

# Package ‘PVplr’

February 14, 2023

**Type** Package

**Title** Performance Loss Rate Analysis Pipeline

**Version** 0.1.2

**Description** The pipeline contained in this package provides tools used in the Solar Durability and Lifetime Extension Center (SDLE) for the analysis of Performance Loss Rates (PLR) in real world photovoltaic systems. Functions included allow for data cleaning, feature correction, power predictive modeling, PLR determination, and uncertainty bootstrapping through various methods [doi:10.1109/PVSC40753.2019.8980928](https://doi.org/10.1109/PVSC40753.2019.8980928).  
The vignette “Pipeline Walkthrough” gives an explicit run through of typical package usage.  
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<code>all_na</code>	<i>function to test if an entire column is NA</i>
---------------------	---

---

**Description**

This function tests for completely NA columns

**Usage**

```
all_na(x)
```

**Arguments**

`x` any column in a dataframe

**Value**

Returns boolean TRUE if column is all NA, FALSE if not

**Examples**

```
test <- all_na(c(NA, "a", NA))
```

---

<code>anomalies</code>	<i>Fixes the anomlies</i>
------------------------	---------------------------

---

**Description**

This function gets the data and finds the anomlies in weekends and weekdays and gives a dataframe with anomalies and anomaly columns

**Usage**

```
anomalies(df)
```

**Arguments**

`df` structured dataframe

**Value**

df with two columns of cleaned\_energy and anom\_flag

**Author(s)**

Arash Khalilnejad

---

anomaly_detector	<i>detects rhw anomalies and returns a dataframw with cleaned and anom_flag column</i>
------------------	--

---

**Description**

detects rhw anomalies and returns a dataframw with cleaned and anom\_flag column

**Usage**

```
anomaly_detector(df, batch_days = 90)
```

**Arguments**

df	the strucutred data
batch_days	the batch of data that the anomaly detection is applied. Since time series decomposition is used, one seasonality will be applied for whole data which is inefficeint, if NA, will pass whole

**Value**

data with anomalies

**Author(s)**

Arash Khalilnejad

---

data\_quality\_check      *checks the quality of the data after and before cleaning*

---

### Description

calculates the percentage of anomalies, missings + zeros, gaps, and length of the data and reports the quality of data before and after cleaning.

### Usage

```
data_quality_check(  
  energy_data,  
  col = "elec_cons",  
  id = "pv_df",  
  batch_days = 90  
)
```

### Arguments

energy_data	structured energy dataframe
col	Input column
id	PV system ID
batch_days	the batch of data that the anomaly detection is applied. Since time series decomposition is used, one seasonality will be applied for whole data which is inefficient, if NA, will pass whole

### Details

The quality grading criteria is as following: anomalies A: less than 10 missing percentage: A: less than 10 largest gap: A: less than 120 hours, B: 120 to 164 hours, C: 164 to 240 hours D: more than 240 hours length P: more than 2 years, F: less than 2 years

### Value

a table with grading of the quality after and before cleaning

### Author(s)

Arash Khalilnejad

---

data_structure	<i>Reads jci files gotten in budget period 2</i>
----------------	--

---

**Description**

Reads the jci file and modifies the timestamp intervals and based on location modifies the timezone using googleapi and then generates the useful columns

**Usage**

```
data_structure(df, col = "elec_cons", timestamp_col = "timestamp")
```

**Arguments**

df	dataframe containing at least the timestamp column and the variable to be plotted with the heatmap
col	the character name of the column to be plotted
timestamp_col	the character name of the timestamp column which i is the number of file in the list

**Value**

a dataframe with fixed timestamps and useful cooumns

**Author(s)**

Arash

---

day_time_start_end	<i>finds median start and end time of PV operation</i>
--------------------	--

---

**Description**

finds median start and end time of PV operation

**Usage**

```
day_time_start_end(df)
```

**Arguments**

df	with num_time Column
----	----------------------

**Value**

dataframe with start and end time

**Author(s)**

Arash Khalilnejad

---

df\_With\_on\_time      *data with PV on time flag.*

---

**Description**

returns dataframe of PV with approximate operating period, baed on median of start and end time.

**Usage**

```
df_With_on_time(df)
```

**Arguments**

df                      df with num\_time

**Value**

input data with one more column of on\_time

**Author(s)**

Arash Khalilnejad

---

grade\_pv                      *returns quality information of time series data of PV*

---

**Description**

returns quality information of time series data of PV

**Usage**

```
grade_pv(  
  df,  
  col = "poay",  
  id = "pv_id",  
  timestamp_col = "tmst",  
  timestamp_format = "%Y-%m-%d %H:%M:%S",  
  batch_days = 90  
)
```

**Arguments**

df	the PV time series data. It can be the direct output of read.csv(file_name, stringsAsFactors = F)
col	column of the grading, default 'poay'
id	The name of the pv data
timestamp_col	the character name of the timestamp column
timestamp_format	the POSIXct format of the timestamp if conversion is needed
batch_days	the batch of data that the anomaly detection is applied. Since time series decomposition is used, one seasonality will be applied for whole data which is inefficeint, if NA, will pass whole

**Author(s)**

Arash Khalilnejad

---

Int

*Largest Intervals*

---

**Description**

Largest Intervals

**Usage**

Int(df)

**Arguments**

df	Dataframe
----	-----------

**Value**

Intervals

**Author(s)**

Arash Khalilnejad



---

ip_num_time	<i>Numerical time interim predictor.</i>
-------------	--

---

**Description**

Convert the hour and minute component of each timestamp to a numerical representation.

**Usage**

```
ip_num_time(data, ts_col = "timestamp")
```

**Arguments**

data	A dataframe with a timestamp column.
ts_col	The timestamp column name in data. Default value is 'timestamp'.

**Value**

data with a num\_time column added.

**Author(s)**

Arash Khalilnejad

---

lin_inter_hrly_to_fifteen	<i>Linearly interpolate hourly data to 15 min data.</i>
---------------------------	---

---

**Description**

Many weather data sets are hourly and we need values for every 15 minutes.

**Usage**

```
lin_inter_hrly_to_fifteen(data, data_ts)
```

**Arguments**

data	A data frame with hourly data.
data_ts	The column name for the data timestamp.

**Details**

Any value that can not be linearly interpolated such as a string will remain the same.

**Value**

The resulting fifteen minute data frame.

**Author(s)**

Arash Khalilnejad

---

`lin_inter_missing_energy`

*Linearly interpolate missing energy values.*

---

**Description**

If there exist less than four missing values, represented by NA values, fill with linearly interpolated values.

**Usage**

```
lin_inter_missing_energy(data, threshold = 4)
```

**Arguments**

<code>data</code>	A data frame with an 'elec_cons' column.
<code>threshold</code>	The maximum number of consecutive values that may be filled with interpolated values. By default four.

**Value**

The data frame with 'missing values' filled in.

**Examples**

```
## Not run:  
lin_inter_missing_energy(data)  
  
## End(Not run)
```

---

mbm_resample	<i>Dataframe resample function</i>
--------------	------------------------------------

---

**Description**

This function resamples data from a given dataframe. Dataframe must have columns created through plr\_cleaning to denote time segments

**Usage**

```
mbm_resample(df, fraction, by)
```

**Arguments**

df	dataframe
fraction	fraction of data to resample from dataframe
by	timescale over which to resample, day, week, or month

**Value**

Returns randomly resampled dataframe

**Examples**

```
# build var_list
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrad_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrad_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)

dfc_resampled <- mbm_resample(test_dfc, fraction = 0.65, by = "week")
```

---

nc	<i>function to convert to character then numeric</i>
----	--

---

**Description**

The function is a shorthand for converting factors to numeric

**Usage**

```
nc(x)
```

**Arguments**

x                    any factor to convert to numeric

**Value**

Returns supplied parameter as numeric

**Examples**

```
num <- nc(test_df$power)
```

---

num\_test                    *function to test is the values in a column should be numeric*

---

**Description**

This function tests a column to see if it should be numeric

**Usage**

```
num_test(col)
```

**Arguments**

col                    any column in a dataframe

**Value**

Returns boolean TRUE if column should be numeric, FALSE if not

**Examples**

```
test <- num_test(test_df$power)
```

---

parallel\_cluster\_export

*Export variables to a cluster.*


---

### Description

Ghost cluster export call to make sure testCoverage's trace function and environment are available.

### Usage

```
parallel_cluster_export(cluster, varlist, envir = .GlobalEnv)
```

### Arguments

cluster	Cluster
varlist	Character vector of names of objects to export.
envir	Environment from which to export variables

---

plr\_6k\_model

*6k Method for PLR Determination*


---

### Description

This function groups data by the specified time interval and performs a linear regression using the formula:  $\text{power\_var} \sim \text{irrad\_var/istc} * (\text{nameplate\_power} + a * \log(\text{irrad\_var/istc}) + b * \log(\text{irrad\_var/istc})^2 + c * (\text{temp\_var} - \text{tref}) + d * (\text{temp\_var} - \text{tref}) * \log(\text{irrad\_var/istc}) + e * (\text{temp\_var} - \text{tref}) * \log(\text{irrad\_var/istc})^2 + f * (\text{temp\_var} - \text{tref})^2)$ . Predicted values of irradiance, temperature, and wind speed (if applicable) are added for reference. These values are the lowest daily high irradiance reading (over 300W/m<sup>2</sup>), the average temperature over all data, and the average wind speed over all data.

### Usage

```
plr_6k_model(
  df,
  var_list,
  nameplate_power,
  by = "month",
  data_cutoff = 30,
  predict_data = NULL
)
```

**Arguments**

df	A dataframe containing pv data.
var_list	A list of the dataframe's standard variable names, obtained from the output of <a href="#">plr_variable_check</a> .
nameplate_power	The rated power capability of the system, in watts.
by	String, either "day", "week", or "month". The time periods over which to group data for regression.
data_cutoff	The number of data points needed to keep a value in the final table. Regressions over less than this number and their data will be discarded.
predict_data	optional; Dataframe; If you have preferred estimations of irradiance, temperature, and wind speed, include them here to skip automatic generation. Format: Irradiance, Temperature, Wind (optional).

**Value**

Returns dataframe of results per passed time scale from 6K modeling

---

plr\_bootstrap\_output *Bootstrap: Resampling from individual Models*

---

**Description**

This function determines uncertainty of a PLR measurement by sampling results from individual models. Specify the model you would like to find the uncertainty of, and the function will put the dataframe through the selected model and return the uncertainties of the model's results.

**Usage**

```
plr_bootstrap_output(
  df,
  var_list,
  model,
  by = "month",
  fraction = 0.65,
  n = 1000,
  predict_data = NULL,
  np = NA,
  power_var = "power_var",
  time_var = "time_var",
  ref_irrad = 900,
  irrad_range = 10
)
```



---

```
plr_bootstrap_output_from_results
```

*Bootstrap: Resample from individual Models*

---

## Description

The function samples and bootstraps data that has already been put through a power predictive model. The PLR and Uncertainty are returned in a dataframe.

## Usage

```
plr_bootstrap_output_from_results(  
  data,  
  power_var,  
  time_var,  
  weight_var,  
  by = "month",  
  model,  
  fraction = 0.65,  
  n = 1000  
)
```

## Arguments

data	Result of modeling data with a PLR determining model, i.e. <code>plr_xbx_model</code> , <code>plr_6k_model</code> , etc.
power_var	Variable name of power in the dataframe. Typically <code>power_var</code>
time_var	Variable name of time in the dataframe. Typically <code>time_var</code>
weight_var	Variable name of weightings in the dataframe. Typically <code>sigma</code>
by	String, either "day", "month", or "year". Time over which to perform <a href="#">plr_yoy_regression</a> and <a href="#">plr_weighted_regression</a> .
model	The name of the model the data has been put through. This option is only included for the user's benefit in keeping bootstrap outputs consistent.
fraction	The fractional size of the data to be sampled each time.
n	The number of resamples to take.

## Value

Returns PLR value and uncertainty calculated with bootstrap of data going into power correction models



## Examples

```
# build var_list

var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrad_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrad_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)

# Perform the power predictive modeling step
test_xbx_wbw_res <- plr_xbx_model(test_dfc, var_list, by = "week",
                                data_cutoff = 30, predict_data = NULL)

xbx_mbm_plr_result_uncertainty <- plr_bootstrap_output_from_results(test_xbx_wbw_res,
                                                                    power_var = 'power_var',
                                                                    time_var = 'time_var',
                                                                    weight_var = 'sigma',
                                                                    by = "month", model = 'xbx',
                                                                    fraction = 0.65, n = 10)
```

---

plr\_bootstrap\_uncertainty

*Bootstrap: Resampling data going into each Model*

---

## Description

This function determines the uncertainty of a PLR measurement through resampling data for each model, prior to putting the data through the model.

## Usage

```
plr_bootstrap_uncertainty(
  df,
  n,
  fraction = 0.65,
  var_list,
  model,
  by = "month",
  power_var = "power_var",
  time_var = "time_var",
  data_cutoff = 100,
  np = NA,
  pred = NULL
)
```



---

**plr\_build\_var\_list**      *Build a Custom Variable List*

---

**Description**

The default var\_list generator, plr\_variable\_check, assumes data comes from SDLE's sources. If you are using this package with your own data, the format may not line up appropriately. Use this function to create a variable list to be passed to other functions so they can keep track of what column names mean.

**Usage**

```
plr_build_var_list(time_var, power_var, irrad_var, temp_var, wind_var)
```

**Arguments**

time_var	The variable representing time. Typically, a timestamp.
power_var	The variable representing time. Typically, in watts.
irrad_var	The variable representing irradiance. Typically, either poa or ghi irradiance.
temp_var	The variable representing temperature. Package functions assume Celcius.
wind_var	optional; The variable representing wind speed.

**Value**

Returns dataframe of variable names for the given photovoltaic data for use with later functions

**Examples**

```
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrad_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)
```

---

**plr\_cleaning**      *Basic Data Cleaning*

---

**Description**

Removes entries with irradiance and power readings outside cutoffs, fixes timestamps to your specified format, and converts columns to numeric when appropriate - see [plr\\_convert\\_columns](#). Also, adds columns for days/weeks/years of operation that are used by other functions.

**Usage**

```
plr_cleaning(
  df,
  var_list,
  irrads_thresh = 100,
  low_power_thresh = 0.05,
  high_power_cutoff = NA,
  tmst_format = "%Y-%m-%d %H:%M:%S"
)
```

**Arguments**

`df` A dataframe containing pv data.

`var_list` A list of the dataframe's standard variable names, obtained from the output of [plr\\_variable\\_check](#).

`irrads_thresh` The lowest meaningful irradiance value. Values below are filtered.

`low_power_thresh` The lowest meaningful power output. Values below are filtered.

`high_power_cutoff` The highest meaningful power output. Values above are filtered.

`tmst_format` The desired timestamp format.

**Value**

Returns dataframe with rows filtered out based on passed cleaning parameters

**Examples**

```
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrads_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

test_dfc <- plr_cleaning(test_df, var_list, irrads_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)
```

---

plr\_convert\_columns    *Fix Column Typings*

---

**Description**

Converts appropriate columns to numeric without specifying the name of the column. All columns from hbase are read as factors. Columns are tested to see if they should be numeric by forcing conversion to numeric. Columns that subsequently contain NA's are not numeric; if not, they are set to numeric.

**Usage**

```
plr_convert_columns(df)
```

**Arguments**

df                    A dataframe containing pv data.

**Value**

Returns original dataframe with columns corrected to proper classes

**Examples**

```
df <- PVplr::plr_convert_columns(test_df)
```

---

plr\_decomposition        *Decompose Seasonality from Data*

---

**Description**

Decomposes seasonality from a dataframe that has already passed through a PLR Determination test, e.g. [plr\\_xbx\\_model](#). This method has the option of creating plot and data files.

**Usage**

```
plr_decomposition(  
  data,  
  freq,  
  power_var,  
  time_var,  
  plot = FALSE,  
  plot_file = NULL,  
  title = NULL,  
  data_file = NULL  
)
```

**Arguments**

data                    a dataframe containing PV data that has undergone a power predictive model, e.g. [plr\\_xbx\\_model](#).

freq                    the frequency of seasonality. This is typically 4 but depends on the location of the system.

power\_var                name of the power variable, e.g. iacp

time\_var                name of the time variable, e.g. tvar

plot                    boolean indicating if you wish to save a plot.

plot\_file        location to save the plot, if the plot param is given TRUE.  
 title            the title of the plot created if the plot param is given TRUE.  
 data\_file        location to save data. Currently non-functional.

### Value

Dataframe containing decomposed time series features

### Examples

```
#' # build var_list
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrad_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrad_thresh = 100,
                         low_power_thresh = 0.01, high_power_cutoff = NA)

# Perform power modeling step
test_xbx_wbw_res <- plr_xbx_model(test_dfc, var_list, by = "week",
                                 data_cutoff = 30, predict_data = NULL)

test_xbx_wbw_decomp <- plr_decomposition(test_xbx_wbw_res, freq = 4,
                                         power_var = 'power_var', time_var = 'time_var',
                                         plot = FALSE, plot_file = NULL, title = NULL,
                                         data_file = NULL)
```

---

plr\_kmeans\_test

*Statistical k-means Test*

---

### Description

The method builds linear models by day, identifies outliers, and performs 2-means clustering by slopes. If the lower identified cluster is significantly less than the higher mean, and constitutes less than 25% of the data, it is identified as soiled and returned. Otherwise, the outlier points are identified as soiled and returned.

### Usage

```
plr_kmeans_test(
  df,
  var_list,
  mean_ratio = 0.7,
  plot = FALSE,
  file_path,
  file_name,
  set_cutoff = FALSE
)
```

**Arguments**

df	A df containing pv data. Should be 'cleaned' by <a href="#">plr_cleaning</a> .
var_list	A list of the dataframe's standard variable names, obtained from the output of <a href="#">plr_variable_check</a> .
mean_ratio	This scales the higher identified cluster's mean for comparison. Higher values will be more likely to identify the second mean as soiled, and vice versa. Values should range from 0 to 1.
plot	optional; Boolean; whether to return the box plot generated by the method to identify outliers.
file_path	optional; location to store the boxplot if plot is set TRUE. Note this is not necessary if you select to plot - only if you wish to save it.
file_name	optional; name of file to save boxplot if plot is set to TRUE.
set_cutoff	Defaults to FALSE; pass a numeric value to cut off all slopes less than the cutoff value. This bypasses entirely the outlier and clustering calculations to remove slope values you believe to be soiled.

**Value**

The method returns a dataframe containing the values that should be removed. If you want to discard them, try using `dplyr::filter()`.

---

plr_pvheatmap	<i>Title Heatmap generation for PV data</i>
---------------	---

---

**Description**

Title Heatmap generation for PV data

**Usage**

```
plr_pvheatmap(
  df,
  col,
  timestamp_col,
  timestamp_format = "%Y-%m-%d %H:%M:%S",
  upper_threshold = 1,
  lower_threshold = 0,
  font_size = 12
)
```

**Arguments**

df	dataframe containing at least the timestamp column and the variable to be plotted with the heatmap
col	the character name of the column to be plotted
timestamp_col	the character name of the timestamp column
timestamp_format	the POSIXct format of the timestamp if conversion is needed
upper_threshold	the fraction of upper data to include, 1 removes no data, 0.9 remove the top 1 percent etc.
lower_threshold	the fraction of lower data to remove, 0 removes no data, 0.01 remove the bottom 1 percent etc.
font_size	font size of the output plot

**Value**

returns a ggplot object heatmap of the specified column

**Examples**

```
# build heatmap
heat <- plr_pvheatmap(test_df, col = "g_poa", timestamp_col = "timestamp",
                      upper_threshold = 0.99, lower_threshold = 0)

# display heatmap
plot(heat)
```

---

plr\_pvusa\_model

*PVUSA Method for PLR Determination*

---

**Description**

This function groups data by the specified time interval and performs a linear regression using the formula:  $P = G_{POA} * (\beta_0 + \beta_1 G + \beta_2 T_{amb} + \beta_3 W)$ . Predicted values of irradiance, temperature, and wind speed (if applicable) are added for reference. These values are the lowest daily high irradiance reading (over 300), the average temperature over all data, and the average wind speed over all data.

**Usage**

```
plr_pvusa_model(
  df,
  var_list,
  by = "month",
  data_cutoff = 30,
  predict_data = NULL
)
```



**Arguments**

df	A dataframe containing pv data.
var_list	A list of the dataframe's standard variable names, obtained from the output of <a href="#">plr_variable_check</a> .
by	String, either "day", "week", or "month". The time periods over which to group data for regression.
data_cutoff	The number of data points needed to keep a value in the final table. Regressions over less than this number and their data will be discarded.
predict_data	optional; Dataframe; If you have preferred estimations of irradiance, temperature, and wind speed, include them here to skip automatic generation. Format: Irradiance, Temperature, Wind (optional).

**Value**

Returns dataframe of results per passed time scale from PVUSA modeling

**Examples**

```
# build var_list
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrad_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrad_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)

# Perform the power predictive modeling step
test_xbx_wbw_res <- plr_pvusa_model(test_dfc, var_list, by = "week",
                                   data_cutoff = 30, predict_data = NULL)
```

---

plr\_remove\_outliers     *Filter outliers from Power Predicted Data*

---

**Description**

This function is used to remove outliers (if desired) after putting data through a power predictive model, e.g. [plr\\_xbx\\_model](#).

**Usage**

```
plr_remove_outliers(data)
```

**Arguments**

data	A resulting dataframe from a power predictive model.
------	--

**Value**

Returns dataframe with outliers flagged by other functions removed

**Examples**

```
# build var_list
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrads_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrads_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)

# Perform the power predictive modeling step
test_xbx_wbw_res <- plr_xbx_model(test_dfc, var_list, by = "week",
                                data_cutoff = 30, predict_data = NULL)

# Remove outliers from the modeled data
test_xbx_wbw_res_no_outliers <- plr_remove_outliers(test_xbx_wbw_res)
```

---

plr\_saturation\_removal

*Removing Saturated Data*

---

**Description**

Tests for readings which may indicate saturation of the system. Removes values above the power saturation limit (calculated by multiplying `sat_limit` and `power_thresh`).

**Usage**

```
plr_saturation_removal(df, var_list, sat_limit, power_thresh = 0.99)
```

**Arguments**

<code>df</code>	A dataframe containing pv data.
<code>var_list</code>	A list of the dataframe's standard variable names, obtained from the output of <a href="#">plr_variable_check</a> .
<code>sat_limit</code>	An upper limit on power saturation. This is multiplied by the power threshold, and power values above this point are filtered from the dataframe. The value depends on the system's inverter.
<code>power_thresh</code>	An upper limit on power.

**Value**

Returns passed data frame with rows removed which contain power values above the specified threshold

**Examples**

```
# build var_list
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrad_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrad_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)

test_dfc_removed_saturation <- plr_saturation_removal(test_dfc, var_list,
                                                    sat_limit = 3000, power_thresh = 0.99)
```

---

 plr\_seg\_extract

*Segmented linear PLR extraction function*


---

**Description**

Segmented linear PLR extraction function

**Usage**

```
plr_seg_extract(
  df,
  per_year,
  psi = NA,
  n_breakpoints,
  power_var,
  time_var,
  return_model = FALSE
)
```

**Arguments**

df	data frame of corrected power measurements, typically the output of a weather correction model
per_year	number of data point defining one seasonal year (365 for days, 52 for weeks etc.)
psi	vector of 1 or more breakpoint estimates for the model. If not given will evenly space breakpoints across time series

**n\_breakpoints**    number of desired breakpoints. Determines number of linear models  
**power\_var**        character name of the power variable  
**time\_var**         character name of the time variable  
**return\_model**    logical to return model object. If FALSE returns PLR results from model

### Value

if `return_model` is FALSE it returns PLR results from model, otherwise returns segmented linear model object

### Examples

```

# build var_list
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrad_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrad_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)

#' # Perform power modeling step
test_xbx_wbw_res <- plr_xbx_model(test_dfc, var_list, by = "week",
                                data_cutoff = 30, predict_data = NULL)

decomp <- plr_decomposition(test_xbx_wbw_res, freq = 4,
                           power_var = 'power_var', time_var = 'time_var',
                           plot = FALSE, plot_file = NULL, title = NULL,
                           data_file = NULL)

# evaluate segmented PLR results
seg_plr_result <- PVplr::plr_seg_extract(df = decomp, per_year = 365,
                                       n_breakpoints = 1, power_var = "trend",
                                       time_var = "age")

# return segmented model instead of PLR result
model <- PVplr::plr_seg_extract(df = decomp, per_year = 365, n_breakpoints = 1,
                              power_var = "trend", time_var = "age", return_model = TRUE)

# predict data along time-series with piecewise model for plotting
pred <- data.frame(age = seq(1, max(decomp$age, na.rm = TRUE), length.out = 10000))
pred$seg <- predict(model, newdata = pred)
  
```

**Description**

This function returns the standard deviation of a PLR calculated from a linear model

**Usage**

```
plr_var(mod, per_year)
```

**Arguments**

mod	linear model
per_year	number of data points in a given year baesd on which time scale was selected

**Value**

Returns standard deviation of PLR value

**Examples**

```
# build var_list
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrad_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrad_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)

# Perform the power predictive modeling step
test_xbx_wbw_res <- plr_xbx_model(test_dfc, var_list, by = "week",
                                data_cutoff = 30, predict_data = NULL)

# obtain standard deviation from model
mod <- lm(power_var ~ time_var, data = test_xbx_wbw_res)
plr_sd <- plr_var(mod, per_year = 52)
```

---

plr\_variable\_check      *Define Standard Variable Names*

---

**Description**

The method determines the variable names used by the input dataframe. It looks for the following labels:

- power\_var <- iacp; if not, sets to idcp
- time\_var <- tmst; if not ,sets to tute
- irrad\_var <- poay; if not, sets to ghir

- temp\_var <- temp; if not, sets to modt
- wind\_var <- wspa; if applicable, else NULL

This function assumes data is in a standard HBase format. If you are using other data (as you most likely are) you should use the companion function, [plr\\_build\\_var\\_list](#).

### Usage

```
plr_variable_check(df)
```

### Arguments

df                    A dataframe containing pv data.

### Value

Returns a dataframe containing standard variable names (no data). It will not include windspeed if the variable was not already included. This is frequently an input of other functions.

### Examples

```
var_list <- plr_variable_check(test_df)
```

---

```
plr_weighted_regression  
                          Weighted Regression
```

---

### Description

Automatically calculates Performance Loss Rate (PLR) using weighted linear regression. Note that it needs data from a power predictive model.

### Usage

```
plr_weighted_regression(  
  data,  
  power_var,  
  time_var,  
  model,  
  per_year = 12,  
  weight_var = NA  
)
```

**Arguments**

data	The result of a power predictive model
power_var	String name of the variable used as power
time_var	String name of the variable used as time
model	String name of the model that the data was passed through
per_year	the time step count per year based on the model - 12 for month-by-month, 52 for week-by-week, and 365 for day-by-day
weight_var	Used to weight regression, typically sigma.

**Value**

Returns PLR value and error evaluated with linear regression

**Examples**

```
# build var_list
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrad_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrad_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)

# Perform the power predictive modeling step
test_xbx_wbw_res <- plr_xbx_model(test_dfc, var_list, by = "week",
                                data_cutoff = 30, predict_data = NULL)

# Calculate Performance Loss Rate
xbx_wbw_plr <- plr_weighted_regression(test_xbx_wbw_res,
                                     power_var = 'power_var',
                                     time_var = 'time_var',
                                     model = "xbx",
                                     per_year = 52,
                                     weight_var = 'sigma')
```

---

plr\_xbx\_model

*XbX Method for PLR Determination*

---

**Description**

This function groups data by the specified time interval and performs a linear regression using the formula:  $P_{pred.} = \beta_0 + \beta_1 G + \beta_2 T + \epsilon$ . This is the simplest of the PLR determining methods. Predicted values of irradiance, temperature, and wind speed (if applicable) are added to the output for reference. These values are the lowest daily high irradiance reading (over 300), the average temperature over all data, and the average wind speed over all data. Outliers are detected and labeled in a column as TRUE or FALSE.





---

plr\_xbx\_utc\_model      *UTC Method for PLR Determination*

---

### Description

This function groups data by the specified time interval and performs a linear regression using the formula:  $\text{power\_corr} \sim \text{irrad\_var} - 1$ . Predicted values of irradiance, temperature, and wind speed (if applicable) are added for reference. The function uses a universal temperature correction, rather than the monthly regression correction done in other PLR determining methods.

### Usage

```
plr_xbx_utc_model(
  df,
  var_list,
  by = "month",
  data_cutoff = 30,
  predict_data = NULL,
  ref_irrad = 900,
  irrad_range = 10
)
```

### Arguments

df	A dataframe containing pv data.
var_list	A list of the dataframe's standard variable names, obtained from the output of <a href="#">plr_variable_check</a> .
by	String, either "day", "week", or "month". The time periods over which to group data for regression.
data_cutoff	The number of data points needed to keep a value in the final table. Regressions over less than this number and their data will be discarded.
predict_data	optional; Dataframe; If you have preferred estimations of irradiance, temperature, and wind speed, include them here to skip automatic generation. Format: Irradiance, Temperature, Wind (optional).
ref_irrad	The irradiance value at which to calculate the universal temperature coefficient. Since irradiance is a much stronger influencer on power generation than temperature, it is important to specify a small range of irradiance data from which to estimate the effect of temperature.
irrad_range	The range of the subset used to calculate the universal temperature coefficient. See above.

### Value

Returns dataframe of results per passed time scale from XbX with universal temperature correction modeling

**Examples**

```
# build var_list
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrاد_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrاد_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)

# Perform the power predictive modeling step
test_xbx_wbw_res <- plr_xbx_utc_model(test_dfc, var_list, by = "week",
                                     data_cutoff = 30, predict_data = NULL,
                                     ref_irrad = 900, irrاد_range = 10)
```

---

plr\_yoy\_regression      *Year-on-Year Regression*

---

**Description**

Automatically calculates Performance Loss Rate (PLR) using year on year regression. Note that it needs data from a power predictive model.

**Usage**

```
plr_yoy_regression(
  data,
  power_var,
  time_var,
  model,
  per_year = 12,
  return_PLR = TRUE
)
```

**Arguments**

data	Result of a power predictive model
power_var	String name of the variable used as power
time_var	String name of the variable used as time
model	String name of the model the data was passed through
per_year	Time step count per year based on model. Typically 12 for MbM, 365 for DbD.
return_PLR	boolean; option to return PLR value, rather than the raw regression data.

**Value**

Returns PLR value and error evaluated with YoY regression, if return\_PLR is false it will return the individual YoY calculations

**Examples**

```
# build var_list
var_list <- plr_build_var_list(time_var = "timestamp",
                              power_var = "power",
                              irrad_var = "g_poa",
                              temp_var = "mod_temp",
                              wind_var = NA)

# Clean Data
test_dfc <- plr_cleaning(test_df, var_list, irrad_thresh = 100,
                        low_power_thresh = 0.01, high_power_cutoff = NA)

# Perform the power predictive modeling step
test_xbx_wbw_res <- plr_xbx_model(test_dfc, var_list, by = "week",
                                data_cutoff = 30, predict_data = NULL)

# Calculate Performance Loss Rate
xbx_wbw_plr <- plr_yoy_regression(test_xbx_wbw_res,
                                 power_var = 'power_var',
                                 time_var = 'time_var',
                                 model = "xbx",
                                 per_year = 52,
                                 return_PLR = TRUE)
```

---

spline\_timestamp\_sync *Spline columns to match timestamps.*

---

**Description**

Often timestamps of two data frames will be mismatched. To produced matching timestamps, columns that may be splined will be and then corresponding values at the 'correct' timestamp are used.

**Usage**

```
spline_timestamp_sync(
  data,
  data_ts = "timestamp",
  merge_data,
  merge_ts = "timestamp"
)
```

**Arguments**

data	A data frame with a correct timestamp column.
data_ts	The column name for the data timestamp. Defaults to 'timestamp'
merge_data	A data frame that will be linearly interpolated and merged with data.
merge_ts	The column name for the merge_data timestamp. Defaults to 'timestamp'.

**Details**

Any value that can not be linearly interpolated such as a string will remain the same.

**Value**

The resulting merged data frame.

**Author(s)**

Arash Khalilnejad

---

test_df	<i>DOE RTC Sample PV System Data</i>
---------	--------------------------------------

---

**Description**

A dataset containing a small, randomly taken sample of PV data from SDLE's data collection. It is included for the purposes of unit tests and vignettes, serving as an example of how the package's functions work.

**Usage**

```
test_df
```

**Format**

A .csv file that can be read as a dataframe. 16265 rows and 22 variables.

---

time_frequency	<i>Determines the minutes between data points in a time-series</i>
----------------	--

---

**Description**

Determines the minutes between data points in a time-series

**Usage**

```
time_frequency(data)
```

**Arguments**

data	A time-series dataframe containing a column named 'timestamp'.
------	--

**Value**

a numeric value of the minutes between data points

**Author(s)**

Arash Khalilnejad

---

ts_inflate	<i>Inflate a time series data set.</i>
------------	--

---

**Description**

Shifts known values to the nearest equidistant timestamp and fills in any missing timestamps with NA values. An additional binary column named <column to impute>\_imp is added where 1 represents an unknown value and zero represents a known value.

**Usage**

```
ts_inflate(data, ts_col, col_to_imp, dt)
```

**Arguments**

data	A data frame containing columns ts_col and col_to_imp.
ts_col	The name of the timestamp column.
col_to_imp	The name of the column to impute.
dt	The expected time between consecutive timestamps, in minutes.

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