pyVPLM Documentation

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A.REYSSET, S.DELBECQ, M.BUDINGER

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CONTENTS

PY VPLM

Regression Analysis Tool

CHAPTER

ONE

ABOUT

pyVPLM is a package that is developed to help scientist, engineer, etc., to construct power-law and/or polynomial regression models on different type of data such as finite-element simulation results, manufacturer data-sheets…

It integrates various functionalities such as :

- Model parameters reduction based on Buckingham Theorem dimensional analysis and
- Pint package with derived functions.
- Sensitivity and dependency analysis on dimensionless parameter and limited experiments to simplify further model expressions.
- Construction of optimized experimental design on feasible-physical variables leading to full-factorial design within dimensionless space. Those DOE are the inputs of parametrized finite-element models.
- Regression models construction with increasing complexity (terms sorted based on their impact) and validation based on relative error repartition analysis.

CHAPTER

TWO

CAPABILITIES

2.1 Dimensional analysis

The dimensional analysis has to be conducted on a defined set of physical parameters. It can be performed using alternatively buckingham_theorem which will return the default solution or automatic_buckingham which will propose different alternate sets.

Based on the obtained solutions, advanced user can also define manually a new solution set with force_buckingham function.

```
from pyvplm.core.definition import PositiveParameter, PositiveParameterSet
from pyvplm.addon.variablepowerlaw import buckingham_theorem
d = PositiveParameter('d', [10e-3, 150e-3],'m', 'pipe internal diameter')
e = PositiveParameter('e', [.1e-3, 10e-3], 'm', 'pipe thickness')
parameter_set = PositiveParameterSet(d,e)
pi_set, _ = buckingham_theorem(parameter_set, track=False)
```

2.2 Sensitivity & dependency analysis

Once dimensional analysis is done, there may be still a huge number of dimensionless parameter to describe a performance criteria (mostly form factor) and DOE construction phase may lead to big experiments number and long simulation times.

This is to answer this problematic that pi_sensitivity and pi_dependency functions have been designed. The obtained graph for analysis are based on primary vs. secondary parameters analysis that can be easily adapted using configuration parameters:

docs/source/_static/Pictures/variablepowerlaw_pi_sensitivity.png

---

docs/source/_static/Pictures/variablepowerlaw_pi_dependency.png

2.3 Optimized design of experiments

The non-constrained nor reduced experimental set are defined using pyDOE2 package. It integrates automatic sizing of physical/dimensionless initial test plans and functions for selection based on distance criteria (dimensionless mapping) and spread quality (physical mapping).

docs/source/_static/Pictures/pixdoe_create_const_doe1.png

---

docs/source/_static/Pictures/pixdoe_create_const_doe2.png

2.4 Regression models construction

The `regression_models` function interpolate results to fit a given order polynomial model within linear or logarithmic space.

Within log space, the model obtained can be transformed into variable power-law model, indeed:

$$ \begin{align} log(\pi_0) = a_0+a_1 \cdot log(\pi_1) + a_{11} \cdot log(\pi_1)^2+a_{12} \cdot log(\pi_1) \cdot log(\pi_2) + a_2 \cdot log(\pi_2) +… \end{align} $$

Can be expressed in the following form:

$$ \begin{align} \pi_0 = 10^{a_0} \cdot \pi_1 ^{a_1 + a_{11} \cdot log(\pi_1)+a_{12} \cdot log(\pi_2)+…} \cdot \pi_2^{a_2+…} \cdot … \end{align} $$

This is the origin of package name since variable power-law model is one of the current research subject of MS2M team in ICA Laboratory (Toulouse-France).

Regression coefficients are sorted with increasing magnitude while considering standardized values regression (first order terms are selected at the beginning to avoid singularity issues):

docs/source/_static/Pictures/variablepowerlaw_regression_models1.png

The four criteria to evaluate model fidelity with leave-one-out cross-validation are:

1. Maximal relative error magnitude
2. Average value of the magnitude of relative error which is a good indicator of both average and standard deviation
3. Average value of the relative error

4. Standard deviation of the relative error

On this example with 2 dimensionless parameters and order 3 polynomial expression, a 5-terms model seems to have good representation capabilities.

Once regression models have been constructed, each one of them can be analyzed through the analysis of their relative error using `perform_regression` function:

docs/source/_static/Pictures/variablepowerlaw_perform_regression1.png

CHAPTER

THREE

EXAMPLES AND NOTES

Four Jupyter Notebooks have been developed to present tool capabilities and functions. They can be launched using Jupyter Notebook application and opening `.ipynb` files from `master/notebooks` folder.

Additional documentation on sub-packages (`pyvplm.core`, `pyvplm.addon`) and functions can be found on the online readthedocs documentation.

CHAPTER FOUR

INSTALL

To install pyVPLM, simply run:

```
pip install pyvplm
```

CHAPTER

FIVE

CREDIT

pyVPLM is an adaptation of the work performed by MS2M team at ICA Laboratory - France and covers the work done during different doctorate thesis:

CHAPTER

SIX

AUTHOR

A. Reysset

CHAPTER SEVEN

REFERENCES

- F. Sanchez, M. Budinger, I. Hazyuk, "*Dimensional analysis and surrogate models for thermal modeling of power
- electronic components*", Electrimacs conference (2017), Toulouse
- F. Sanchez, M. Budinger, I. Hazyuk, "*Dimensional analysis and surrogate models for the thermal modeling of Multi-physics systems*", Applied Thermal Engineering 110 (August 2016)

CHAPTER

EIGHT

PYVPLM.CORE PACKAGE

8.1 Submodules

8.2 pyvplm.core.definition module

Core module defining elementary class and methods for SizingLab

class `pyvplm.core.definition.`**`Constraint`**(*expression*, *desc=''*)

Bases: `object`

Class defining a Constraint.

`description`

additional text to describe equation

Type str

`parameters`

list of all the parameters names

Type list(str)

`function`

is the computational expression of the constraint

Type func

`function_expr`

is the literal expression of the constraint

Type str

Example

`compute`(*parameters_dict*)

class `pyvplm.core.definition.`**`ConstraintSet`**(**constraints*)

Bases: `object`

Class defining a ConstraintSet.

`parameters`

list of all the parameters names from all constraints

Type list(str)

constraints_list
is the list of Constraint

Type list(*Constraint*)

Example

declare_doe_constraint(*parameter_set*)
Specific method to generate constraint function for pyvplm pixdoe use.

class pyvplm.core.definition.**Parameter**(*name: str, defined_bounds: list, defined_units: str, description: str*)

Bases: `object`

Class defining one physical parameter.

name

the parameter name as a convention will be converted to :

- upper char(s) for constant
- lower char(s) for variable

Type str

defined_bounds
converted to float and checked that defined_bounds[0]<defined_bounds[1], set to [] for constant

Type [1*2] list of int or float

value
converted to float, set to [] for variable

Type int or float

defined_units
the parameters defined units (expression checked using PINT package)

Type str

description
some description on the parameter

Type str

_SI_bounds(*private*)
the parameter bounds expressed into SI units automatically derived from defined bounds using PINT package

Type [1*2] list of float

_SI_units(*private*)
SI units are automatically derived from defined units using PINT package

Type str

_dimensionality(*private*)
the parameter dimensions derived from units using PINT package (ex: meter->[length])

Type str

Examples

save a parameter:

```
>>> In [1]: m = Parameter('m', [50, 100], 'kg', 'mass')
```

save a constant:

```
>>> In [2]: k = Parameter('k', [2], '', 'oversizing coefficient')
```

get k parameter value in equation:

```
>>> In [3]: a = float(k)*2.0
>>> Out[3]: 4.0
```

print parameters'attributes:

```
>>> In [4]: print(m)
m.name=m
m.defined_bounds=[50.0, 100.0]
...
m._dimensionality=[mass]
```

change parameter's attribute values:

```
>>> In [5]: m.description = 'body mass'
```

`__float__`()
: Method to return parameter value with syntax **float(parameter_name)**. If value is empty (i.e. parameter is a variable), returns NaN.

`__getattribute__`(*attribute_name*)
: Method to access parameter attribute value (for private attributes, warning is displayed). Access is granted using command: **parameter_name.attribute_name**.

`__repr__`()
: Method to represent parameter definition when entering only parameter_name command.

`__setattr__`(*attribute_name*, *value*, *check_units=True*)
: Method to write parameter attribute value, **parameter_name.attribute_name=value** (private attribute writing access denied).

`__str__`()
: Method used to print parameter, called with **print(parameter_name)** function.

`check_bounds`(*defined_bounds*)
: Method (*internal*) to check bounds syntax and value(s).

`check_units`(*defined_units*)
: Method (*internal*) to check units value.

`ureg = <pint.registry.UnitRegistry object>`

class `pyvplm.core.definition.`**`ParameterSet`**(**parameters_list*)
: Bases: `object`

Class defining a set of different Parameter(s).

`dictionary`
: The Parameter are registered in oredered dictionary at key [Parameter.name]

Type OrderedDict of Parameter

Example

save parameters m and k:

```
>>> In [1]: m = PositiveParameter('m', [50, 100], 'g', 'mass')
>>> In [2]: K1 = Parameter('K1', [2], 'g', 'oversizing coefficient')
>>> In [3]: parameter_set = ParameterSet(m, K1)
```

add a parameter afterwards:

```
>>> In [4]: K2 = Parameter('K2', [1.5], '', 'oversizing coefficient')
>>> In [5]: parameter_set['K2'] = K2
```

get K1 parameter value:

```
>>> In [6]: a = float(parameter_set['K1'])
```

change parameters order:

```
>>> In [7]: parameter_set.first('K2', 'K1')
>>> In [8]: print(parameter_set)
K2: K2=1.5, oversizing coefficient
K1: K1=2gram, oversizing coefficient
m: m in [50.0,100.0]gram, mass
```

delete K2 parameter:

```
>>> In [9]: del parameter_set['K2']
```

Note: While using print function, display differs between variable and constraint.

`__delitem__`(*key*)
Method to delete a parameter in a parameter set: **del parameter_set[parameter.name]**.

`__getitem__`(*index*)
Method to return a parameter from a parameter set using its name as key: **parameter=parameter_set[parameter.name]**.

`__getstate__`()
Method to save parameter set using pickle.

`__setitem__`(*key*, *value*)
Method to replace parameter in a parameter set or expend dictionary if new key.

`__setstate__`(*dict*)
Method to read parameter set using picklerLoad().

`__str__`()
Method used to print parameters in the set with function: **print(parameter_set)**.

`check_parameters`(*parameters_list: tuple*)
Method (*internal*) to check parameters.

first(**parameters_list*)
Run through parameters_list tuple to move dictionary key to its position in the list.

latex_render(*textArea=False*)
Method used to print parameters in latex form: **latex_render(parameter_set)** When parameter name is of the form name_indice this will lead to $name_{indice}$ latex form, number is automatically rendered as indice. Greek letters will also be escaped automatically lambda_wind will lead to $lambda_{wind}$.

class pyvplm.core.definition.**PositiveParameter**(*name: str, defined_bounds: list, defined_units: str, description: str*)
Bases: `pyvplm.core.definition.Parameter`

Subclass of the class Parameter.

Note: This class has identical methods and parameters as the Parameter class except for internal check_bounds method, therefore Parameter should be defined with strictly positive bounds: 0<defined_bounds[0]<defined_bounds[1]

For more details see `Parameter()`

---

check_bounds(*defined_bounds*)
Method (*internal*) to check bounds syntax and value(s).

class pyvplm.core.definition.**PositiveParameterSet**(**parameters_list*)
Bases: `pyvplm.core.definition.ParameterSet`

Subclass of the class Parameter.

Note: This class has identical methods and parameters as the Parameter class except for internal check_parameters method, therefore parameters_list should be a tuple of PositiveParameter or a single PositiveParameter

For more details see `ParameterSet()`

__setitem__(*key, value*)
Method to replace parameter in a parameter set or expend dictionary if new key.

check_parameters(*parameters_list: tuple*)
Method (*internal*) to check parameters.

pyvplm.core.definition.**logg_exception**(*ex: Exception*)

8.3 Module contents

CHAPTER NINE

PYVPLM.ADDON PACKAGE

9.1 Submodules

9.2 pyvplm.addon.comsoladdon module

Specific module to interface variablepowerlaw module with comsol FEM software

`pyvplm.addon.comsoladdon.`**`import_file`**(*file_name: str*, *parameter_set: pyvplm.core.definition.PositiveParameterSet*, *units: str*)

Function to import .txt file generated by COMSOL (output format). Values can be either expressed within SI units, user defined units or specified units in the parameter name : 'parameter_name (units)'.

Parameters

- **file_name** (*str*) – Name of the saved file with path (example: file_name = './subfolder/name')
- **parameter_set** (*PositiveParameterSet*) – Defines the n physical parameters for the studied problem
- **units** (*str*) – Define what units should be considered for parameters from set * 'SI': means parameter is expressed within SI units, no adaptation needed and '(units)' in column name is ignored. * 'defined': means parameter is expressed within defined units written in parameter and '(units)' in column name is ignored, adaptation may be performed. * 'from_file': means parameter is expressed with file units and adaptation may be performed.

  If units are unreadable and **from_file** option is chosen, it is considered to be expressed in SI units. For parameters not in the defined set, if units are unreadable, there are no units or **SI** option is chosen, it is considered to be SI otherwise adaptation is performed.

`pyvplm.addon.comsoladdon.`**`save_file`**(*doe_x: numpy.ndarray*, *file_name: str*, *parameter_set: pyvplm.core.definition.PositiveParameterSet*, *is_SI: bool*, ***kwargs*)

Function to save .txt file within COMSOL input format. Values can be either expressed with SI units or user defined units (is_SI, True by default).

Parameters

- **doe_x** (*DOE of the parameter_set either in defined_units or SI units*)
- **file_name** (*Name of the saved file with path (example: file_name = './subfolder/name')*)
- **parameter_set** (*Defines the n physical parameters for the studied problem*)
- **is_SI** (*Define if parameters values are expressed in SI units or units defined by user*)

9.3 pyvplm.addon.pixdoe module

Addon module generating constrained full-factorial DOE on 2-spaces (pi/x) problems

`pyvplm.addon.pixdoe.`**`apply_constraints`**`(`*X: numpy.ndarray*, *Constraints*`)`

Function to test declared constraint and return true vector if an error occurs.

Parameters

- **X** (*[m*n] numpy.ndarray of float or int*) – Defines the m DOE points values over the n physical parameters
- **Constraints** (*function that should return a [1*m] numpy.ndarray of bool, that validates the m points constraint*)

Returns **Constraints(X)** – If dimension mismatch or constraint can't be applied returns True values (no constraint applied)

Return type [1*m] numpy.ndarray of bool

`pyvplm.addon.pixdoe.`**`create_const_doe`**`(`*parameter_set:* pyvplm.core.definition.PositiveParameterSet, *pi_set:* pyvplm.core.definition.PositiveParameterSet, *func_x_to_pi*, *wished_size:* int, ***kwargs*`)`

Function to generate a constrained feasible set DOE with repartition on PI not far from nominal fullfact DOE.

Parameters

- **parameter_set** (*Defines the n physical parameters for the studied problem*)
- **pi_set** (*Defines the k (k<n) dimensionless parameters of the problem (WARNING: no cross-validation with*) – parameter_set, uses func_x_to_pi for translation)
- **func_x_to_pi** (*Function that translates X physical values into Pi dimensionless values (space transformation matrix)*)
- **wished_size** (*Is the wished size of the final elected X-DOE that represents a constrained fullfact Pi-DOE*)
- ****kwargs** (*additional argumens*) –
  - **level_repartition** (*numpy.array* of *int*): defines the parameters levels relative repartition,

  default is equaly shared (same number of levels) * **parameters_constraints** (*function*): returns numpy.array of bool to validate each point in X-DOE, default is [] * **pi_constraints** (*function*): returns numpy.array of bool to validate each point in Pi-DOE, default is [] * **choice_nb** (*int*): number of returned nearest point from DOE for each nominal DOE point, default is 3 * **spacing_division_criteria** (*int*): (>=2) defines the subdivision admitted error in Pi nominal space for feasible point, default is 5 * **log_space** (*bool*): defines if fullfact has to be in log space or when false, linear (default is log - True) * **track** (*bool*): defines if the different process steps information have to be displayed (default is False) * **test_mode** (*bool*): set to False to show plots (default is False)

Returns

- **doeXc** (*[j*n] numpy.array of float*) – Represents the elected feasible constrained sets of physical parameters matching spacing criteria with j >= whished_size
- **doePIc** (*[j*n] numpy.array of float*) – Represents the elected feasible constrained sets of dimensionless parameters matching spacing criteria with j >= whished_size

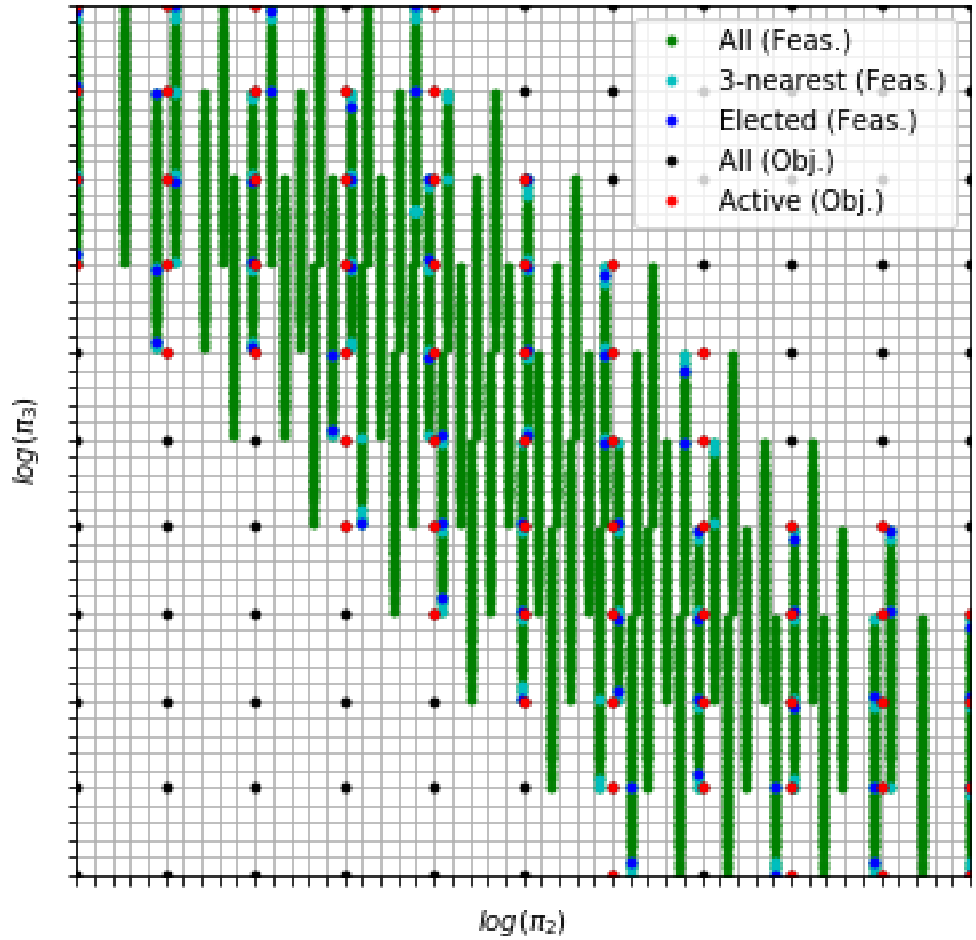
Example

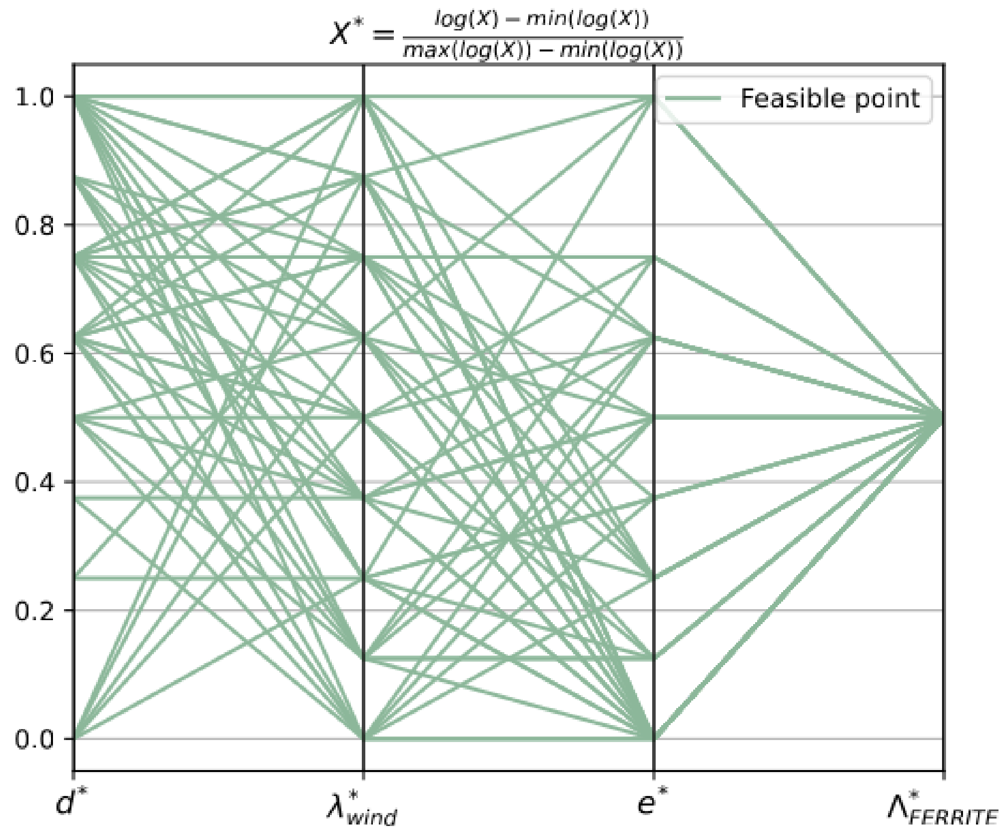
define properly the parameter, pi set and transformation function:

```
>>> In [1]: from pyvplm.core.definition import PositiveParameter,␣
↪PositiveParameterSet
>>> In [2]: from pyvplm.addon.variablepowerlaw import buckingham_theorem,␣
↪declare_func_x_to_pi,
reduce_parameter_set
>>> In [3]: u = PositiveParameter('u', [1e-9, 1e-6], 'm', 'Deflection')
>>> In [4]: f = PositiveParameter('f', [150, 500], 'N', 'Load applied')
>>> In [5]: l = PositiveParameter('l', [1, 3], 'm', 'Cantilever length')
>>> In [6]: e = PositiveParameter('e', [60e9, 80e9], 'Pa', 'Young Modulus')
>>> In [7]: d = PositiveParameter('d', [10, 60], 'mm', 'Diameter of cross-
↪section')
>>> In [8]: parameter_set = PositiveParameterSet(u, f, l, e, d)
>>> In [9]: parameter_set.first('u','l')
>>> In [10]: pi_set, _ = buckingham_theorem(parameter_set, False)
>>> In [11]: reduced_parameter_set, reduced_pi_set = reduce_parameter_
↪set(parameter_set, pi_set, 'l')
>>> In [12]: func_x_to_pi = declare_func_x_to_pi(reduced_parameter_set, reduced_
↪pi_set)
```

then create a complete DOE:

```
>>> In [13]: doeXc, doePIc = create_const_doe(reduced_parameter_set, reduced_pi_
↪set, func_x_to_pi, 30,
track=True)
```


All (Feas.)
3-nearest (Feas.)
Elected (Feas.)
All (Obj.)
Active (Obj.)
$log(\pi_3)$
$log(\pi_2)$



pyvplm.addon.pixdoe.**create_doe**(*bounds: numpy.ndarray*, *parameters_level: numpy.ndarray*, *log_space: bool = True*) → Tuple[numpy.ndarray, numpy.ndarray]

Functions that generates a fullfact DOE mesh using bounds and levels number.

Parameters

- **bounds** (*[n*2] numpy.ndarray of floats, defines the n parameters [lower, upper] bounds*)
- **parameters_level** (*[1*n] numpy.ndarray of int, defines the parameters levels*)
- **log_space** (*Defines if fullfact has to be in log space or when false, linear (default is True)*)

Returns

- **doe_values** (*[m*n] numpy.ndarray of float*) – A fullfact DOE, with n the number of parameters and m the number of experiments (linked to level repartition)
- **spacing** (*[1*n] numpy.ndarray*) – Represents the DOE's points spacing on each paramater axis in the space

Example

define bounds and parameters' levels:

```
>>> In [1]: bounds = numpy.array([[10, 100], [100, 1000]], float)
>>> In [2]: parameters_level = numpy.array([2, 3], int)
```

generate doe in log space:

```
>>> In [3]: doe_values, spacing = create_doe(bounds, parameters_level, True)
```

returns:

```
>>> In [4]: doe_values.tolist()
>>> Out[4]: [[10, 100], [100, 100], [10, 316.228], [100, 316.228], [10, 1000],␣
↪[100, 1000]]
>>> In [5]: spacing.tolist()
>>> Out[5]: [1.0, 0.5]
```

`pyvplm.addon.pixdoe.`**`declare_does`**(*x_Bounds: numpy.ndarray*, *x_levels: numpy.ndarray*, *parameters_constraints*, *pi_constraints*, *func_x_to_pi*, *log_space: bool = True*)

Function to generate X and Pi DOE with constraints (called as sub-function script).

Parameters

- **x_Bounds** (*[n*2] numpy.ndarray of floats, defines the n parameters [lower, upper] bounds*)
- **x_levels** (*[1*n] numpy.ndarray of int, defines the parameters levels*)
- **parameters_constraints, pi_constraints** (*functions that define parameter and Pi constraints*)
- **func_x_to_pi** (*function that translates X physical values into Pi dimensionless values*) – (space transformation matrix)
- **log_space** (*Defines if full-factorial has to be in log space or when false, linear (default is True)*)

Returns

- **doeX** (*[m*n] numpy.ndarray of float*) – A full-factorial DOE, with n the number of parameters and m the number of experiments (linked to level)
- **doePI** (*[k*n] numpy.ndarray of float*) – Represents the Pi DOE's points computed from doeX and applying both X and Pi constraints (k<=m)

`pyvplm.addon.pixdoe.`**`elect_nearest`**(*doe: numpy.ndarray*, *nominal_doe: numpy.ndarray*, *index: numpy.ndarray*)

Function that tries to assign for each point in nominal DOE, one point in feasible DOE elected from its 'choice_nb' found indices. The assignments are done point-to-point electing each time the one maximizing minimum relative distance with current elected set. If from available indices they all are already in the set, point is deleted and thus: j<=k (not likely to happen).

Parameters

- **doe** (*[m*n] numpy.ndarray of int or float*) – DOE representing m feasible experiments expressed with n parameters with non-optimal spacing
- **nominal_doe** (*[k*n] numpy.ndarray of int or float*) – Fullfact DOE with k wished experiment (k<<m) expressed with the same n parameters

- **index** (*[k*nb_choice] numpy.ndarray of int*) – Gathers the corresponding 'choice_nb' nearest DOE points indices (computed with :~pixdoe.find_nearest)

Returns

- **doe_elected** (*[j*n] numpy.ndarray of int or float*) – Returned DOE with feasible points assigned to reduced nominal DOE (deleted points with no assignment, i.e. all indices already assigned)
- **reduced_nominal_doe** (*[j*n] numpy.ndarray of int or float*) – Reduced nominal DOE (j<=k), all point are covered with feasible point

Example

to define DOEs and find the nearest points, see `surroundings()`

then elect one point for each nominal point:

```
>>> In [7]: doe_elected, reduced_nominal_doe, max_error = elect_nearest(doe,␣
↪nominal_doe, index)
>>> In [8]: doe_elected.tolist()
>>> Out[8]: [[100.0, 100.0], [10.0, 251.18864315095797], [100.0, 251.
↪18864315095797], [10.0, 1000.0],
[100.0, 1000.0]]
>>> In [9]: reduced_nominal_doe.tolist()
>>> Out[9]: [[100.0, 100.0], [10.0, 316.22776601683796], [100.0, 316.
↪22776601683796], [10.0, 1000.0],
[100.0, 1000.0]]
>>> In [10]: max_error.tolist()
>>> Out[10]: [0.0, 0.10000000000000009, 0.10000000000000009, 0.0, 0.0]
```

`pyvplm.addon.pixdoe.`**`find_nearest`**(*doe*, *nominal_doe*, *choice_nb*, *proper_spacing*, *log_space=True*)

Function that returns for each point in nominal DOE point, the indices and max relative error for choice_nb nearest points in feasible DOE. As a distance has to be computed to select nearest in further functions, it is the max value of the relative errors (compared to the bounds) that is returned (this avoids infinite relative error for [0, 0] origin point).

Parameters

- **doe** (*[m*n] numpy.ndarray of int or float*) – DOE representing m feasible experiments expressed with n parameters with non-optimal spacing
- **nominal_doe** (*[k*n] numpy.ndarray of int or float*) – Fullfact DOE with k wished experiment (k<<m) expressed with the same n parameters
- **choice_nb** (*int*) – Number of the nearest points returned from DOE for each nominal DOE point, criteria is max relative distance error max(x-x_n/(max(x_n)-min(x_n)))
- **proper_spacing** (*[n*1] numpy.ndarray of float*) – Represents max distance criteria on each DOE axis (i.e. parameter scale)
- **log_space** (*bool*) – Defines if fullfact has to be in log space or when false, linear (default is True)

Returns **nearest_index_in_doe** – Gathers the corresponding 'choice_nb' nearest DOE points indices

Return type [k*choice_nb] numpy.ndarray of int

Example

to define DOEs, see surroundings()

then extract the 2 nearest feasible points for each nominal point:

```
>>> In [6]: index, max_rel_distance = find_nearest(doe, nominal_doe, 2, proper_
↪spacing, True)
>>> In [7]: index.tolist()
>>> Out[7]: [[0, 4], [3, 7], [8, 12], [11, 15], [20, 16], [23, 19]]
>>> In [8]: max_rel_distance.tolist()
>>> Out[8]: [[0.0, 0.20000000000000018], [0.0, 0.20000000000000018],
[0.10000000000000009, 0.10000000000000009], [0.10000000000000009, 0.
↪10000000000000009]
[0.0, 0.20000000000000018], [0.0, 0.20000000000000018]]
```

pyvplm.addon.pixdoe.**logg_exception**(*ex: Exception*)

pyvplm.addon.pixdoe.**surroundings**(*doe*, *nominal_doe: numpy.ndarray*, *proper_spacing: numpy.ndarray*, *LogLin: bool = True*) → Tuple[numpy.ndarray, numpy.ndarray]

Function to reduce a given nominal DOE on a max distance criteria with points from feasible DOE ('reachable' points).

Parameters

- **doe** (*[m*n] numpy.ndarray of int or float*) – DOE representing m feasible experiments expressed with n parameters with non-optimal spacing
- **nominal_doe** (*[k*n] numpy.ndarray of int or float*) – Fullfact DOE with k wished experiment (k<<m) expressed with the same n parameters
- **proper_spacing** (*[n*1] numpy.ndarray of float*) – Represents max distance criteria on each DOE axis (i.e. parameter scale)
- **LogLin** (*defines if fullfact has to be in log space or when false, linear (default is True)*)

Returns

- **reduced_nominal_doe** (*[l*n] numpy.ndarray*) – A reduced set of nominal_doe (l<=k) validating proper_spacing criteria with feasible points from DOE
- **to_be_removed** (*numpy.ndarray of bool*) – Returns the corresponding indices that do not validate proper_spacing criteria

Example

define bounds and parameters' levels:

```
>>> In [1]: bounds = numpy.array([[10, 100], [100, 1000]], float)
>>> In [2]: parameters_level_nominal = numpy.array([2, 3], int)
>>> In [3]: parameters_level_feasible = numpy.array([4, 6], int)
```

generate doe(s) in log space:

```
>>> In [4]: doe, _ = create_doe(bounds, parameters_level_feasible, True)
>>> In [5]: nominal_doe, proper_spacing = create_doe(bounds, parameters_level_
↪nominal, True)
```

search surrounding points:

```
>>> In [6]: reduced_nominal_doe, to_be_removed = surroundings(doe, nominal_doe,␣
↪proper_spacing, True)
>>> In [7]: reduced_nominal_doe.tolist()
>>> Out[7]: [[10.0, 100.0], [100.0, 100.0], [10.0, 316.22776601683796], [100.0,␣
↪316.22776601683796],
>>>     ...: [10.0, 1000.0], [100.0, 1000.0]]
>>> In [8]: to_be_removed.tolist()
>>> Out[8]: [False, False, False, False, False, False]
```

9.4 pyvplm.addon.variablepowerlaw module

Addon module fitting variable power law response surface on dimensionless parameter computed with FEM

pyvplm.addon.variablepowerlaw.**adapt_parameter_set**(*parameter_set:* pyvplm.core.definition.PositiveParameterSet, *pi_set:* pyvplm.core.definition.PositiveParameterSet, *doe_x: pandas.core.frame.DataFrame*, *replaced_parameter: str*, *new_parameter: str*, *expression: str*, *description: str*) → Tuple[*pyvplm.core.definition.PositiveParameterSet*, *pyvplm.core.definition.PositiveParameterSet*, pandas.core.frame.DataFrame]

Function that transform physical parameters' problem (and corresponding DOE) after FEM calculation.

Parameters

- **parameter_set** (*Defines the n physical parameters for the studied problem*)
- **pi_set** (*Defines the k (k<n) dimensionless parameters of the problem*)
- **doe_x** (*DOE of the parameter_set in SI units (column names should be of the form 'parameter_i')*)
- **replaced_parameter** (*Name of the replaced parameter (should not be a repetitive term, i.e. present in only*)
- **one PI (PI0) term to ensure proper PI spacing)**
- **new_parameter** (*Name of new parameter (units has to be identical to replaced parameter)*)
- **expression** (*Relation between old and new parameter if x_new = 2*x_old+3*other_parameter,*)
- **write '2*x_old+3*other_parameter'**
- **description** (*Saved description for new parameter*)

Returns

- **new_parameter_set** (*Represents the new physical problem*)
- **new_pi_set** (*Dimensionless parameters set derived from pi_set replacing parameter*)
- **new_doeX** (*Computed DOE from doeX using expression (relation between parameters)*)

Example

to define the parameter, pi sets and calculate DOE refer to: *regression_models()*

save DOE into dataframe:

```
>>> In [9]: labels = list(parameter_set.dictionary.keys())
>>> In [10]: doe_x = pandas.DataFrame(doe_x, columns=labels)
```

then imagine you want to replace one parameter (after FEM simulation):

```
>>> In [11]: (new_parameter_set, new_pi_set, new_doeX)
>>>     ...: = adapt_parameter_set(parameter_set, pi_set, doe_x, 'd', 'd_out',
↪'d+2*e', 'outer diameter')
```

you are able to perform new regression calculation!

pyvplm.addon.variablepowerlaw.**automatic_buckingham**(*parameter_set: pyvplm.core.definition.PositiveParameterSet*, *track: bool = False*) → Tuple[Any, Dict[str, Any]]

Function that returns all possible pi_set (with lower exponent) from a set of physical parameters. Based on buckingham_theorem function call.

Parameters

- **parameter_set** (*Defines the n physical parameters for the studied problem*)
- **track** (*Activates information display (default is False)*)

Returns

- **combinatory_pi_set** (*dict of [1*2] tuples*) – Stores pi_set at [0] tuple index and Pi expression (str) list at [1] tuple index
- **alternative_set_dict** (*dict of str*) – Stores the alternate expressions for widgets display

Example

define a positive set first, see: *write_dimensional_matrix()*

search corresponding pi_set:

```
>>> In [7]: combinatory_pi_set = automatic_buckingham(parameter_set, True)
    [AUTO. BUCKINGHAM] Testing repetitive set 1/120: total alternative pi set␣
↪size is 1
    [AUTO. BUCKINGHAM] Testing repetitive set 2/120: total alternative pi set␣
↪size is 1
    [AUTO. BUCKINGHAM] Testing repetitive set 3/120: total alternative pi set␣
↪size is 1
    ...
>>> In [8]: print(combinatory_pi_set[1][0])
    pi1: pi1 in [1000000.0,2999999999.9999995], l**1.0*u**-1.0
    pi2: pi2 in [1.2e-10,0.00053333333333333334], e**1.0*f**-1.0*u**2.0
    pi3: pi3 in [10000.0,59999999.99999999], d**1.0*u**-1.0
```

`pyvplm.addon.variablepowerlaw.buckingham_theorem(parameter_set: pyvplm.core.definition.PositiveParameterSet, track: bool = False) → Tuple[pyvplm.core.definition.PositiveParameterSet, List[str]]`

Function that returns pi_set dimensionless parameters from a set of physical parameters. The Pi expression is lower integer exponent i.e. Pi1 = x1**2*x2**-1 and not x1**1*x2**-0.5 or x1**4*x2**-2

Parameters

- **parameter_set** (*Defines the n physical parameters for the studied problem*)
- **track** (*Activates information display (default is False)*)

Returns

- **pi_set** (*PositiveParameterSet*) – Defines the k (k<n) dimensionless parameters of the problem
- **pi_list** (*[1*k] list of str*) – The dimensionless parameters' expression

Example

define a positive set first, see: *write_dimensional_matrix()*

orient repetitive set (using if possible d and l):

```
>>> In [8]: parameter_set.first('d', 'l')
```

search corresponding pi_set:

```
>>> In [9]: (pi_set, pi_list) = buckingham_theorem(parameter_set, True)
>>> In [10]: print(pi_set)
    Chosen repetitive set is: {d, l}
    pi1: pi1 in [1.6666666666666667e-08,9.999999999999999e-05], d**-1.0*u**1.0
    pi2: pi2 in [16.666666666666668,300.0], d**-1.0*l**1.0
    pi3: pi3 in [12000.0,1920000.0000000002], d**2.0*e**1.0*f**-1.0
```

Note: Repetitive parameters are elected as first pivot point in the order of arrival in parameter set dictionary keys, therefore user can orient repetitive set applying the 'first' method on the parameter set (see example)

`pyvplm.addon.variablepowerlaw.compute_echelon_form(in_matrix: numpy.ndarray)`

Function that computes a matrix into its echelon form.

Parameters **in_matrix** (*[m*n] numpy.ndarray of float or int*)

Returns

- **out_matrix** (*[m*n] matrix with echelon form derived from in_matrix*)
- **pivot_matrix** (*[m*m] pivot matrix to link out_matrix to in_matrix*)
- **pivot_points** (*[1*k] index of pivot points k = rank(in_matrix)<= min(m, n)*)

Example

define dimensional matrix:

```
>>> In [1]: in_matrix = numpy.array([[0, 1, 0], [1, 1, -2], [0, 1, 0], [1, -1, -
↪2], [0, 1, 0]], int)
```

perform echelon function:

```
>>> In [2]: (out_matrix, pivot_matrix, pivot_points) = compute_echelon_form(in_
↪matrix)
>>> In [3]: nc = len(out_matrix[0]
>>> In [4]: nr = len(out_matrix)
>>> In [5]: print([[float(out_matrix[ir][ic]) for ic in range(nc)] for ir in␣
↪range(nr)])
    [[1.0, 0.0, -2.0], [0.0, 1.0, 0.0], [0.0, 0.0, 0.0], [0.0, 0.0, 0.0], [0.0,␣
↪0.0, 0.0]]
>>> In [6]: print([[float(pivot[nr][nc]) for nc in range(len(pivot[0]))] for nr␣
↪in range(len(pivot))])
    [[-1.0, 1.0, 0.0, 0.0, 0.0], [1.0, 0.0, 0.0, 0.0, 0.0], [-1.0, 0.0, 1.0, 0.
↪0, 0.0],
    [2.0, -1.0, 0.0, 1.0, 0.0], [-1.0, 0.0, 0.0, 0.0, 1.0]]
>>> In [7]: print(pivot_points)
    [1, 0]
```

pyvplm.addon.variablepowerlaw.**concatenate_expression**(*expression: str*, *pi_list: List[str]*) → str

Function that transform regression model expression into latex form with concatenation (only for power-laws).

Parameters

- **expression** (*Expression of the regression model*)
- **pi_list** (*Defines the pi expressions (default is pi1, pi2. . .)*)

Returns new_expression

Return type Represents the new model formula in latex form

Example

define expression and list:

```
>>> In [1]: expression = 'log(pi1) = 2.33011+1.35000*log(pi2)-0.
↪25004*log(pi3)+0.04200*log(pi2)*log(pi3)+'
>>>     ...: '0.17000*log(pi2)**2'
>>> In [2]: pi_list = ['\pi_{1}','\pi_{2}','\pi_{3}']
```

adapt expression: concatenate_expression(expression, pi_list)

pyvplm.addon.variablepowerlaw.**declare_constraints**(*parameters_set: pyvplm.core.definition.PositiveParameterSet*, *constraint_set: pyvplm.core.definition.ConstraintSet*)

Functions that declare constraint=f(X_doe)/f(PI_doe) to return validity of a DoE set .

Parameters

- **parameters_set** (*Defines the n physical/dimensionless parameters (be careful to share set)*)
- **with pixdoe.create_const_doe)**
- **constraint_set** (*Defines the constraints that apply on the parameters from parameters_set*)

Returns **f** – a function of X, **X** being a [m*k] (k<=n) numpy.ndarray of float representing parameters values which returns a [m*1] numpy.ndarray of bool corresponding to the DoE validity

Return type function

`pyvplm.addon.variablepowerlaw.`**`declare_func_x_to_pi`**(*parameters_set:* pyvplm.core.definition.PositiveParameterSet, *pi_set:* pyvplm.core.definition.PositiveParameterSet)

Functions that declare pi=f(x) to transform parameters set values into pi set values.

Parameters

- **parameters_set** (*Defines the n physical parameters for the studied problem*)
- **pi_set** (*Defines the k (k<n) dimensionless parameters of the problem*)

Returns **f** – a function of x, **x** being a [m*n] numpy.ndarray of float representing physical parameters values which returns a [m*k] numpy.ndarray of float corresponding to the dimensionless parameters values

Return type function

Example

define a positive set first, see: `write_dimensional_matrix()`

define pi set using buckingham:

```
>>> In [7]: pi_set, _ = buckingham_theorem(parameter_set, False)
```

set x values:

```
>>> In [8]: x = [[1, 1.5, 2, 3, 5],[0.1, 2, 1, 2, 1],[2, 1, 3, 1.5, 2]]
```

declare function and compute y values:

```
>>> In [9]: func_x_to_pi = declare_func_x_to_pi(parameter_set, pi_set)
>>> In [10]: func_x_to_pi(x)
    array([[ 2.   ,  2.   ,  5.   ],
           [10.   ,  0.01, 10.   ],
           [ 1.5  ,  6.   ,  1.   ]])
```

`pyvplm.addon.variablepowerlaw.`**`force_buckingham`**(*parameter_set:* pyvplm.core.definition.PositiveParameterSet, **pi_list: Union[Iterable, Tuple[*str*]]*) → *pyvplm.core.definition.PositiveParameterSet*

Function used to define manually a dimensionless set of parameters. Parameters availability, pi expression and dimension or even pi matrix rank are checked.

Parameters

- **parameter_set** (*Defines the n physical parameters for the studied problem*)
- ***pi_list** (*Defines the Pi dimensionless parameters' expression of the problem*)

Returns **pi_set** – Defines the k (k<n) dimensionless parameters of the problem

Return type *PositiveParameterSet*

Example

define a positive set first, see: `write_dimensional_matrix()`

force pi set:

```
>>> In [7]: pi_set = force_buckingham(parameter_set, 'l/u', 'e/f*u^2', 'd/u')
>>> In [8]: print(pi_set)
    pi1: pi1 in [1000000.0,2999999999.9999995], u**-1.0*l**1.0
    pi2: pi2 in [1.2e-10,0.00053333333333333334], u**2.0*f**-1.0*e**1.0
    pi3: pi3 in [10000.0,59999999.99999999], u**-1.0*d**1.0
```

Note: The analysis is conducted on Pi dimension, rank of Pi-parameter exponents, global expression and number of Pi compared to dimensional matrix rank and parameters number. The 'understood expression' is visible by printing pi_set.

`pyvplm.addon.variablepowerlaw.`**`import_csv`**(*file_name: str*, *parameter_set: pyvplm.core.definition.PositiveParameterSet*)

Function to import .CSV with column label syntax as 'param_name' or 'param_name [units]'. Auto-adaptation to SI-units is performed and parameters out of set are ignored/deleted.

Parameters

- **file_name** (*Name of the saved file with path (example: file_name = './subfolder/name')*)
- **parameter_set** (*Defines the n physical parameters for the studied problem*)

`pyvplm.addon.variablepowerlaw.`**`latex_pi_expression`**(*pi_set: pyvplm.core.definition.PositiveParameterSet*, *parameter_set: pyvplm.core.definition.PositiveParameterSet*)

Function to write pi description in latex form: ***internal*** to `pi_sensitivity()` and `pi_dependency()`

`pyvplm.addon.variablepowerlaw.`**`logg_exception`**(*ex: Exception*)

`pyvplm.addon.variablepowerlaw.`**`perform_regression`**(*doe_pi: numpy.ndarray*, *models*, *chosen_model*, ***kwargs*)

Function to perform regresion using models expression form (with replaced coefficients).

Parameters

- **doe_pi** (*numpy.ndarray*) – DOE of the pi_set
- **models** (*specific*) – Output of `variablepowerlaw()`.
- **chosen_model** (*int*) – The elected regression model number
- ****kwargs** (*additional argumens*) –
  - **pi_list** (*list* of *str*): the name/expression of pi (default is pi1, pi2, pi3…)
  - **latex** (*bool*): define if graph legend font should be latex (default is False) - may cause some

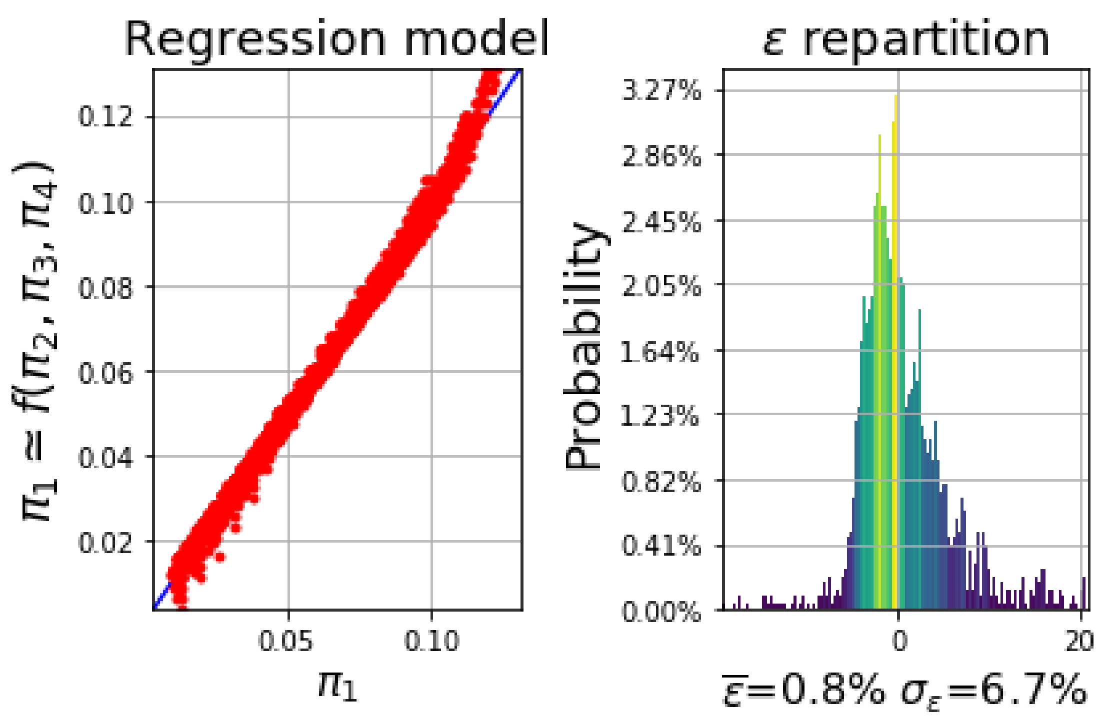
issues if used * **removed_pi** (**list**): list of indexes of removed pi numbers * **max_pi_nb** (*int*): maximum potential pi number that could appear in any expression (only useful if some pi mubers have been removed) * **eff_pi_0** (*int*): effective pi0 index in pi_list (used only if some pi numbers have been removed) * **no_plots** (*bool*): for GUI use, will return Y and Yreg as well as expression and latex_expression, will not plot anything

Example

to define regression models refer to: `regression_models()`

then perform regression on model n°8 to show detailed results on model fit and error:

```
>>> In[24]: perform_regression(doe_pi, models, chosen_model=8)
```



`pyvplm.addon.variablepowerlaw.`**`pi_dependency`**(*pi_set:* pyvplm.core.definition.PositiveParameterSet, *doe_pi: numpy.ndarray*, *useWidgets:* bool, ***kwargs*)

Function to perform dependency analysis on dimensionless parameters.

Parameters

- **pi_set** (*Set of dimensionless parameters*)
- **doe_pi** (*DOE of the complete pi_set (except pi0)*)
- **useWidgets** (*Boolean to choose if widgets displayed (set to True within Jupyther Notebook)*)
- ****kwargs** (*additional argumens*) –
  - **x_list** (*list* of *str*): name of the different pi to be defined as x-axis (default: all)
  - **y_list** (*list* of *str*): name of the different pi to be defined as y-axis (default: all)
  - **order** (*int*): the order chosen for power-law or polynomial regression model (default is 2)
  - **threshold** (*float*): in]0,1[the lower limit to consider regression for plot (default is 0.9)

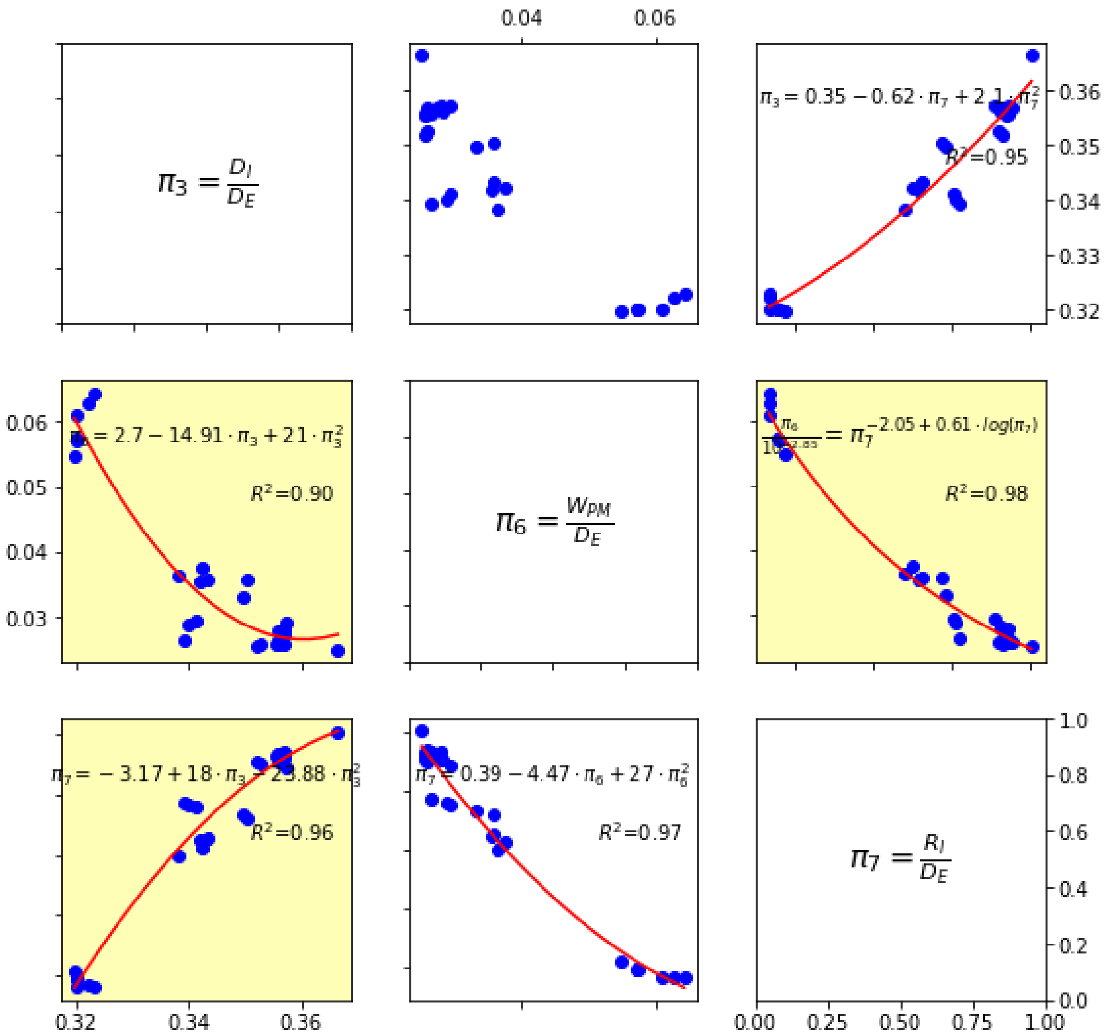
- **figwidth** (*int*): change figure width (default is 16 in widgets mode)
- **xlabel_size** (*int*): set x-axis label font size (default is 16)

Example

to load a doe example: see `pi_sensitivity()`

then perform dependency analysis:

```
>>> In [11]: pi_dependency(pi_set, doe_pi, useWidgets=False)
```



pyvplm.addon.variablepowerlaw.**pi_dependency_sub**(*pi_set: pyvplm.core.definition.PositiveParameterSet, doe_pi: numpy.ndarray, **kwargs*)

Sub-function of `pi_dependency()`

pyvplm.addon.variablepowerlaw.**pi_sensitivity**(*pi_set: pyvplm.core.definition.PositiveParameterSet, doe_pi: numpy.ndarray, use_widgets: bool, **kwargs*)

Function to perform sensitivity analysis on dimensionless parameters according to specific performance.

Parameters

- **pi_set** (*Set of dimensionless parameters*)
- **doe_pi** (*DOE of the complete pi_set (except pi0)*)
- **use_widgets** (*Boolean to choose if widgets displayed (set to True within Jupyther Notebook)*)
- ****kwargs** (*additional argumens*) –
  - **pi0** (*list* of *str*): name of the different pi0 = f(pi…) considered as design drivers
  - **piN** (*list* of *str*): name of the f(pi1, pi2, …, piN) considered as secondary parameters
  - **latex** (*bool*): display in latex format
  - **figwidth** (*int*): change figure width (default is 16 in widgets mode)
  - **zero_ymin** (*bool*): set y-axis minimum value to 0 (default is False)
  - **xlabel_size** (*int*): set x-axis label font size (default is 18)

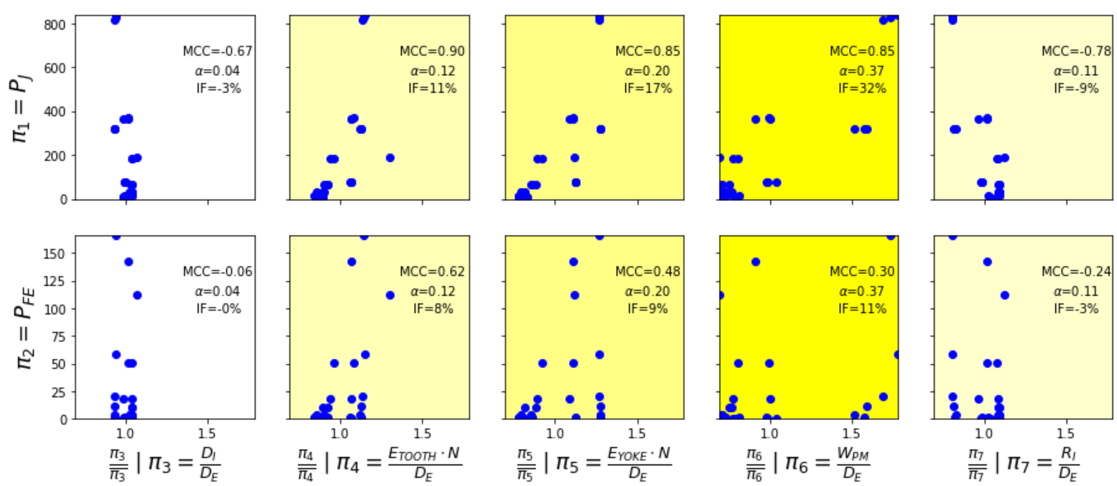
Example

to load a doe example:

```
>>> In [1]: doe_pi = pandas.read_excel('./pi_analysis_example.xls')
>>> In [2]: doe_pi = doe[['pj','pfe','pi2','pi3','pi4','pi5','pi6']].values
>>> In [3]: pi1 = PositiveParameter('pi1',[0.1,1],'','p_j')
>>> In [4]: pi2 = PositiveParameter('pi2',[0.1,1],'','p_fe')
>>> In [5]: pi3 = PositiveParameter('pi3',[0.1,1],'','d_i*d_e**-1')
>>> In [6]: pi4 = PositiveParameter('pi4',[0.1,1],'','e_tooth*d_e**-1*n')
>>> In [7]: pi5 = PositiveParameter('pi5',[0.1,1],'','e_yoke*d_e**-1*n')
>>> In [8]: pi6 = PositiveParameter('pi6',[0.1,1],'','w_pm*d_e**-1')
>>> In [9]: pi7 = PositiveParameter('pi7',[0.1,1],'','r_i*d_e**-1')
>>> In [10]: pi_set = PositiveParameterSet(pi1, pi2, pi3, pi4, pi5, pi6, pi7)
```

then perform sensitivity analysis:

```
>>> In [11]: pi_sensitivity(pi_set, doe_pi, False, pi0=['pi1', 'pi2'], piN=['pi3
↪', 'pi4', 'pi5', 'pi6',
>>>     ...: 'pi7'])
```



Note: Within Jupyter Notebook, rendering will be slightly different with compressed size in X-axis to be printed within one page width and labels adapted consequently. The graph indices are:

- MCC: Maximum Correlation Coefficient is the maximum value between Spearman and Pearson coefficients
- alpha: variability coefficient is the ratio between parameter standard deviation and average value
- IF: Impact Factor is the product of both previous coefficients

`pyvplm.addon.variablepowerlaw.`**`pi_sensitivity_sub`**(*pi_set: pyvplm.core.definition.PositiveParameterSet, doe_pi: numpy.ndarray, **kwargs*)

Sub-function of `pi_sensitivity()`

`pyvplm.addon.variablepowerlaw.`**`reduce_parameter_set`**(*parameter_set: pyvplm.core.definition.PositiveParameterSet, pi_set: pyvplm.core.definition.PositiveParameterSet, elected_output: str*) → Tuple[*pyvplm.core.definition.PositiveParameterSet, pyvplm.core.definition.PositiveParameterSet*]

Function that reduces physical parameters and Pi set extracting output physical parameter and Pi0.

Parameters

- **parameter_set** (*Defines the n physical parameters for the studied problem*)
- **pi_set** (*Defines the k (k<n) dimensionless parameters of the problem*)
- **elected_output** (*Parameter that represents FEM output*)

Returns

- **reduced_parameter_set** (*Parameter set reduced by elected_output*)
- **reduced_pi_set** (*Pi set reduced by Pi0 (dimensionless parameter countaining output parameter)*)

Example

to define the parameter and pi sets refer to: `buckingham_theorem()`

reduce sets considering 'u' is the output:

```
>>> In [9]: reduced_parameter_set, reduced_pi_set = reduce_parameter_
↪set(parameter_set, pi_set, 'u')
```

then declare transformation function and create DOE:

```
>>> In [10]: func_x_to_pi = declare_func_x_to_pi(reduced_parameter_set, reduced_
↪pi_set)
>>> In [11]: from pyvplm.addon.pixdoe import create_const_doe
>>> In [12]: doeX, _ = create_const_doe(reduced_parameter_set, reduced_pi_set,␣
↪func_x_to_pi, 50)
>>> In [13]: doeX = pandas.DataFrame(doeX, columns=list(reduced_parameter_set.
↪dictionary.keys()))
```

`pyvplm.addon.variablepowerlaw.regression_models(doe: numpy.ndarray, elected_pi0: str, order: int, **kwargs) → Union[Tuple[Dict, Any, Any], Dict]`

Functions that calculate the regression model coefficient with increasing model complexity. The added terms for complexity increase are sorted depending on their regression coefficient value on standardized pi. For more information on regression see Scipy linalg method `lstsq()`

Parameters

- **doe** (*[m*k] numpy.ndarray of float or int*) – Represents the elected feasible constrained sets of m experiments values expressed over the k dimensionless parameters
- **elected_pi0** (*Selected pi for regression: syntax is 'pin' with n>=1 and n<=k*)
- **order** (*Model order >=1*) –
  - **Order 2 in log_space=True is :** log(pi0) = log(cst) + a1*log(pi1) + a11*log(pi1)**2 + a12*log(pi1)*log(pi2) + a2*log(pi2) + a22*log(pi2)**2
  - **Order 2 in log_space=False is :** pi0 = cst + a1*pi1 + a11*pi1**2 + a12*pi1*pi2 + a2*pi2 + a22*pi2
- ****kwargs** (*additional argumens*) –
  - **ymax_axis** (*float*): set y-axis maximum value representing relative error, 100=100%

  (default value) * **log_space** (*bool*): define if polynomial regression should be performed within logarithmic space (True) or linear (False) * **latex** (*bool*): define if graph legend font should be latex (default is False) - may cause some issues if used * **plots** (*bool*): overrules test_mode and allows showing plots * **skip_cross_validation** (**bool**): for a big amount of data (data nb > 10 * nb models) you may want to skip cross-validation for time-calculation purpose, in that case only a trained dataset is calculated and error calculation is only performed on trained set (default is False). * **force_choice** (*int*): forces the choice of the regression criteria (1 => max(abs(error)), …) * **removed_pi** (*list*): list of indexes of removed pi to be ignored * **eff_pi0** (*int*): effective pi0 index in the modfied DOE (used only with removed_pi) * **return_axes** (*bool*): returns the axes objects for the plots if True (default is False) * **fig_size** (*tuple*): tuple of 2 numbers specifying the width and height of the plot in inches

Returns

models –

Stores the different regression models information as for model 'i':

- dict[i][0]: str of the model expression
- dict[i][1]: numpy.ndarray of the regression coefficients
- dict[i][2]: pandas.DataFrame of the trained set (**max abs(e)**, **average abs(e)**,

average e and **sigma e**) * dict[i][3]: pandas.DataFrame of the tested set (**max abs(e)**, **average abs(e)**, **average e** and **sigma e**)

Where **e** represents the relative error on elected_pi0>0 in %

Additional data is saved in:

- dict['max abs(e)']: (1*2) tuple containing trained and test sets max absolute relative error
- dict['ave. abs(e)']: (1*2) tuple containing trained and test sets average absolute relative error
- dict['ave. e']: (1*2) tuple containing trained and test sets average relative error

- dict['sigma e']: (1*2) tuple containing trained and test sets standard deviation on relative error

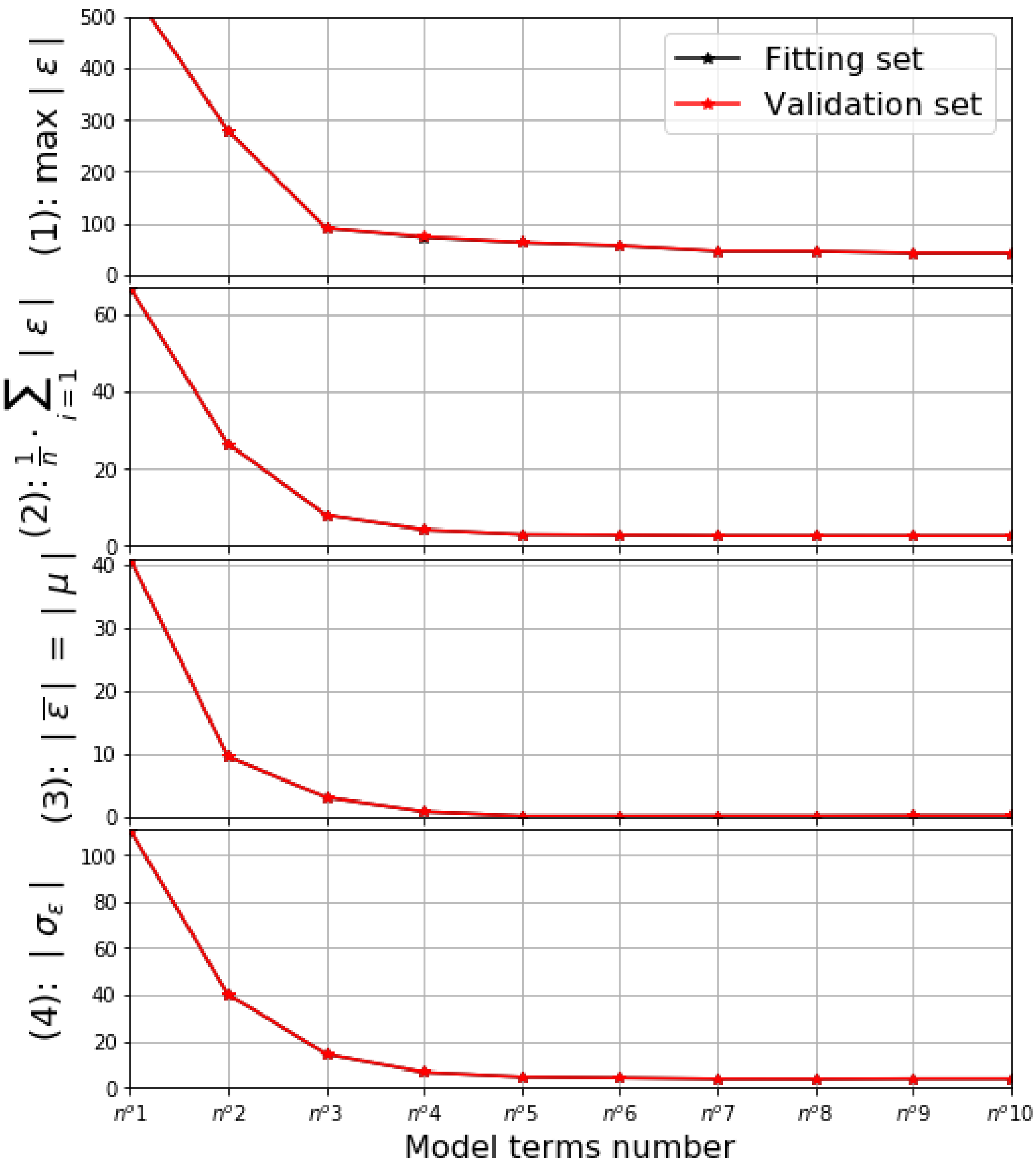
Return type dict of [1*4] tuple

Example

to define the parameter and pi sets and generate DOE: to define the parameter and pi sets refer to: *reduce_parameter_set()*

generate mathematic relation between Pi parameters knowing pi1=l/u and following formulas:

```
>>> In [14]: PI2 = doeX['e']*(1/doeX['f'])* doeX['u']**2
>>> In [15]: PI3 = doeX['d']*(1/doeX['u'])
>>> In [16]: PI1 = numpy.zeros(len(PI2))
>>> In [17]: for idx in range(len(PI1)):
>>>     ...:         PI1[idx] = (10**2.33)*
>>>     ...:         (PI2[idx]**(1.35+0.17*numpy.log10(PI2[idx])+0.042*numpy.
↪log10(PI3[idx])))*
>>>     ...:         (PI3[idx]**-0.25) + (random.random()-0.5)/1000000
>>> In [18]: l_values = PI1 * doeX['u']
>>> In [19]: doeX['l'] = l_values
>>> In [20]: doeX = doeX[list(parameter_set.dictionary.keys())]
>>> In [21]: func_x_to_pi = declare_func_x_to_pi(parameter_set, pi_set)
>>> In [22]: doePI = func_x_to_pi(doeX.values)
>>> In [23]: models = regression_models(doePI, 'pi1', 3)
```



`pyvplm.addon.variablepowerlaw.`**`save_csv`**(*doe_x: numpy.ndarray*, *file_name: str*, *parameter_set: pyvplm.core.definition.PositiveParameterSet*, *is_SI: bool*)

Function to save .CSV with column label syntax as 'param_name [units]'. With units either defined by user or SI (is_SI, True by default).

Parameters

- **doe_x** (*DOE of the parameter_set either in defined_units or SI units*)
- **file_name** (*Name of the saved file with path (example: file_name = './subfolder/name')*)
- **parameter_set** (*Defines the n physical parameters for the studied problem*)
- **is_SI** (*Define if parameters values are expressed in SI units or units defined by user*)

pyvplm.addon.variablepowerlaw.**write_dimensional_matrix**(*parameter_set: pyvplm.core.definition.PositiveParameterSet*) → pandas.core.frame.DataFrame

Function to extract dimensional matrix from a PositiveParameterSet.

Parameters **parameter_set** (*defines the n physical parameters for the studied problem*)

Returns **dimensional_matrix**

Return type column labels refers to the parameters names and rows to the dimensions

Example

define a positive set first:

```
>>> In [1]: u = PositiveParameter('u', [1e-9,1e-6], 'm', 'Deflection')
>>> In [2]: f = PositiveParameter('f', [150,500], 'N', 'Load applied')
>>> In [3]: l = PositiveParameter('l', [1,3], 'm', 'Cantilever length')
>>> In [4]: e = PositiveParameter('e', [60e9,80e9], 'Pa', 'Young Modulus')
>>> In [5]: d = PositiveParameter('d', [10,60], 'mm', 'Diameter of cross-section
↪')
>>> In [6]: parameter_set = PositiveParameterSet(u, f, l, e, d)
```

then, apply function:

```
>>> In [7]: dimensional_matrix = write_dimensional_matrix(parameter_set)
>>> In [8]: dimensional_matrix.values
>>> Out[8]: [[1, 0, 0], [1, 1, -2], [1, 0, 0], [-1, 1, -2], [1, 0, 0]]
```

9.5 Module contents

CHAPTER TEN

INDICES AND TABLES:

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PYTHON MODULE INDEX

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