 28.9% | 28.7% |
| 4 | Presidio | 32.5% | 31.5% |
| 2512 | Randall | 29.2% | 28.9% |
| 906 | Reagan | 29.1% | 28.5% |
| 3236 | Real | 26.3% | 25.5% |
| 439 | Reeves | 31.4% | 30.5% |
| 2548 | Runnels | 27.6% | 27.0% |
| 3005 | San Saba | 27.0% | 26.4% |
| 1487 | Schleicher | 27.6% | 26.8% |
| 2010 | Scurry | 28.5% | 28.0% |
| 3075 | Shackelford | 27.6% | 27.2% |
| 1161 | Starr | 26.6% | 25.7% |
| 3284 | Stephens | 27.1% | 26.7% |
| 1488 | Sterling | 28.9% | 28.3% |
| 2791 | Stonewall | 28.0% | 27.6% |
| 1633 | Sutton | 27.3% | 26.5% |
| 2536 | Swisher | 29.1% | 28.8% |

| SITE ID | County | NCF Single | NCF Dual |
|---|---|---|---|
| 2416 | Taylor | 28.3% | 27.8% |
| 509 | Terrell | 29.8% | 29.1% |
| 1162 | Terry | 29.6% | 29.2% |
| 3225 | Throckmorton | 27.5% | 27.1% |
| 1919 | Tom Green | 27.9% | 27.2% |
| 5044 | Travis | 25.1% | 24.4% |
| 647 | Upton | 30.0% | 29.4% |
| 2723 | Uvalde | 25.6% | 24.8% |
| 736 | Val Verde | 28.8% | 28.0% |
| 5375 | Van Zandt | 25.2% | 24.7% |
| 5198 | Victoria | 25.2% | 24.4% |
| 555 | Ward | 30.6% | 29.9% |
| 1097 | Webb | 26.6% | 25.6% |
| 5804 | Wharton | 25.1% | 24.4% |
| 4671 | Wichita | 26.7% | 26.3% |
| 2916 | Willacy | 26.4% | 25.4% |
| 4927 | Williamson | 25.3% | 24.6% |
| 704 | Winkler | 30.4% | 29.8% |
| 903 | Yoakum | 30.1% | 29.6% |
| 3839 | Young | 26.9% | 26.5% |
| 1158 | Zapata | 26.6% | 25.6% |
| 1914 | Zavala | 25.8% | 24.9% |

# APPENDIX E - COUNTIES IN ERCOT CDR ZONES

**Table E.1: Counties by CDR Zone (Coastal, Houston, North, and Panhandle)**

| Coastal | Houston | North | North *(cont.)* | Panhandle |
|---|---|---|---|---|
| Aransas | Chambers | Anderson | McLennan | Armstrong |
| Brazoria | Fort Bend | Angelina | Mills | Bailey |
| Calhoun | Galveston | Bell | Montague | Briscoe |
| Cameron | Harris | Bosque | Nacogdoches | Carson |
| Kenedy | Montgomery | Brazos | Navarro | Castro |
| Kleberg | Waller | Brown | Palo Pinto | Childress |
| Matagorda | | Cherokee | Parker | Cochran |
| Nueces | | Collin | Rains | Collingsworth |
| Refugio | | Comanche | Red River | Crosby |
| San Patricio | | Cooke | Robertson | Dallam |
| Willacy | | Coryell | Rockwall | Deaf Smith |
| | | Dallas | Rusk | Dickens |
| | | Delta | San Saba | Donley |
| | | Denton | Smith | Floyd |
| | | Eastland | Somervell | Gray |
| | | Ellis | Stephens | Hale |
| | | Erath | Tarrant | Hall |
| | | Falls | Titus | Hansford |
| | | Fannin | Van Zandt | Hartley |
| | | Franklin | Wise | Hemphill |
| | | Freestone | Wood | Hockley |
| | | Grayson | | Hutchinson |
| | | Grimes | | Lamb |
| | | Hamilton | | Lipscomb |
| | | Henderson | | Lubbock |
| | | Hill | | Moore |
| | | Hood | | Motley |
| | | Hopkins | | Ochiltree |
| | | Houston | | Oldham |
| | | Hunt | | Parmer |
| | | Jack | | Potter |
| | | Johnson | | Randall |
| | | Kaufman | | Roberts |
| | | Lamar | | Sherman |
| | | Lampasas | | Swisher |
| | | Leon | | Wheeler |
| | | Limestone | | |
| | | Madison | | |

**Table E.2: Counties by CDR Zone (South and West)**

| South |
|---|
| Atascosa |
| Austin |
| Bandera |
| Bastrop |
| Bee |
| Bexar |
| Blanco |
| Brooks |
| Burleson |
| Burnet |
| Caldwell |
| Colorado |
| Comal |
| DeWitt |
| Dimmit |
| Duval |
| Edwards |
| Fayette |
| Frio |
| Gillespie |
| Goliad |
| Gonzales |
| Guadalupe |
| Hays |
| Hidalgo |
| Jackson |
| Jim Hogg |
| Jim Wells |
| Karnes |
| Kendall |
| Kerr |
| Kimble |
| Kinney |
| La Salle |
| Lavaca |
| Lee |
| Live Oak |
| Llano |

| South *(cont.)* |
|---|
| Mason |
| Maverick |
| McCulloch |
| McMullen |
| Medina |
| Milam |
| Real |
| Starr |
| Travis |
| Uvalde |
| Victoria |
| Washington |
| Webb |
| Wharton |
| Williamson |
| Wilson |
| Zapata |
| Zavala |

| West |
|---|
| Andrews |
| Archer |
| Baylor |
| Borden |
| Brewster |
| Callahan |
| Clay |
| Coke |
| Coleman |
| Concho |
| Cottle |
| Crane |
| Crockett |
| Culberson |
| Dawson |
| Ector |
| El Paso |
| Fisher |
| Foard |
| Gaines |
| Garza |
| Glasscock |
| Hardeman |
| Haskell |
| Howard |
| Hudspeth |
| Irion |
| Jeff Davis |
| Jones |
| Kent |
| King |
| Knox |
| Loving |
| Lynn |
| Martin |
| Menard |
| Midland |
| Mitchell |

| West *(cont.)* |
|---|
| Nolan |
| Pecos |
| Presidio |
| Reagan |
| Reeves |
| Runnels |
| Schleicher |
| Scurry |
| Shackelford |
| Sterling |
| Stonewall |
| Sutton |
| Taylor |
| Terrell |
| Terry |
| Throckmorton |
| Tom Green |
| Upton |
| Val Verde |
| Ward |
| Wichita |
| Wilbarger |
| Winkler |
| Yoakum |
| Young |