

Experimental Planning - Particular Study

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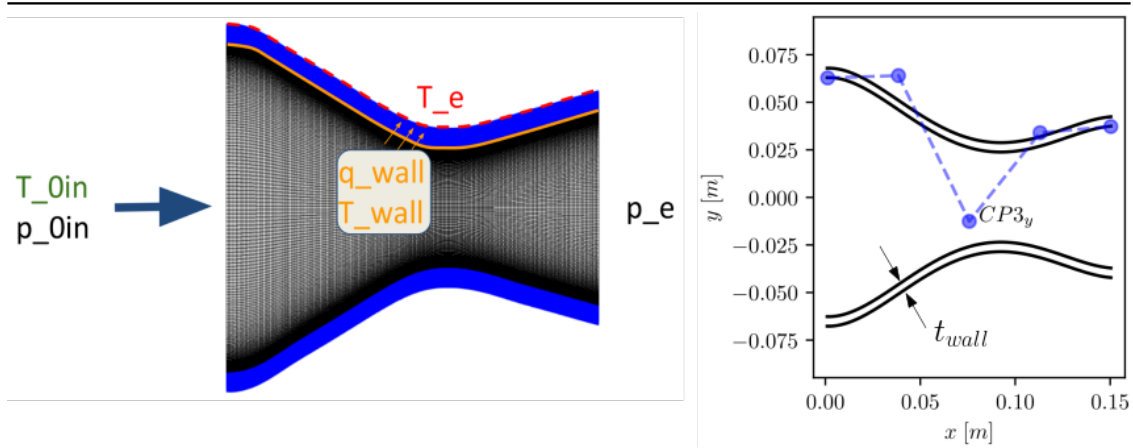
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1 Proposal Study

This proposal employs a factorial design approach to construct a surrogate model. The aim is the reconstruction of 2D fields acquired through Reynolds Averaged Navier Stokes (RANS) solutions, involving conjugate heat transfer of the nozzle flow.

1.1 Nozzle Flow and Heat Transfer

Rocket nozzles hold paramount importance in aerospace propulsion. The optimal aerodynamic design of these nozzles is inherently limited by the need to maintain structural integrity, as they are subjected to intense heat transfer from the hot gases to the inner walls.



Representation of Nozzle numerical domain and boundary conditions

2 Main Hypotesis

The central hypothesis poses that the factorial design could be effective in acquiring a model with the capacity to predict the principal components of a reduced-order model of fluid flow and heat transfer. This model, once established, can then be used to reconstruct complete two-dimensional flow fields from the designated independent variables.

2.1 Experimental Samples

To test this hypothesis, a series of numerical experiments will be conducted following the Central Composite Design (CCD)

- Inlet Total Temperature, T_{0in} [K]
- Inlet Total Pressure, p_{0in} [Pa]
- Wall Thickness, t_{wall} [m]
- Nozzle Shape Control Point, $CP3_y$ [m]
- External Nozzle Wall Temperature, T_e [K]

The [SU2](#) software ([Economon et al., 2016](#)) was employed to address the conjugate heat transfer interfaces between the fluid and solid in the nozzle. In the fluid domain, the Reynolds Averaged Navier-Stokes equations were solved using the finite volume method and the SST (Shear Stress Transport) turbulence model. To obtain the steady-state solution, the implicit Euler integration method was utilized in conjunction with time marching. On the other hand, for the solid domain, the energy equation was solved.

3 Central Composite Design

The range of variables were chosen in order to be within real experiments made by ([Back et al., 1964](#)) . Another factor taking into account to limit variable ranges is the numerical stability of conjugate heat transfer CFD.

```
[1]: from explann.doe import CentralCompositeDesign
import pandas as pd

variables = {
    't_wall': [0.001, 0.010],          # [m]
    'CP3_y': [-0.01255805, 0.0],      # [m]
    'T_0in': [400.0, 650.0],          # [K]
    'p_0in': [4.0e5, 1.0e6],          # [Pa]
    'T_e': [290.0, 400.0],            # [K]
}

# variable ranges
pd.DataFrame(variables)
```

```
[1]:   t_wall   CP3_y  T_0in   p_0in   T_e
0   0.001 -0.012558  400.0  400000.0  290.0
1   0.010  0.000000  650.0 1000000.0  400.0
```

A CCD (Central Composite Design) was chosen in order to be able to capture any high order interaction for the design variables.

```
[2]: ccd = CentralCompositeDesign(
    variables=variables,
    center=(1,0),
    alpha='r',
    face='ccc',
)
ccd.doe
```

```
[2]:
```

	t_wall	CP3_y	T_0in	p_0in	T_e
Index					
1	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000
2	1.000000	-1.000000	-1.000000	-1.000000	-1.000000
3	-1.000000	1.000000	-1.000000	-1.000000	-1.000000
4	1.000000	1.000000	-1.000000	-1.000000	-1.000000
5	-1.000000	-1.000000	1.000000	-1.000000	-1.000000
6	1.000000	-1.000000	1.000000	-1.000000	-1.000000
7	-1.000000	1.000000	1.000000	-1.000000	-1.000000
8	1.000000	1.000000	1.000000	-1.000000	-1.000000
9	-1.000000	-1.000000	-1.000000	1.000000	-1.000000
10	1.000000	-1.000000	-1.000000	1.000000	-1.000000
11	-1.000000	1.000000	-1.000000	1.000000	-1.000000
12	1.000000	1.000000	-1.000000	1.000000	-1.000000
13	-1.000000	-1.000000	1.000000	1.000000	-1.000000
14	1.000000	-1.000000	1.000000	1.000000	-1.000000
15	-1.000000	1.000000	1.000000	1.000000	-1.000000
16	1.000000	1.000000	1.000000	1.000000	-1.000000
17	-1.000000	-1.000000	-1.000000	-1.000000	1.000000
18	1.000000	-1.000000	-1.000000	-1.000000	1.000000
19	-1.000000	1.000000	-1.000000	-1.000000	1.000000
20	1.000000	1.000000	-1.000000	-1.000000	1.000000
21	-1.000000	-1.000000	1.000000	-1.000000	1.000000
22	1.000000	-1.000000	1.000000	-1.000000	1.000000
23	-1.000000	1.000000	1.000000	-1.000000	1.000000
24	1.000000	1.000000	1.000000	-1.000000	1.000000
25	-1.000000	-1.000000	-1.000000	1.000000	1.000000
26	1.000000	-1.000000	-1.000000	1.000000	1.000000
27	-1.000000	1.000000	-1.000000	1.000000	1.000000
28	1.000000	1.000000	-1.000000	1.000000	1.000000
29	-1.000000	-1.000000	1.000000	1.000000	1.000000
30	1.000000	-1.000000	1.000000	1.000000	1.000000
31	-1.000000	1.000000	1.000000	1.000000	1.000000
32	1.000000	1.000000	1.000000	1.000000	1.000000
33	0.000000	0.000000	0.000000	0.000000	0.000000
34	-2.378414	0.000000	0.000000	0.000000	0.000000
35	2.378414	0.000000	0.000000	0.000000	0.000000
36	0.000000	-2.378414	0.000000	0.000000	0.000000
37	0.000000	2.378414	0.000000	0.000000	0.000000
38	0.000000	0.000000	-2.378414	0.000000	0.000000
39	0.000000	0.000000	2.378414	0.000000	0.000000
40	0.000000	0.000000	0.000000	-2.378414	0.000000
41	0.000000	0.000000	0.000000	2.378414	0.000000
42	0.000000	0.000000	0.000000	0.000000	-2.378414
43	0.000000	0.000000	0.000000	0.000000	2.378414

```
[3]: ccd.levels
```

```
[3]:
```

	t_wall	CP3_y	T_0in	p_0in	T_e
Levels					
-2.378414	0.001000	-0.012558	400.000000	400000.000000	290.000000
-1.000000	0.003608	-0.008919	472.443974	573865.537712	321.875349
0.000000	0.005500	-0.006279	525.000000	700000.000000	345.000000
1.000000	0.007392	-0.003639	577.556026	826134.462288	368.124651
2.378414	0.010000	0.000000	650.000000	1000000.000000	400.000000

This DoE variables was then used as boundary conditions for the CFD(Computational Fluid Dynamics) numerical experiments. The 43 runs accounts for accounts for 429.6MB of data stored in a HDF5 file, from wich, the seleceted fields were choosen to build snapshot matrices

```
'Heat_Flux_UPPER_WALL', 'Mach', 'Pressure', 'Temperature', 'Temperature_Solid',
'Temperature_Solid_INNERWALL'
```

For each experiment a snapshot vector \mathbf{S}_i , corresponding to the concatation of fluid and solid domain 2D numerical solutions were obtained.

$$\mathbf{S}_i(T_{0in}, p_{0in}, t_{wall}, CP3_y) = \begin{bmatrix} \mathbf{q}_{upperWall} \\ \mathbf{P}_{fluid} \\ \mathbf{T}_{fluid} \\ \mathbf{M}_{fluid} \\ \mathbf{T}_{solid} \\ \mathbf{T}_{solidInner} \end{bmatrix}^{252840 \times 1}$$

, the snapshots \mathbf{S}_i were then concatenated to form the snapshot matrix \mathbf{A} of the Design of Experimen (DoE).

$$\mathbf{A} = \begin{bmatrix} \mathbf{S}_1^T \\ \mathbf{S}_2^T \\ \vdots \\ \mathbf{S}_N^T \end{bmatrix}^{43 \times 252840}$$

```
[4]: import sys
sys.path.append('/home/ppiper/Dropbox/local/github/frog')

from frog.datahandler import HDF5Handler

hfdh = HDF5Handler(
    datapath='/home/ppiper/Dropbox/local/github/explann/data/
    ↪experimental_planning_T0in_limit_clear/hf_transpose.h5',
    datasets = ['Heat_Flux_UPPER_WALL', 'Mach', 'Pressure', 'Temperature',
    ↪'Temperature_Solid', 'Temperature_Solid_INNERWALL'],
)
```

4 Dependent variables (Order Reduction)

The high dimensional space of samples will subsequently be submitted to an order reduction, given by Principal Component Analysis (PCA), resulting in a more manageable, low-dimensional orthogonal basis. Subsequently, a factorial model will be fitted to predict the principal components as a function of the independent variables. The resultant model will then be applied to reconstruct flow field and heat transfer aspects for a designated test set of independent variables. This reconstructed output will be compared against the CFD solutions for error analysis.

The dependent variables are principal components of a POD (Proper Orthogonal Decomposition) of the snapshots matrix \mathbf{A}

$$\mathbf{A} = \mathbf{U} \mathbf{V}^T$$

by truncating the diagonal matrix of singular values, the snapshot matrix can be represented in terms of a reduced basis $\tilde{\mathbf{U}}$ and principal components $\tilde{\mathbf{V}}$

$$\tilde{\mathbf{A}} = \tilde{\mathbf{U}} \tilde{\mathbf{V}}$$

The data were then compressed using 10 principal components of the orthogonal projection, resulting in 24.3MB of data. An approximated 20-fold reduction in storage requirements.

```
[5]: from sklearn.pipeline import Pipeline
from sklearn.decomposition import PCA
from frog.normalization import Normalization, DataHandlerNormalization
import pickle

rom = Pipeline([
    ('scaler', Normalization(bounds=[-1,1])),
    ('pca', PCA(n_components=10)),
])

rom.fit(hfdh.data)

results_pc = rom.transform(hfdh.data)

with open('/home/ppiper/Dropbox/local/github/explann/data/
    ↪experimental_planning_T0in_limit_clear/rom.pkl','wb') as f:
    pickle.dump(rom,f)

with open('/home/ppiper/Dropbox/local/github/explann/data/
    ↪experimental_planning_T0in_limit_clear/rom.pkl','rb') as f:
    rom = pickle.load(f)
```

The principal components are then joined to the CCD DoE to form full tables for factorial model construction.

```
[6]: import pandas as pd
results = {f'L{i}': results_pc[:,i] for i in range(results_pc.shape[1])}

ccd.append_results(results)
ccd.doe
```

```
[6]:
```

	t_wall	CP3_y	T_0in	p_0in	T_e	L0	L1 \
Index							
1	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000	47.655208	-2.574525
2	1.000000	-1.000000	-1.000000	-1.000000	-1.000000	47.657308	-2.584284
3	-1.000000	1.000000	-1.000000	-1.000000	-1.000000	47.482853	2.523185
4	1.000000	1.000000	-1.000000	-1.000000	-1.000000	47.484867	2.512161
5	-1.000000	-1.000000	1.000000	-1.000000	-1.000000	47.629272	-2.501821
6	1.000000	-1.000000	1.000000	-1.000000	-1.000000	47.632879	-2.517772
7	-1.000000	1.000000	1.000000	-1.000000	-1.000000	47.456260	2.599557
8	1.000000	1.000000	1.000000	-1.000000	-1.000000	47.459997	2.581783
9	-1.000000	-1.000000	-1.000000	1.000000	-1.000000	-47.418552	-3.711689
10	1.000000	-1.000000	-1.000000	1.000000	-1.000000	-47.415844	-3.725914
11	-1.000000	1.000000	-1.000000	1.000000	-1.000000	-47.666183	3.624649
12	1.000000	1.000000	-1.000000	1.000000	-1.000000	-47.663805	3.609438
13	-1.000000	-1.000000	1.000000	1.000000	-1.000000	-47.451135	-3.618356
14	1.000000	-1.000000	1.000000	1.000000	-1.000000	-47.446400	-3.641930
15	-1.000000	1.000000	1.000000	1.000000	-1.000000	-47.698985	3.721687
16	1.000000	1.000000	1.000000	1.000000	-1.000000	-47.694650	3.696741
17	-1.000000	-1.000000	-1.000000	-1.000000	1.000000	47.655208	-2.574525
18	1.000000	-1.000000	-1.000000	-1.000000	1.000000	47.657308	-2.584284
19	-1.000000	1.000000	-1.000000	-1.000000	1.000000	47.482853	2.523185
20	1.000000	1.000000	-1.000000	-1.000000	1.000000	47.484867	2.512161
21	-1.000000	-1.000000	1.000000	-1.000000	1.000000	47.629272	-2.501821
22	1.000000	-1.000000	1.000000	-1.000000	1.000000	47.632879	-2.517772
23	-1.000000	1.000000	1.000000	-1.000000	1.000000	47.456260	2.599557
24	1.000000	1.000000	1.000000	-1.000000	1.000000	47.459997	2.581783
25	-1.000000	-1.000000	-1.000000	1.000000	1.000000	-47.418552	-3.711689
26	1.000000	-1.000000	-1.000000	1.000000	1.000000	-47.415844	-3.725914
27	-1.000000	1.000000	-1.000000	1.000000	1.000000	-47.666183	3.624649
28	1.000000	1.000000	-1.000000	1.000000	1.000000	-47.663805	3.609438
29	-1.000000	-1.000000	1.000000	1.000000	1.000000	-47.451135	-3.618356
30	1.000000	-1.000000	1.000000	1.000000	1.000000	-47.446400	-3.641930
31	-1.000000	1.000000	1.000000	1.000000	1.000000	-47.698985	3.721687
32	1.000000	1.000000	1.000000	1.000000	1.000000	-47.694650	3.696741
33	0.000000	0.000000	0.000000	0.000000	0.000000	0.025936	-0.038532
34	-2.378414	0.000000	0.000000	0.000000	0.000000	0.022612	-0.015342
35	2.378414	0.000000	0.000000	0.000000	0.000000	0.029698	-0.056069
36	0.000000	-2.378414	0.000000	0.000000	0.000000	0.137596	-7.218266
37	0.000000	2.378414	0.000000	0.000000	0.000000	-0.381774	7.591583
38	0.000000	0.000000	-2.378414	0.000000	0.000000	0.059251	-0.135482
39	0.000000	0.000000	2.378414	0.000000	0.000000	-0.009178	0.056877

40	0.000000	0.000000	0.000000	-2.378414	0.000000	113.128140	-0.016841
41	0.000000	0.000000	0.000000	2.378414	0.000000	-113.070333	-0.076683
42	0.000000	0.000000	0.000000	0.000000	-2.378414	0.025936	-0.038532
43	0.000000	0.000000	0.000000	0.000000	2.378414	0.025936	-0.038532

	L2	L3	L4	L5	L6	L7	L8 \
Index							
1	1.054864	0.116466	0.006886	0.026542	-0.019255	0.012261	-0.003517
2	1.705080	-0.057877	0.004462	0.046149	-0.004435	-0.013983	0.008446
3	1.070312	0.115771	0.007093	0.020386	-0.025199	0.005370	-0.005530
4	1.748841	-0.031342	0.003471	0.026343	-0.011534	-0.007418	0.008019
5	-1.897897	0.122485	-0.010489	-0.061067	0.013869	0.004764	0.001125
6	-0.854666	-0.157822	-0.009886	-0.029965	0.015498	-0.008033	0.008307
7	-1.962213	0.058714	-0.004065	-0.022829	-0.001661	-0.012595	-0.013704
8	-0.875525	-0.179893	-0.005059	-0.016389	-0.003456	-0.008670	-0.003721
9	1.184190	0.148468	0.003752	-0.001800	0.000860	0.003282	-0.012650
10	2.135199	-0.085025	-0.001124	-0.016591	0.008043	-0.013796	-0.002655
11	1.288358	0.170554	-0.002338	-0.021060	0.008651	-0.001266	-0.003357
12	2.268540	-0.022280	-0.010885	-0.053166	0.020144	0.008198	0.006091
13	-2.496137	0.145204	0.006485	0.028797	0.001590	-0.001518	0.004297
14	-0.984372	-0.229059	0.005923	0.006421	-0.017370	0.012474	-0.000379
15	-2.469012	0.095408	0.006392	0.063492	0.008184	-0.021897	0.007073
16	-0.914726	-0.216737	0.001333	0.009757	-0.010209	0.027114	0.000185
17	1.054864	0.116466	0.006886	0.026542	-0.019255	0.012261	-0.003517
18	1.705080	-0.057877	0.004462	0.046149	-0.004435	-0.013983	0.008446
19	1.070312	0.115771	0.007093	0.020386	-0.025199	0.005370	-0.005530
20	1.748841	-0.031342	0.003471	0.026343	-0.011534	-0.007418	0.008019
21	-1.897897	0.122485	-0.010489	-0.061067	0.013869	0.004764	0.001125
22	-0.854666	-0.157822	-0.009886	-0.029965	0.015498	-0.008033	0.008307
23	-1.962213	0.058714	-0.004065	-0.022829	-0.001661	-0.012595	-0.013704
24	-0.875525	-0.179893	-0.005059	-0.016389	-0.003456	-0.008670	-0.003721
25	1.184190	0.148468	0.003752	-0.001800	0.000860	0.003282	-0.012650
26	2.135199	-0.085025	-0.001124	-0.016591	0.008043	-0.013796	-0.002655
27	1.288358	0.170554	-0.002338	-0.021060	0.008651	-0.001266	-0.003357
28	2.268540	-0.022280	-0.010885	-0.053166	0.020144	0.008198	0.006091
29	-2.496137	0.145204	0.006485	0.028797	0.001590	-0.001518	0.004297
30	-0.984372	-0.229059	0.005923	0.006421	-0.017370	0.012474	-0.000379
31	-2.469012	0.095408	0.006392	0.063492	0.008184	-0.021897	0.007073
32	-0.914726	-0.216737	0.001333	0.009757	-0.010209	0.027114	0.000185
33	-0.035311	-0.020620	-0.031631	0.018992	-0.033009	0.004036	-0.009210
34	-1.611487	0.417478	-0.036272	-0.035432	-0.028328	0.022534	0.024267
35	1.020713	-0.226146	-0.035953	-0.007553	-0.032945	0.004386	0.014950
36	-0.059227	-0.014131	0.189392	-0.011965	0.017133	0.001690	0.000903
37	0.028908	-0.014403	0.190904	-0.011537	0.015566	0.002630	-0.000132
38	3.737966	0.092381	-0.044229	-0.044475	-0.002733	-0.021055	0.002082
39	-3.682362	-0.139727	-0.048415	-0.052666	-0.000609	-0.014789	-0.004364
40	0.340592	-0.011511	-0.054779	0.059510	0.105344	0.029156	-0.003415

41	0.329156	-0.028152	-0.069653	0.037104	0.058162	-0.005234	-0.002726
42	-0.035311	-0.020620	-0.031631	0.018992	-0.033009	0.004036	-0.009210
43	-0.035311	-0.020620	-0.031631	0.018992	-0.033009	0.004036	-0.009210

L9

Index

1	-0.003013
2	-0.001133
3	-0.004666
4	-0.007382
5	-0.008234
6	0.003685
7	0.005997
8	0.009605
9	0.009544
10	0.007812
11	0.001258
12	-0.006560
13	-0.008894
14	-0.001259
15	0.003627
16	-0.000820
17	-0.003013
18	-0.001133
19	-0.004666
20	-0.007382
21	-0.008234
22	0.003685
23	0.005997
24	0.009605
25	0.009544
26	0.007812
27	0.001258
28	-0.006560
29	-0.008894
30	-0.001259
31	0.003627
32	-0.000820
33	-0.002065
34	0.016765
35	0.010513
36	-0.000792
37	0.000395
38	-0.007991
39	-0.012773
40	0.004612
41	-0.003670


```
42     -0.002065
43     -0.002065
```

5 Fitting Factorial Model

The CCD factorial model accounts for second order terms in each L_i component of the \mathbf{L} matrix.

```
[7]: from explann.models import FactorialModel
from explann.dataio import ImportString, ImportXLSX
from explann.plot import ParetoPlot
import matplotlib.pyplot as plt

expressions = {f'{key}': f'{key} ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e +
    np.power(t_wall, 2) + np.power(T_0in, 2) + np.power(p_0in, 2) + np.
    power(CP3_y,2) + np.power(CP3_y, 2)' for key in results.keys()}

fm_ccd = FactorialModel(
    data = ccd.doe,
    functions = expressions,
    levels = ccd.levels,
)
expressions
```

```
[7]: {'L0': 'L0 ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e + np.power(t_wall, 2) +
np.power(T_0in, 2) + np.power(p_0in, 2) + np.power(CP3_y,2) + np.power(CP3_y,
2)',
'L1': 'L1 ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e + np.power(t_wall, 2) +
np.power(T_0in, 2) + np.power(p_0in, 2) + np.power(CP3_y,2) + np.power(CP3_y,
2)',
'L2': 'L2 ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e + np.power(t_wall, 2) +
np.power(T_0in, 2) + np.power(p_0in, 2) + np.power(CP3_y,2) + np.power(CP3_y,
2)',
'L3': 'L3 ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e + np.power(t_wall, 2) +
np.power(T_0in, 2) + np.power(p_0in, 2) + np.power(CP3_y,2) + np.power(CP3_y,
2)',
'L4': 'L4 ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e + np.power(t_wall, 2) +
np.power(T_0in, 2) + np.power(p_0in, 2) + np.power(CP3_y,2) + np.power(CP3_y,
2)',
'L5': 'L5 ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e + np.power(t_wall, 2) +
np.power(T_0in, 2) + np.power(p_0in, 2) + np.power(CP3_y,2) + np.power(CP3_y,
2)',
'L6': 'L6 ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e + np.power(t_wall, 2) +
np.power(T_0in, 2) + np.power(p_0in, 2) + np.power(CP3_y,2) + np.power(CP3_y,
2)',
'L7': 'L7 ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e + np.power(t_wall, 2) +
np.power(T_0in, 2) + np.power(p_0in, 2) + np.power(CP3_y,2) + np.power(CP3_y,
```

```

2) ',
  'L8': 'L8 ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e + np.power(t_wall, 2) +
np.power(T_0in, 2) + np.power(p_0in, 2) + np.power(CP3_y,2) + np.power(CP3_y,
2) ',
  'L9': 'L9 ~ 1 + t_wall * CP3_y * T_0in * p_0in * T_e + np.power(t_wall, 2) +
np.power(T_0in, 2) + np.power(p_0in, 2) + np.power(CP3_y,2) + np.power(CP3_y,
2) '}

```

As can be viewed in pareto plots, not all terms are significant, so we can retain fewer terms.

```

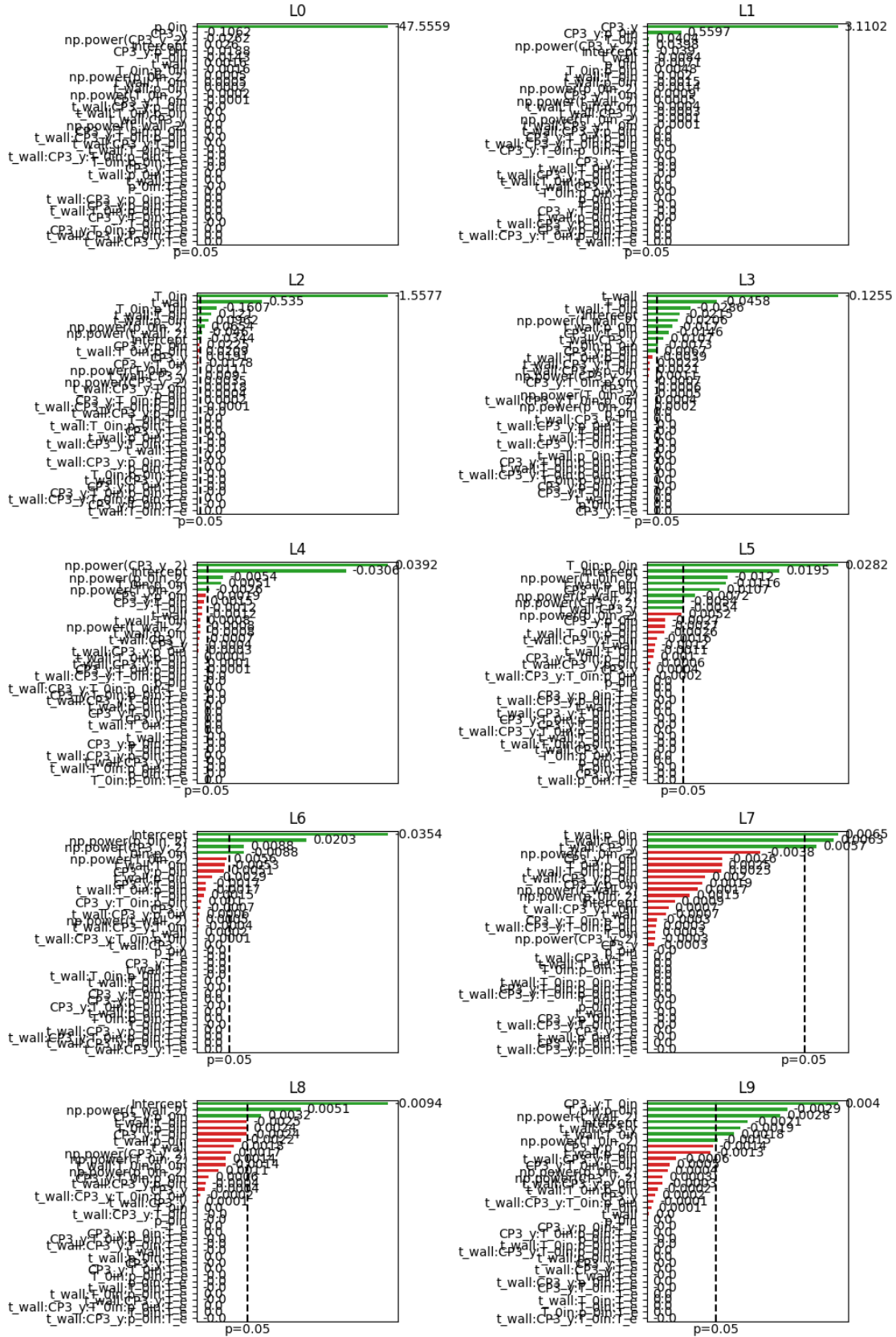
[8]: from explann.plot import ParetoPlot
import matplotlib.pyplot as plt

fig, ax = plt.subplots(5,2, figsize=(10,15))
ax = ax.flatten()

pp = ParetoPlot(fm_ccd)

pp.plot(ax=ax)
plt.tight_layout()

```



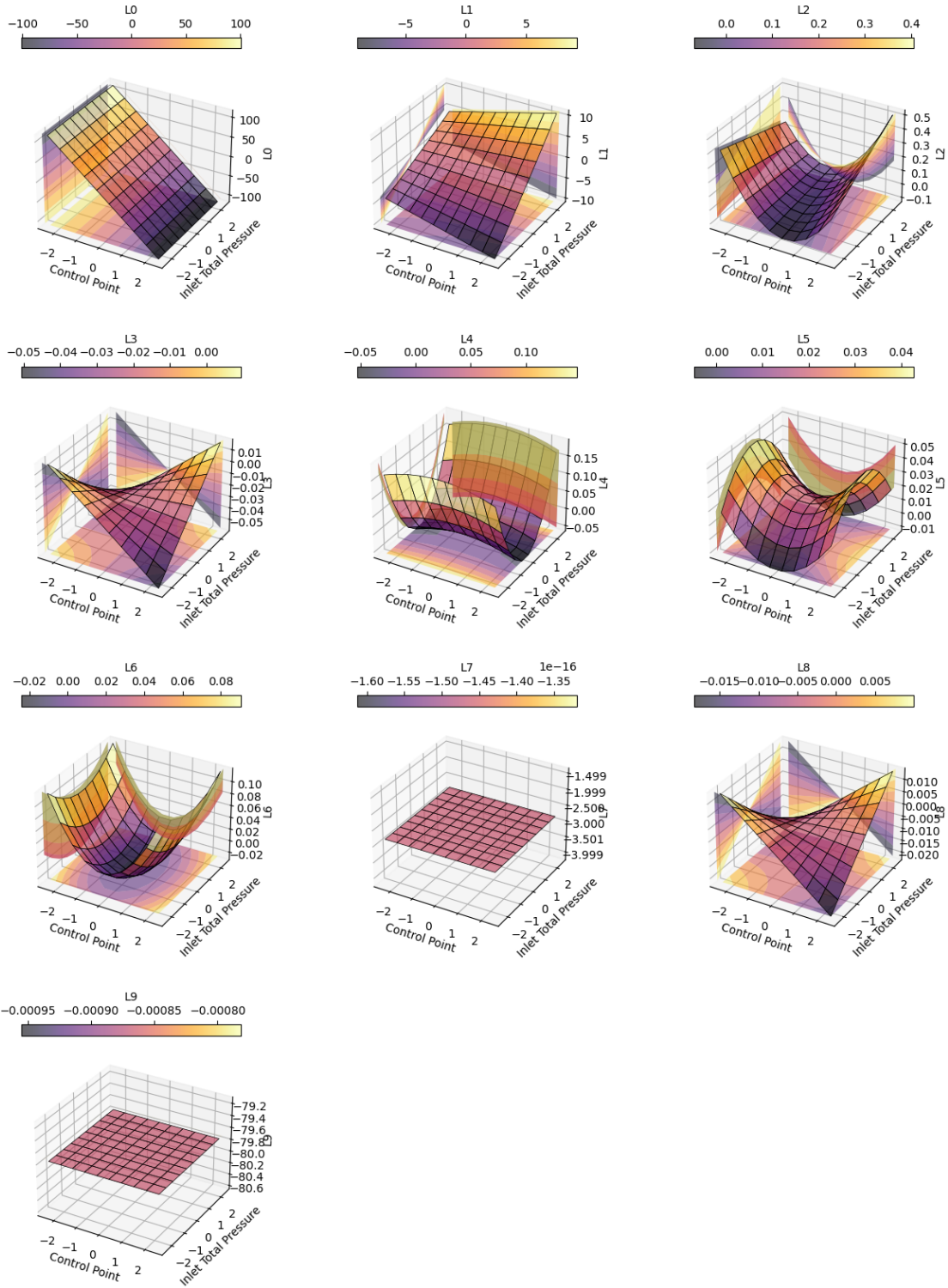
```
[9]: fm_ccd.get_significant_model_functions()
fm_ccd_full = fm_ccd
fm_ccd = fm_ccd.build_significant_models()
```

6 Resulting Model for principal components

```
[10]: from explann.plot import plot_surface

fig, ax = plt.subplots(4,3, figsize=(15,20), subplot_kw={"projection": "3d"})
ax = ax.flatten()

for i,axi in enumerate(ax):#fm_ccd.functions.items():
    if i<len(fm_ccd.functions.items()):
        key = list(fm_ccd.functions.keys())[i]
        plot_surface(x='p_0in', y='CP3_y', z=key,
                      model=fm_ccd,
                      n_pts=10,
                      ax=ax[i],
                      other_params=dict(t_wall=0,T_0in=0,T_e=0),
                      labels=dict(xlabel='Control Point', ylabel='Inlet Total Pressure',
                                ↪zlabel=key), cmap='inferno', scaled=False)
    else:
        ax[i].set_axis_off()
```



7 Test Model Accuracy

The model accuracy was tested by comparing flow reconstruction with full numerical solution for an unseeing set of independent variables

```
[11]: import numpy as np

def surrogate(model, variables, rom=None):
    independent_vars_coded = {}
    independent_vars = variables.copy()
    for var, value in independent_vars.items():
        independent_vars_coded[var] = np.interp(value, model.levels[f'{var}'].
        ↪values, model.levels.index.values)

    L_predicted = []
    for dependent in model.dependent_variables:
        L_predicted.append(model[dependent].predict(independent_vars_coded).
        ↪item())

    L_predicted = np.array(L_predicted)

    if rom is not None:
        L_predicted = rom.inverse_transform(L_predicted)

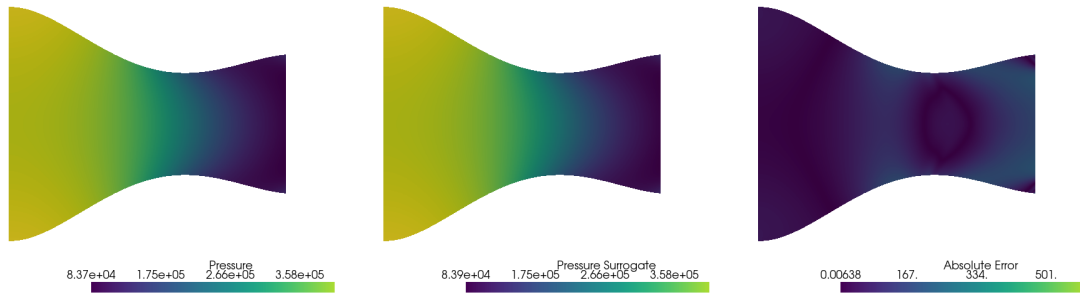
    return L_predicted

surrogate_solution = surrogate(
    model=fm_ccd_full,
    variables={
        't_wall': 0.006044329228014826,
        'CP3_y': -0.001277584765410799,
        'T_0in': 616.0,
        'p_0in': 456429.13834591914,
        'T_e': 318.0
    },
    rom=rom)
```

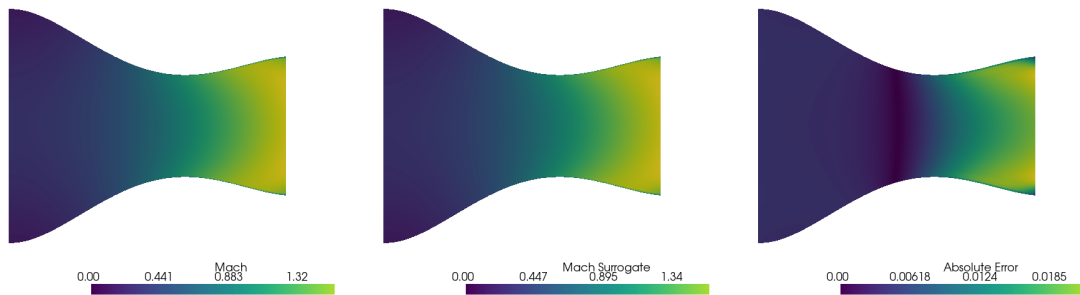
inverse_transform

```
[12]: from plot_2d import plot_property
```

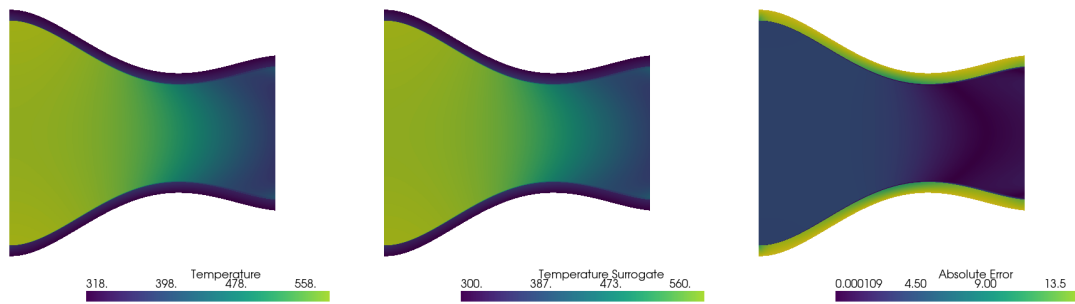
```
[13]: plot_property(
    prop='Pressure',
    unseeing_path='/home/ppiper/Dropbox/local/github/explann/data/lhs/10/SU2/
    ↪outputs/cht_setupSU2.vtm',
    surrogate_solution=surrogate_solution,
    hfdh=hfdh,
    solid=False)
```



```
[14]: plot_property(
    prop='Mach',
    unseeing_path='/home/ppiper/Dropbox/local/github/explann/data/lhs/10/SU2/
    ↪outputs/cht_setupSU2.vtm',
    surrogate_solution=surrogate_solution,
    hfdh=hfdh,
    solid=False)
```



```
[15]: plot_property(
    prop='Temperature',
    unseeing_path='/home/ppiper/Dropbox/local/github/explann/data/lhs/10/SU2/
    ↪outputs/cht_setupSU2.vtm',
    surrogate_solution=surrogate_solution,
    hfdh=hfdh,
    solid=True)
```



8 References

Back, L.H., Massier, P.F. and Gier, H.L., 1964. “Convective heat transfer in a convergent-divergent nozzle”. *International Journal of Heat and Mass Transfer*, Vol. 7, pp. 549–568.

Economon, T.D., Palacios, F., Copeland, S.R., Lukaczyk, T.W. and Alonso, J.J., 2016. “SU2: An open-source suite for multiphysics simulation and design”. *AIAA Journal*, Vol. 54, No. 3, pp. 828–846. doi:10.2514/1.j053813.