Sample

May 12, 2021

[1]:
```
import pandas as pd
from copy import deepcopy
import matplotlib.pyplot as plt
import re
import numpy as np
from matplotlib import gridspec
import matplotlib
```

1 Helper functions

These are borrowed from the `Convert.ipynb` file.

[2]:
```
headings = ['Building Identifier',
            'Country',
             'City',
             'Quality / Stage of Data',
             'Construction Date',
             'Building Type',
             'Gross Floor Area']
```

[3]:
```
df = pd.read_excel('../Dataset/dataset.xlsx',header=1).drop('Unnamed: 0',axis=1)
```

[4]:
```
f = lambda x: x if x[-2] != '.' else x.rsplit('.',1)[0]
df = pd.concat([df[headings],df[[c for c in df.columns if 'kg' in c]].
 ↪groupby(f,axis=1).mean()],axis=1)
```

[5]:
```
name_conversion = pd.read_csv('name_conversion.csv')
building_name_conversion = pd.read_csv('building_type_name_conversion.csv')
```

[6]:
```
building_name_map = {k['Building Code']:k['Building Type'] for _,k in␣
 ↪building_name_conversion.iterrows()}
```

[7]:
```
name_map = {k.Code:k.Category for _,k in name_conversion.iterrows()}
```

[8]:
```
additional_categories_map = {v:k for k,v in {
    'Continuous Footings':'0CF',
    'Foundation Walls':'0FW',
```

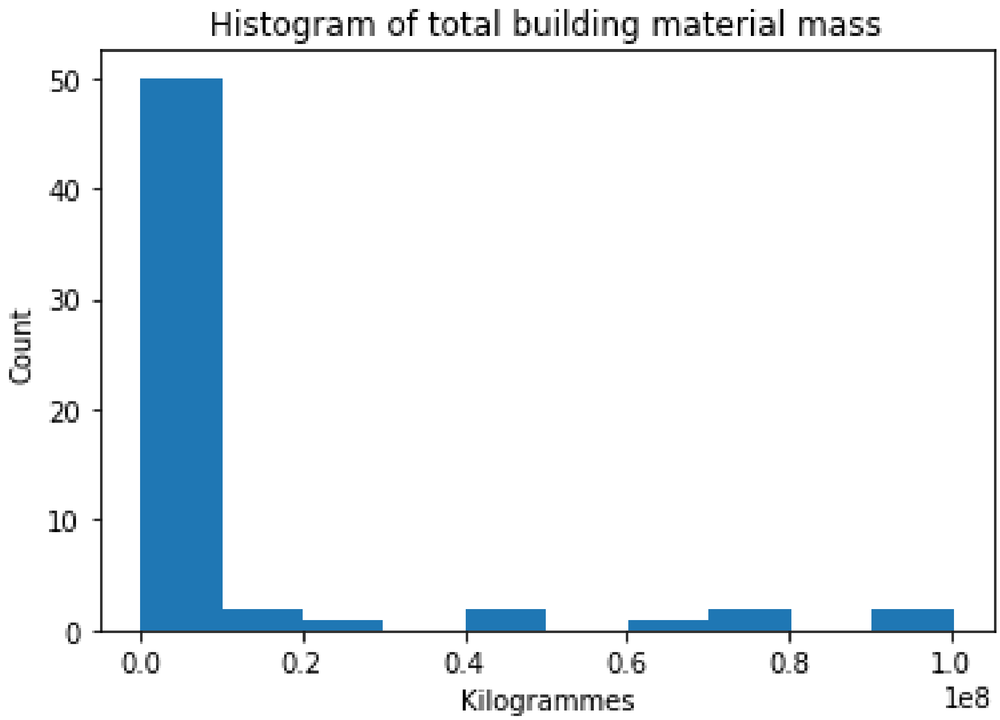
```
    'Spread Footings':'OSF',
    'Column Piers':'OCP',
    'Columns Supporting Floors':'CSF',
    'Floor Girders and Beams':'FGB',
    'Floor Trusses':'OFT',
    'Floor Joists':'OFJ',
    'Columns Supporting Roofs':'CSR',
    'Roof Girders and Beams':'RGB',
    'Roof Trusses':'ORT',
    'Roof Joists':'ORJ',
    'Parking Bumpers':'OPB',
    'Precast Concrete Stair Treads':'PCS',
    'Roof Curbs':'ORC',
    'Exterior Wall Construction':'EWC',
    'Composite Decking':'CPD',
    'Cast-in-Place concrete':'CIC',
    'Floor Structural Frame':'FSF',
    'Associated Metal Fabrications':'AMF',
    'Floor Construction Supplementary Components':'FCS',
    'Roof Construction Supplementary Components':'RCS',
    'Residential Elevators':'ORE',
    'Vegetated Low-Slope Roofing':'VLR',
    'Swimming Pools':'SWP',
    'Excavation Soil Anchors':'ESA',
    'Floor Trusses':'FTS',
    'Roof Window and Skylight Performance':'RWS',
    'Rainwater Storage Tanks':'RST',
    'Gray Water Tanks':'GWT'}.items()
}

additional_categories_map['OFT'] = 'Floor Trusses'
```

2 1. Plot sample figures

Here we plot building material mass.

[9]:
```
plt.hist(df[[c for c in df.columns if 'kg' in c]].sum(axis=1));
plt.title('Histogram of total building material mass')
plt.xlabel('Kilogrammes')
plt.ylabel('Count');
```

[9]: Text(0, 0.5, 'Count')



3 2. Investigate a specific material

In this example, we select only columns that match the MasterFormat code for Structural Concrete. Then, we aggregate based on Level 2 UniFormat code.

[10]:
```
cols = [d for d in df.columns if '03 31 00' in d]
```

[11]:
```
f = lambda x: re.split('[_\.\ ]',x)[1][0:3]
concrete_df = pd.concat([df[headings],df[cols].groupby(f,axis=1).sum()],axis=1).
↪rename(columns=name_map)
```

[12]:
```
concrete_df
```

[12]:
```
    Building Identifier Country City Quality / Stage of Data  \
0                     1      CA  TOR                   00IFC
1                     2      CA  TOR                   00IFC
2                     3      CA  TOR                   00IFC
3                     4      CA  TOR                   00IFC
4                     5      CA  TOR                   00IFC
5                     6      CA  TOR                   00IFC
6                     7      CA  TOR                   00IFC
7                     8      CA  TOR                   00IFC
8                     9      CA  TOR                   00IFC
```

9	10	CA	TOR	00IFC
10	11	CA	TOR	00IFC
11	12	CA	TOR	00IFC
12	13	CA	TOR	00IFC
13	14	CA	TOR	00IFC
14	15	CA	TOR	00IFC
15	16	CA	TOR	00IFC
16	17	CA	TOR	00IFC
17	18	CA	TOR	00IFC
18	19	CA	TOR	00IFC
19	20	CA	TOR	00IFC
20	21	CA	TOR	00IFC
21	22	CA	TOR	00IFC
22	23	CA	TOR	00IFC
23	24	CA	TOR	00IFC
24	25	CA	TOR	00IFC
25	26	CA	TOR	00IFC
26	27	CA	WIN	00IFC
27	28	CA	TOR	00IFC
28	29	CA	TOR	00IFC
29	30	CA	TOR	00IFC
30	31	CA	TOR	00IFC
31	32	CA	TOR	00IFC
32	33	CA	TOR	00IFC
33	34	CA	TOR	00IFC
34	35	CA	TOR	00IFC
35	36	CA	TOR	00IFC
36	37	CA	TOR	00IFC
37	38	CA	TOR	00IFC
38	39	CA	TOR	00IFC
39	40	US	NEW	00IFC
40	41	CA	TOR	00IFC
41	42	CA	TOR	00IFC
42	43	CA	TOR	00IFC
43	44	CA	TOR	00IFC
44	45	CA	TOR	00IFC
45	46	CA	TOR	00IFC
46	47	CA	TOR	00IFC
47	48	CA	RIC	0IARC
48	49	CA	TOR	00IFC
49	50	CA	TOR	00IFC
50	51	CA	TOR	00IFC
51	52	CA	TOR	00IFC
52	53	CA	TOR	00IFC
53	54	CA	TOR	00IFC
54	55	CA	TOR	00IFC
55	56	CA	TOR	00IFC

56	57	CA	TOR	00IFC
57	58	CA	TOR	00IFC
58	59	CA	TOR	0IFBP
59	60	CA	TOR	0IFBP

	Construction Date	Building Type	Gross Floor Area	Foundations \
0	2021	SND	521.18	1.709236e+05
1	2021	SND	389.24	1.082862e+05
2	2021	SND	411.64	1.909299e+05
3	2021	SND	269.56	6.736923e+04
4	2011	OFF	11248.00	0.000000e+00
5	2011	APB	11317.00	0.000000e+00
6	2021	SND	445.99	1.295202e+05
7	2021	SND	438.45	1.174431e+05
8	2021	SND	714.07	1.927680e+05
9	2021	SND	343.24	9.564723e+04
10	2009	OFF	73083.00	0.000000e+00
11	1917	SMR	199.93	9.927316e+04
12	2021	SND	226.89	5.835472e+04
13	2021	SND	611.73	2.061282e+05
14	2021	SND	343.44	1.436814e+05
15	2021	SND	613.38	1.789777e+05
16	1969	SNR	413.72	9.293583e+04
17	1969	SNR	333.49	1.186380e+05
18	2021	SND	178.38	6.408230e+04
19	2021	SND	323.80	4.733438e+04
20	2020	SND	837.56	2.605656e+05
21	2021	SND	587.86	2.455371e+05
22	2021	SND	568.21	1.415184e+05
23	2021	SMD	234.73	8.560215e+04
24	2021	SND	294.84	7.580863e+04
25	2021	SND	496.77	1.205336e+05
26	2007	OFF	73600.00	0.000000e+00
27	2021	SND	643.30	9.718853e+04
28	2021	SND	701.61	1.810933e+05
29	2021	SMD	257.75	8.183304e+04
30	2021	SND	378.70	1.477228e+05
31	2021	SND	324.16	1.188635e+05
32	2020	SND	533.53	1.627046e+05
33	2020	SMD	254.05	8.882102e+04
34	2021	SND	423.03	9.980270e+04
35	2021	SND	328.16	1.238544e+05
36	2021	SND	421.59	1.760423e+05
37	2020	SND	628.59	2.298828e+05
38	2021	SND	464.51	1.886381e+05
39	2017	EDU	8983.00	0.000000e+00
40	2021	SND	346.14	9.748630e+04

41	1913	SNR	161.08	5.362299e+04
42	2021	SND	891.97	2.157609e+05
43	2021	SND	525.61	2.567725e+05
44	2021	SND	502.87	1.372402e+05
45	2021	SND	379.18	1.437386e+05
46	2021	SND	549.65	1.435894e+05
47	2016	EDU	6819.00	0.000000e+00
48	2020	SND	393.82	7.294707e+04
49	2021	SND	648.14	2.216331e+05
50	1988	INS	21934.00	0.000000e+00
51	2018	APB	53146.02	1.115822e+07
52	2018	MIX	33975.25	4.220040e+06
53	2017	APB	69784.00	7.912944e+06
54	2017	APB	39409.04	9.350736e+06
55	2016	APB	53871.00	1.627512e+06
56	2020	LNW	137.23	3.111394e+04
57	2020	LNW	144.92	3.241172e+04
58	2019	LNW	83.10	3.347723e+04
59	2021	LNW	234.79	8.584207e+04

	Subgrade Enclosures	Slabs-On-Grade	Substructure Interior	\
0	0.0	6.721219e+04	0.0	
1	0.0	3.576043e+04	0.0	
2	0.0	3.246461e+04	0.0	
3	0.0	1.595211e+04	0.0	
4	0.0	0.000000e+00	0.0	
5	0.0	0.000000e+00	0.0	
6	0.0	3.521918e+04	0.0	
7	0.0	4.289057e+04	0.0	
8	0.0	8.446873e+04	11307.2	
9	0.0	2.033114e+04	0.0	
10	0.0	0.000000e+00	0.0	
11	0.0	1.971760e+04	0.0	
12	0.0	1.435987e+04	0.0	
13	0.0	4.140039e+04	0.0	
14	0.0	2.246836e+04	0.0	
15	0.0	4.219445e+04	0.0	
16	0.0	3.376814e+04	0.0	
17	0.0	2.622366e+04	0.0	
18	0.0	2.343862e+04	0.0	
19	0.0	2.368485e+04	0.0	
20	0.0	6.344851e+04	0.0	
21	0.0	6.865710e+04	0.0	
22	0.0	6.684690e+04	0.0	
23	0.0	1.294360e+04	0.0	
24	0.0	1.791821e+04	0.0	
25	0.0	5.137996e+04	0.0	

26	0.0	0.000000e+00	0.0
27	0.0	5.230228e+04	0.0
28	0.0	6.233222e+04	0.0
29	0.0	1.211886e+04	0.0
30	0.0	3.514722e+04	0.0
31	0.0	2.011968e+04	0.0
32	0.0	3.674638e+04	0.0
33	0.0	1.160387e+04	0.0
34	0.0	3.329286e+04	0.0
35	0.0	1.931159e+04	0.0
36	0.0	3.304437e+04	0.0
37	0.0	5.528816e+04	0.0
38	0.0	2.866777e+04	0.0
39	0.0	0.000000e+00	0.0
40	0.0	2.237098e+04	0.0
41	0.0	1.235658e+04	0.0
42	0.0	5.949332e+04	0.0
43	0.0	3.378685e+04	0.0
44	0.0	3.951047e+04	0.0
45	0.0	2.913799e+04	0.0
46	0.0	3.506390e+04	0.0
47	0.0	0.000000e+00	0.0
48	0.0	3.364275e+04	0.0
49	0.0	6.099032e+04	0.0
50	0.0	0.000000e+00	0.0
51	2728008.0	3.647520e+05	11033448.0
52	1705680.0	3.834720e+05	5400288.0
53	3246168.0	1.407000e+06	14052000.0
54	3567720.0	9.045840e+05	7607280.0
55	3438168.0	7.174800e+05	22907184.0
56	0.0	1.439848e+04	0.0
57	0.0	2.000253e+04	0.0
58	0.0	5.412759e+03	0.0
59	0.0	1.962799e+04	0.0

	Substructure Related Activities	Superstructure \
0	0.0	1.938810e+03
1	0.0	1.397610e+03
2	0.0	1.528710e+02
3	0.0	1.212090e+01
4	0.0	0.000000e+00
5	0.0	0.000000e+00
6	0.0	5.332590e+02
7	0.0	1.970790e+03
8	0.0	4.049670e+03
9	0.0	9.440170e+02
10	0.0	0.000000e+00

11	0.0	0.000000e+00
12	0.0	9.785830e+02
13	0.0	5.381500e+02
14	0.0	0.000000e+00
15	0.0	0.000000e+00
16	0.0	0.000000e+00
17	0.0	7.514840e+03
18	0.0	0.000000e+00
19	0.0	2.111800e+03
20	0.0	3.270810e+03
21	0.0	2.533580e+03
22	0.0	6.016340e+02
23	0.0	1.827610e+03
24	0.0	5.977480e+02
25	0.0	2.540900e+03
26	0.0	0.000000e+00
27	0.0	7.189470e+02
28	0.0	2.276420e+02
29	0.0	1.587900e+03
30	0.0	1.096510e+04
31	0.0	5.530400e+03
32	0.0	1.360980e+03
33	0.0	2.177290e+03
34	0.0	6.524310e+02
35	0.0	3.944150e+03
36	0.0	4.401230e+02
37	0.0	8.518740e+02
38	0.0	2.593160e+03
39	0.0	0.000000e+00
40	0.0	2.360810e+02
41	0.0	0.000000e+00
42	0.0	8.599660e+02
43	0.0	1.038810e+03
44	0.0	4.881840e+02
45	0.0	1.267510e+03
46	0.0	1.154890e+03
47	0.0	0.000000e+00
48	0.0	1.835120e+02
49	0.0	1.041320e+03
50	0.0	0.000000e+00
51	133464.0	2.780006e+07
52	112872.0	2.226535e+07
53	169896.0	3.204622e+07
54	276264.0	1.483577e+07
55	93048.0	3.239134e+07
56	0.0	0.000000e+00
57	0.0	0.000000e+00

58	0.0	0.000000e+00
59	0.0	0.000000e+00

	Exterior Vertical Enclosures	Exterior Horizontal Enclosures \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
5	0.0	0.0
6	0.0	0.0
7	0.0	0.0
8	0.0	0.0
9	0.0	0.0
10	0.0	0.0
11	0.0	0.0
12	0.0	0.0
13	0.0	0.0
14	0.0	0.0
15	0.0	0.0
16	0.0	0.0
17	0.0	0.0
18	0.0	0.0
19	0.0	0.0
20	0.0	0.0
21	0.0	0.0
22	0.0	0.0
23	0.0	0.0
24	0.0	0.0
25	0.0	0.0
26	0.0	0.0
27	0.0	0.0
28	0.0	0.0
29	0.0	0.0
30	0.0	0.0
31	0.0	0.0
32	0.0	0.0
33	0.0	0.0
34	0.0	0.0
35	0.0	0.0
36	0.0	0.0
37	0.0	0.0
38	0.0	0.0
39	0.0	0.0
40	0.0	0.0
41	0.0	0.0
42	0.0	0.0

43	0.0	0.0
44	0.0	0.0
45	0.0	0.0
46	0.0	0.0
47	0.0	0.0
48	0.0	0.0
49	0.0	0.0
50	0.0	0.0
51	727896.0	537984.0
52	405408.0	392400.0
53	328032.0	799872.0
54	119088.0	0.0
55	159336.0	0.0
56	0.0	0.0
57	0.0	0.0
58	0.0	0.0
59	0.0	0.0

	Interior Construction	Conveying	Plumbing	Special Construction \
0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0
10	0.0	0.0	0.0	0.0
11	0.0	0.0	0.0	0.0
12	0.0	0.0	0.0	0.0
13	0.0	0.0	0.0	0.0
14	0.0	0.0	0.0	0.0
15	0.0	0.0	0.0	0.0
16	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0
18	0.0	0.0	0.0	0.0
19	0.0	0.0	0.0	0.0
20	0.0	0.0	0.0	0.0
21	0.0	0.0	0.0	0.0
22	0.0	0.0	0.0	0.0
23	0.0	0.0	0.0	0.0
24	0.0	0.0	0.0	0.0
25	0.0	0.0	0.0	0.0
26	0.0	0.0	0.0	0.0
27	0.0	0.0	0.0	0.0

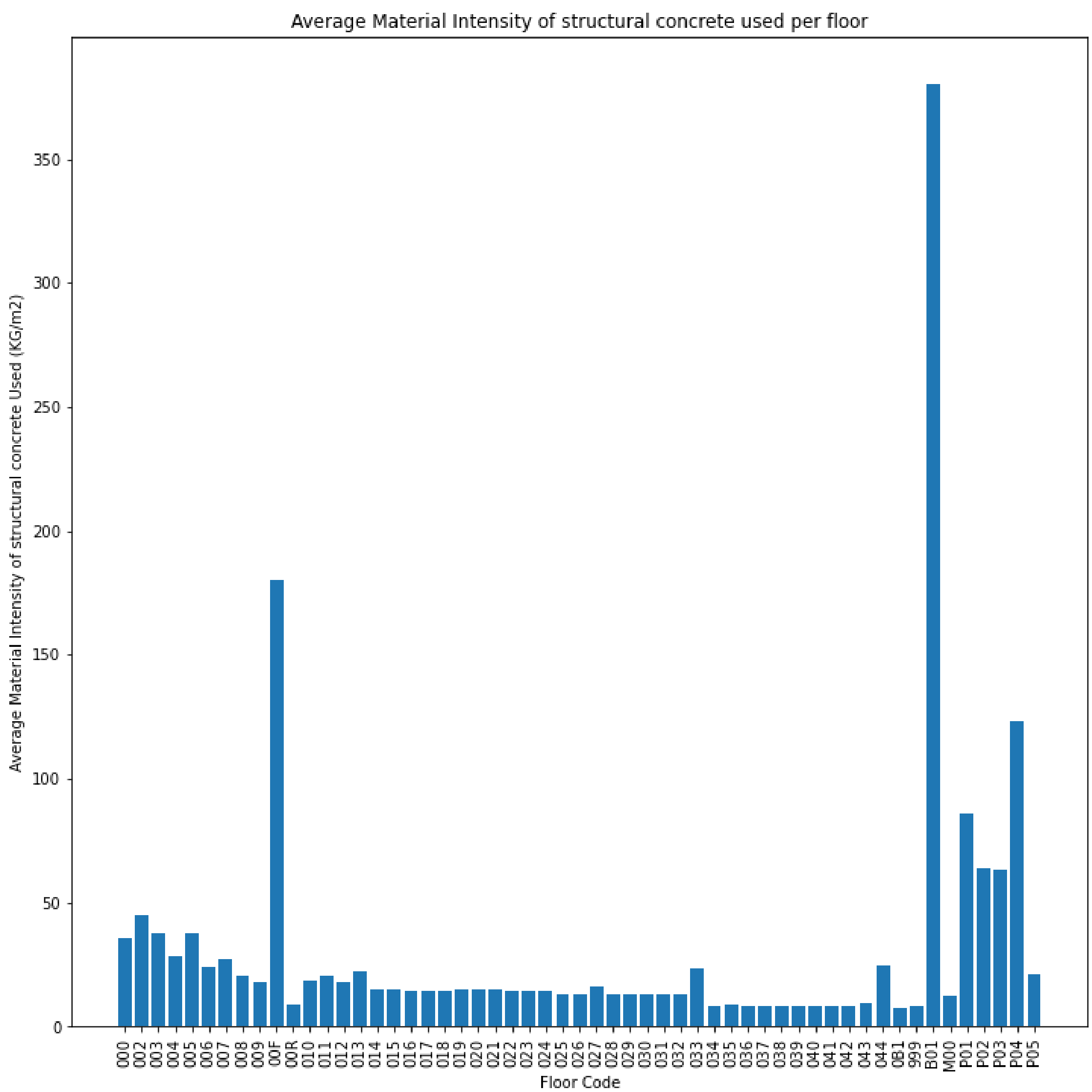
28	0.0	0.0	0.0	0.0
29	0.0	0.0	0.0	0.0
30	0.0	0.0	0.0	0.0
31	0.0	0.0	0.0	0.0
32	0.0	0.0	0.0	0.0
33	0.0	0.0	0.0	0.0
34	0.0	0.0	0.0	0.0
35	0.0	0.0	0.0	0.0
36	0.0	0.0	0.0	0.0
37	0.0	0.0	0.0	0.0
38	0.0	0.0	0.0	0.0
39	0.0	0.0	0.0	0.0
40	0.0	0.0	0.0	0.0
41	0.0	0.0	0.0	0.0
42	0.0	0.0	0.0	0.0
43	0.0	0.0	0.0	0.0
44	0.0	0.0	0.0	0.0
45	0.0	0.0	0.0	0.0
46	0.0	0.0	0.0	0.0
47	0.0	0.0	0.0	0.0
48	0.0	0.0	0.0	0.0
49	0.0	0.0	0.0	0.0
50	0.0	0.0	0.0	0.0
51	6816696.0	2494560.0	0.0	80592.0
52	5893176.0	1829328.0	48816.0	62280.0
53	9050592.0	2304480.0	172032.0	0.0
54	5180976.0	861888.0	130152.0	0.0
55	5604960.0	1664448.0	0.0	220992.0
56	0.0	0.0	0.0	0.0
57	0.0	0.0	0.0	0.0
58	0.0	0.0	0.0	0.0
59	0.0	0.0	0.0	0.0

	Site Improvements
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
5	0.0
6	0.0
7	0.0
8	0.0
9	0.0
10	0.0
11	0.0
12	0.0

13	0.0
14	0.0
15	0.0
16	0.0
17	0.0
18	0.0
19	0.0
20	0.0
21	0.0
22	0.0
23	0.0
24	0.0
25	0.0
26	0.0
27	0.0
28	0.0
29	0.0
30	0.0
31	0.0
32	0.0
33	0.0
34	0.0
35	0.0
36	0.0
37	0.0
38	0.0
39	0.0
40	0.0
41	0.0
42	0.0
43	0.0
44	0.0
45	0.0
46	0.0
47	0.0
48	0.0
49	0.0
50	0.0
51	0.0
52	0.0
53	18384.0
54	97560.0
55	0.0
56	0.0
57	0.0
58	0.0
59	0.0

[13]:
```python
grouping_function = lambda x: x.split('_')[0] #This function takes in a full␣
↪column name, like "000_G2010.20.000_03 00 00.00_m3_1", and returns only the␣
↪floor.
to_draw = df[cols].groupby(grouping_function,axis=1).sum().replace(0,np.NaN).
↪div(df['Gross Floor Area'],axis='rows').mean()
plt.figure(figsize=(12,12))
plt.bar(to_draw.keys(), to_draw.values)
plt.xticks(rotation=90)
plt.title('Average Material Intensity of structural concrete used per floor')
plt.ylabel('Average Material Intensity of structural concrete Used (KG/m2)')
plt.xlabel('Floor Code');
```

[13]: Text(0.5, 0, 'Floor Code')



Now, we will aggregate to Level 3 MasterFormat codes, and display these values for the first three entries.

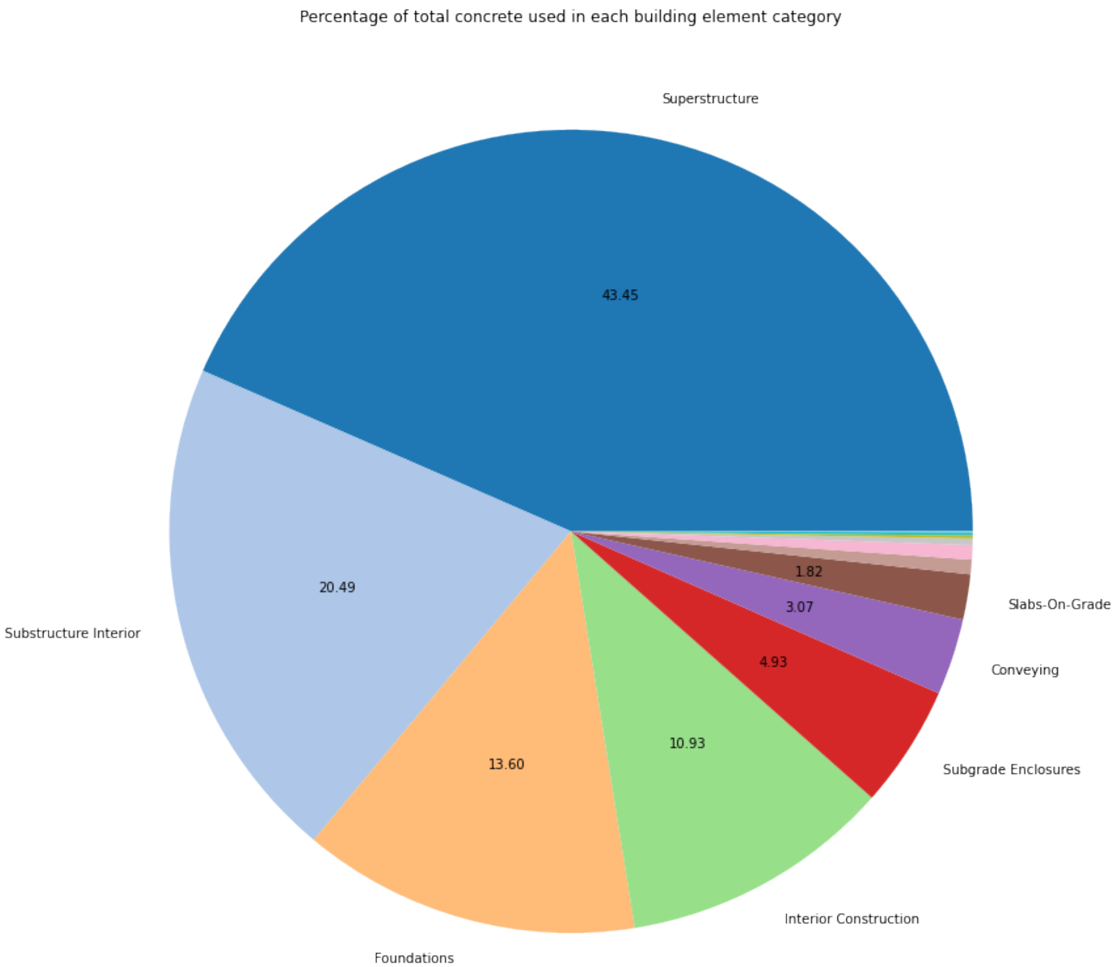
```
[14]: f = lambda x: name_map[re.split('[_\.\ ]',x)[1][0:3]] #This function takes in a␣
      ↪full column name and returns only the Level 3 MasterFormat code.
      concrete_df = df[cols].groupby(f,axis=1).sum()
```

```
[15]: concrete_df.mean().sort_values(ascending=False)
```

```
[15]: Superstructure                      2.156826e+06
      Substructure Interior               1.016858e+06
      Foundations                         6.750566e+05
      Interior Construction               5.424400e+05
      Subgrade Enclosures                 2.447624e+05
      Conveying                           1.525784e+05
      Slabs-On-Grade                      9.043012e+04
      Exterior Vertical Enclosures        2.899600e+04
      Exterior Horizontal Enclosures      2.883760e+04
      Substructure Related Activities     1.309240e+04
      Special Construction                6.064400e+03
      Plumbing                            5.850000e+03
      Site Improvements                   1.932400e+03
      dtype: float64
```

3.1 Pie chart version A: on-pie chart labels for all > 1%

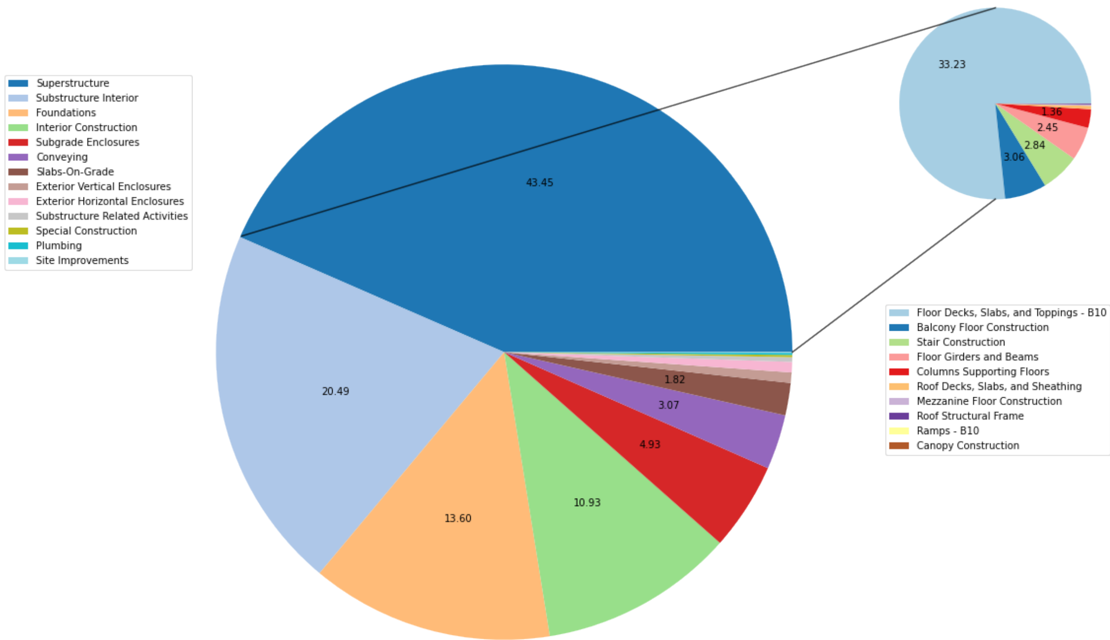
```
[16]: def my_autopct(pct):
          return ('%.2f' % pct) if pct > 1 else ''
      to_plot = concrete_df.mean().sort_values(ascending=False)
      to_plot.plot.pie(figsize=(12,12),colormap='tab20',autopct=my_autopct,labels=[k␣
      ↪if v > 30000 else '' for k,v in to_plot.items()])
      plt.ylabel('')
      plt.title('Percentage of total concrete used in each building element␣
      ↪category');
      # plt.legend(loc='center left',bbox_to_anchor=(-0.20, 0.75));
      plt.tight_layout();
```



3.2 Pie version B: external legend with slice labels

[17]:
```
fig = plt.figure(figsize=(16,12))
gs = gridspec.GridSpec(2, 2, width_ratios=[3, 1])
ax0 = plt.subplot(gs[:,0])

def my_autopct(pct):
    return ('%.2f' % pct) if pct > 1 else ''
to_plot = concrete_df.mean().sort_values(ascending=False)
to_plot.plot.pie(ax=ax0,colormap='tab20',autopct=my_autopct,labeldistance=None)
plt.ylabel('')
plt.legend(loc='center left',bbox_to_anchor=(-0.20, 0.75));
plt.tight_layout();

ax1 = plt.subplot(gs[0,1])
```

```
f = lambda x: \
    additional_categories_map[re.split('[_\.\ ]',x)[3]] \
    if \
    re.split('[_\.\ ]',x)[3] != '000' \
    else \
    name_map['.'.join(re.split('[_\.\ ]',x)[1:3])]

superstructure_df = df[[c for c in cols if 'B10' in c]].groupby(f,axis=1).sum()
to_plot = superstructure_df.mean().sort_values(ascending=False)
def my_autopct(pct):
    return ('%.2f' % ((pct * 0.4335))) if pct > 1 else ''
to_plot.plot.pie(ax=ax1,colormap='Paired',autopct=my_autopct,labeldistance=None)
plt.ylabel('')
plt.legend(loc='center right',bbox_to_anchor=(1, -0.65));
plt.tight_layout();

transFigure = fig.transFigure.inverted()

coord1a = transFigure.transform(ax0.transData.transform([1,0]))
coord2a = transFigure.transform(ax1.transData.transform([0,-0.72]))

coord1b = transFigure.transform(ax0.transData.transform([-0.91,0.35]))
coord2b = transFigure.transform(ax1.transData.transform([0,0.72]))

linea = matplotlib.lines.Line2D((coord1a[0],coord2a[0]),(coord1a[1],coord2a[1]),
                               transform=fig.transFigure,c='black',alpha=0.7)
lineb = matplotlib.lines.Line2D((coord1b[0],coord2b[0]),(coord1b[1],coord2b[1]),
                                transform=fig.transFigure,c='black',alpha=0.7)
fig.lines = linea,lineb,

plt.savefig('concrete_breakdown_pie.pdf')
```



We can produce a pie chart for a single building, also.

[18]:
```
mf_codes = pd.read_csv('mf_name_conversion.csv')
```

[19]:
```
tofind = [
    'Plain Steel Reinforcement Bars',
    'Reinforcement Bars',
    'Structural Steel Framing',
    'Fabric and Grid Reinforcing',
    'Metal Doors',
    'Metal Roof Panel',
    'Metal Stairs',
    'Metal Railings',
    'Steel Decking',
    'Steel Joist Framing',
    'Steel'
] #List of terms we are looking to identify in column names.

tokeep = [
    c for c in mf_codes.Title.values if any(t in c for t in tofind)
] #For each codes' corresponding in MasterFormat

steel_codes = mf_codes[mf_codes.Title.isin(tokeep)]
```

[20]:
```
columns_to_keep = []
for column in df.columns:
    if 'kg' in column:
        code = re.split('_',column)[2]
        for k,c in steel_codes.values:
            if c in code:
                columns_to_keep.append(column)
```

[21]:
```
f = lambda x: mf_codes[mf_codes.Code == str.replace(re.split('_',x)[2],'00','').
↪strip('.')].values[0][0]
steel_df = df[columns_to_keep].groupby(f,axis=1).sum()
```

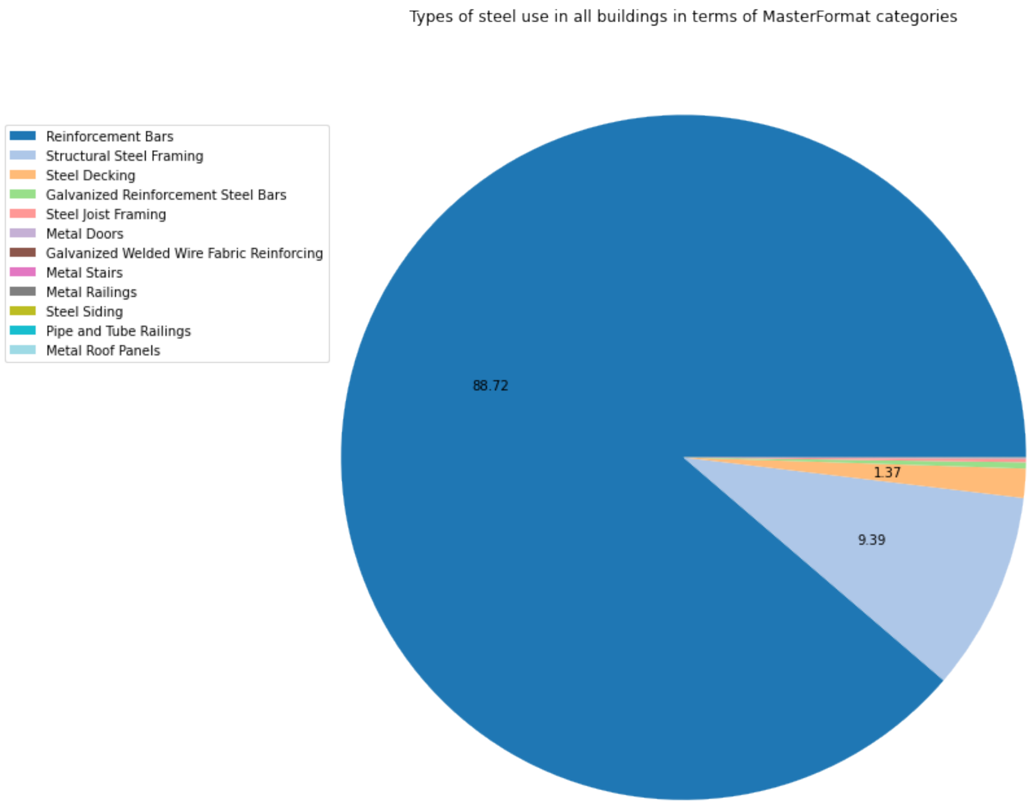
[22]:
```
(steel_df>0).sum(axis=1).sort_values()
```

[22]:
```
15    1
42    1
22    1
36    1
7     1
34    1
31    1
35    1
55    2
58    2
40    2
41    2
1     2
43    2
24    2
23    2
21    2
20    2
54    2
44    2
17    2
16    2
30    2
14    2
45    2
12    2
11    2
32    2
9     2
33    2
3     2
18    2
0     3
```

```
52    3
53    3
56    3
46    3
39    3
29    3
37    3
28    3
27    3
26    3
25    3
13    3
10    3
2     3
38    3
5     3
6     3
8     3
57    4
4     4
49    4
50    4
48    4
47    4
19    4
51    4
59    4
dtype: int64
```

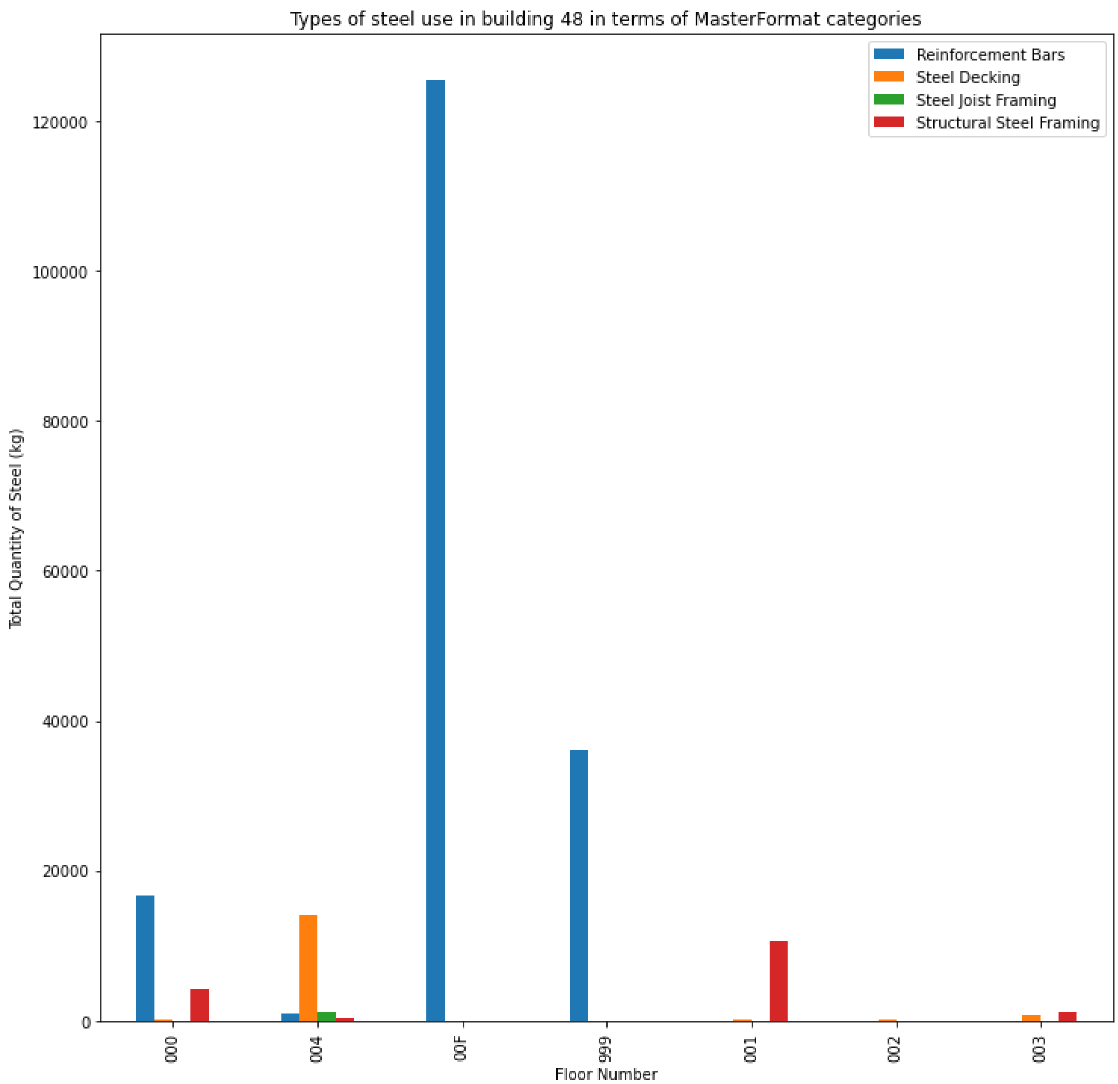
[23]:

```
def my_autopct(pct):
    return ('%.2f' % (pct)) if pct > 1 else ''
to_plot = steel_df.sum().sort_values(ascending=False)
to_plot.plot.
 ↪pie(figsize=(12,12),colormap='tab20',autopct=my_autopct,labeldistance=None)
plt.legend(loc='center left',bbox_to_anchor=(-0.30, 0.75));

plt.ylabel('')
plt.title(f'Types of steel use in all buildings in terms of MasterFormat␣
 ↪categories');
plt.tight_layout();

plt.savefig('steel_composition_pie.pdf')
```



[24]:
```
f = lambda x: mf_codes[mf_codes.Code == str.replace(re.split('_',x)[2],'00','').
 ↪strip('.')].values[0][0] + '/' + x.split('_')[0]
tdf = df[columns_to_keep].groupby(f,axis=1).sum().iloc[47,:]
tdf = tdf[tdf>0]
```

[25]:
```
from collections import defaultdict
todf = defaultdict(dict)
for (a,b),c in zip(tdf.keys().str.split('/'),tdf.values):
    todf[a][b] = c
toplot = pd.DataFrame(todf)
toplot.plot.bar(figsize=(12,12));
plt.xlabel('Floor Number')
plt.ylabel('Total Quantity of Steel (kg)')
plt.title('Types of steel use in building 48 in terms of MasterFormat␣
 ↪categories')
plt.savefig('bar_steel_onebuildingtype_byfloor.pdf')
```



We can also calculate the average for each Level 3 MasterFormat code by year of construction:

[26]:
```
concrete_df = pd.concat([df[headings[1:]],df[cols].groupby(f,axis=1).
 ↪sum()],axis=1)
concrete_df.groupby('Construction Date').mean()
```

[26]:
```
                   Gross Floor Area  Structural Concrete/000  \
Construction Date
1913                     161.080000             1.944380e+03
1917                     199.930000             4.972300e+03
1969                     373.605000             7.262221e+03
1988                   21934.000000             0.000000e+00
2007                   73600.000000             0.000000e+00
2009                   73083.000000             0.000000e+00
```

```
2011                    11282.500000           0.000000e+00
2016                    30345.000000           3.595656e+06
2017                    39392.013333           4.084352e+06
2018                    43560.635000           5.893680e+06
2019                       83.100000           0.000000e+00
2020                      418.528571           9.838121e+03
2021                      445.404444           1.144167e+04

                   Structural Concrete/002  Structural Concrete/003  \
Construction Date
1913                                   0.0                      0.0
1917                                   0.0                      0.0
1969                                   0.0                      0.0
1988                                   0.0                      0.0
2007                                   0.0                      0.0
2009                                   0.0                      0.0
2011                                   0.0                      0.0
2016                             2680512.0                1686228.0
2017                              989280.0                1232336.0
2018                             1511892.0                1347936.0
2019                                   0.0                      0.0
2020                                   0.0                      0.0
2021                                   0.0                      0.0

                   Structural Concrete/004  Structural Concrete/005  \
Construction Date
1913                                   0.0                      0.0
1917                                   0.0                      0.0
1969                                   0.0                      0.0
1988                                   0.0                      0.0
2007                                   0.0                      0.0
2009                                   0.0                      0.0
2011                                   0.0                      0.0
2016                             1057032.0                1056780.0
2017                              778480.0                 683496.0
2018                             1323132.0                2164812.0
2019                                   0.0                      0.0
2020                                   0.0                      0.0
2021                                   0.0                      0.0

                   Structural Concrete/006  Structural Concrete/007  \
Construction Date
1913                                   0.0                      0.0
1917                                   0.0                      0.0
1969                                   0.0                      0.0
1988                                   0.0                      0.0
2007                                   0.0                      0.0
```

2009	0.0	0.0
2011	0.0	0.0
2016	1129680.0	1809852.0
2017	679376.0	632520.0
2018	969060.0	752208.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/008	Structural Concrete/009	… \
Construction Date			…
1913	0.0	0.0	…
1917	0.0	0.0	…
1969	0.0	0.0	…
1988	0.0	0.0	…
2007	0.0	0.0	…
2009	0.0	0.0	…
2011	0.0	0.0	…
2016	857976.0	857844.0	…
2017	651080.0	425544.0	…
2018	734688.0	734688.0	…
2019	0.0	0.0	…
2020	0.0	0.0	…
2021	0.0	0.0	…

	Structural Concrete/044	Structural Concrete/0B1 \
Construction Date		
1913	0.0	0.000000
1917	0.0	0.000000
1969	0.0	0.000000
1988	0.0	0.000000
2007	0.0	0.000000
2009	0.0	0.000000
2011	0.0	0.000000
2016	0.0	0.000000
2017	578032.0	0.000000
2018	0.0	0.000000
2019	0.0	0.000000
2020	0.0	0.000000
2021	0.0	50.970278

	Structural Concrete/999	Structural Concrete/B01 \
Construction Date		
1913	0.0	64035.190000
1917	0.0	114018.460000
1969	0.0	132278.015000
1988	0.0	0.000000

2007	0.0	0.000000
2009	0.0	0.000000
2011	0.0	0.000000
2016	155076.0	0.000000
2017	162008.0	0.000000
2018	561912.0	0.000000
2019	0.0	38889.992166
2020	0.0	141289.905714
2021	0.0	164605.181806

	Structural Concrete/M00	Structural Concrete/P01 \
Construction Date		
1913	0.0	0.0
1917	0.0	0.0
1969	0.0	0.0
1988	0.0	0.0
2007	0.0	0.0
2009	0.0	0.0
2011	0.0	0.0
2016	82056.0	2206668.0
2017	0.0	3359680.0
2018	597624.0	3710520.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/P02	Structural Concrete/P03 \
Construction Date		
1913	0.0	0.0
1917	0.0	0.0
1969	0.0	0.0
1988	0.0	0.0
2007	0.0	0.0
2009	0.0	0.0
2011	0.0	0.0
2016	1715028.0	1596444.0
2017	2479760.0	2440640.0
2018	2637060.0	2756916.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

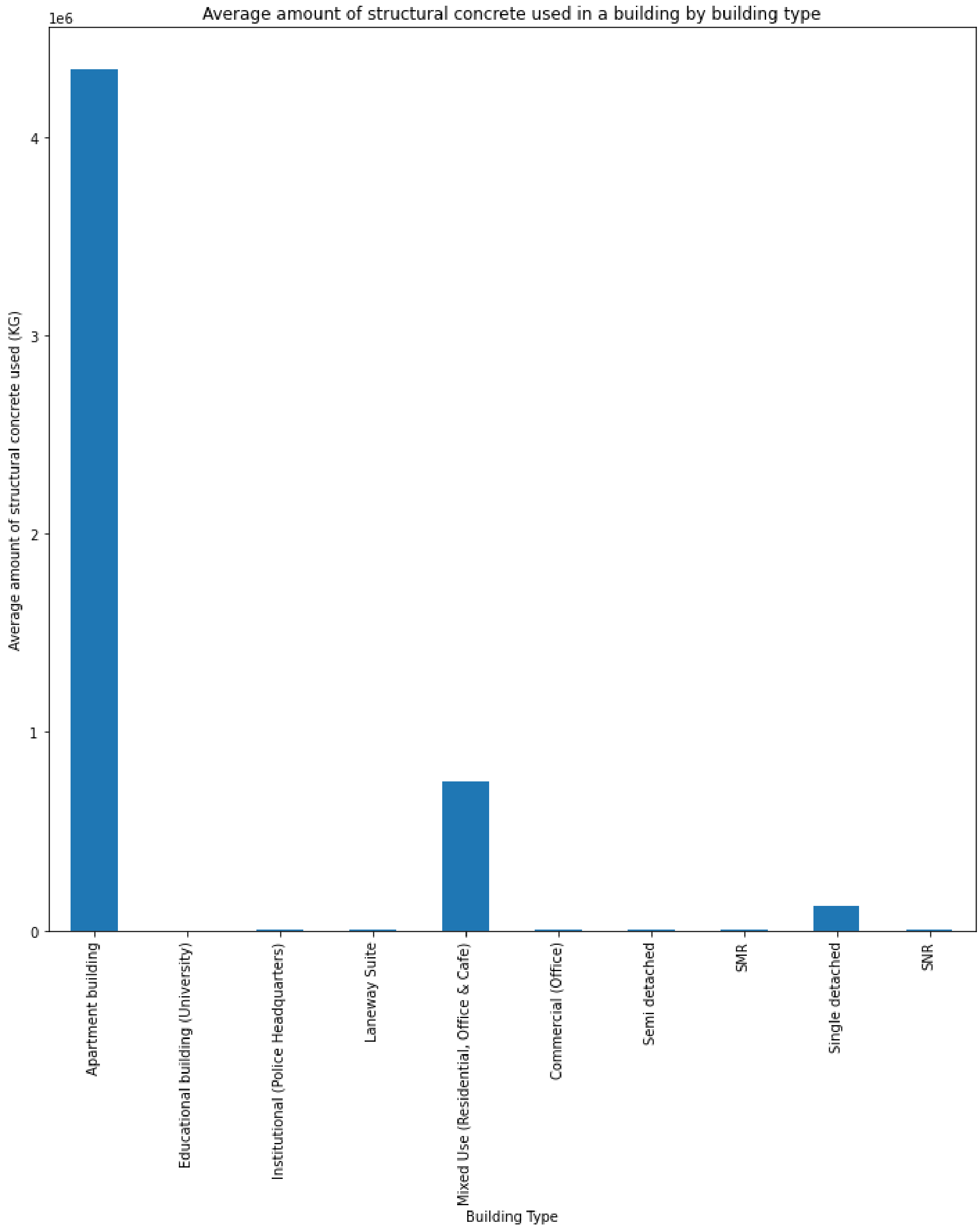
	Structural Concrete/P04	Structural Concrete/P05
Construction Date		
1913	0.0	0.0
1917	0.0	0.0
1969	0.0	0.0

```
1988                                          0.0                        0.0
2007                                          0.0                        0.0
2009                                          0.0                        0.0
2011                                          0.0                        0.0
2016                                    9131976.0                        0.0
2017                                    1865472.0                   489936.0
2018                                    4093284.0                        0.0
2019                                          0.0                        0.0
2020                                          0.0                        0.0
2021                                          0.0                        0.0

[13 rows x 56 columns]
```

We can get the average amount of steel in KG used per building type:

[27]:
```
concrete_df.groupby('Building Type').sum().mean(axis=1).
 ↪rename(index=building_name_map).plot(kind='bar',figsize=(12,12))
plt.ylabel('Average amount of structural concrete used (KG)')
plt.title('Average amount of structural concrete used in a building by building␣
 ↪type');
```

[27]:
```
Text(0.5, 1.0, 'Average amount of structural concrete used in a building by
building type')
```



4 3. Uncertainty by Building Type

In this section, we look at the uncertainty score associated with each material takeoff. We collect these by building type and then report the number of each value per type of building.

[28]:
```
uncertainty_level = {}
for k,v in df.iterrows():
    #Initialise empty lists for each building type as they occur
    if v['Building Type'] not in uncertainty_level.keys():
        uncertainty_level[v['Building Type']] = []
    #Append the uncertainty value for each column that is non-NaN
    for key in v[~v.isna()].keys()[7:]:
        uncertainty_level[v['Building Type']].append(key.split('_')[-1])
```

[29]:
```
from collections import Counter
```

[30]:
```
for k,v in uncertainty_level.items():
    uncertainty_level[k] = Counter(v) #Construct a Counter object per building␣
↪type
```

[31]:
```
uncertainty_level
```

[31]:
```
{'SND': Counter({'1': 1619, '2': 626, '4': 284}),
 'OFF': Counter({'1': 494, '3': 307}),
 'APB': Counter({'1': 1149, '3': 970, '2': 1}),
 'SMR': Counter({'2': 26, '1': 21, '4': 8}),
 'SNR': Counter({'2': 70, '4': 52, '1': 58}),
 'SMD': Counter({'1': 170, '2': 34, '4': 19}),
 'EDU': Counter({'1': 93, '3': 24, '2': 6}),
 'INS': Counter({'3': 77, '1': 90, '2': 1}),
 'MIX': Counter({'3': 276, '1': 363}),
 'LNW': Counter({'4': 21, '1': 152, '2': 48})}
```

Next, we aggregate columns by the purpose of the material and uncertainty combined, and report the average by building type.

[32]:
```
f = lambda x: name_map[re.split('[_\.\ ]',x)[1][0]] + '/' + x.split('_')[-1].
↪split('.')[0] #From a full code, return only the use code and uncertainty␣
↪score.
by_function_df = pd.concat([df[headings[1:]],df[cols].groupby(f,axis=1).
↪sum()],axis=1)
```

[33]:
```
by_function_df.groupby('Building Type').mean().rename(index=building_name_map).
↪drop(['Construction Date'],axis=1).round(2)
```

[33]:
```
                                           Gross Floor Area  Interiors/1  \
Building Type
Apartment building                                 45505.41    5330644.8
Educational building (University)                   7901.00          0.0
Institutional (Police Headquarters)                21934.00          0.0
Laneway Suite                                        150.01          0.0
Mixed Use (Residential, Office & Cafe)             33975.25    5893176.0
```

Commercial (Office)	52643.67	0.0
Semi detached	248.84	0.0
SMR	199.93	0.0
Single detached	478.40	0.0
SNR	302.76	0.0

	Services/1	Shell/1	Shell/2 \
Building Type			
Apartment building	1525512.0	21949118.40	0.00
Educational building (University)	0.0	0.00	0.00
Institutional (Police Headquarters)	0.0	0.00	0.00
Laneway Suite	0.0	0.00	0.00
Mixed Use (Residential, Office & Cafe)	1878144.0	23063160.00	0.00
Commercial (Office)	0.0	0.00	0.00
Semi detached	0.0	1864.27	0.00
SMR	0.0	0.00	0.00
Single detached	0.0	1547.01	13.19
SNR	0.0	2504.95	0.00

	Sitework/1 \
Building Type	
Apartment building	23188.8
Educational building (University)	0.0
Institutional (Police Headquarters)	0.0
Laneway Suite	0.0
Mixed Use (Residential, Office & Cafe)	0.0
Commercial (Office)	0.0
Semi detached	0.0
SMR	0.0
Single detached	0.0
SNR	0.0

	Special Construction And Demolition/1 \
Building Type	
Apartment building	60316.8
Educational building (University)	0.0
Institutional (Police Headquarters)	0.0
Laneway Suite	0.0
Mixed Use (Residential, Office & Cafe)	62280.0
Commercial (Office)	0.0
Semi detached	0.0
SMR	0.0
Single detached	0.0
SNR	0.0

	Substructure/1	Substructure/2
Building Type		

```
Apartment building                               20539176.00        0.00
Educational building (University)                       0.00        0.00
Institutional (Police Headquarters)                     0.00        0.00
Laneway Suite                                       60526.88       44.81
Mixed Use (Residential, Office & Cafe)           11822352.00        0.00
Commercial (Office)                                     0.00        0.00
Semi detached                                       97640.84        0.00
SMR                                                110089.90     8900.86
Single detached                                    181193.28     5347.87
SNR                                                 93180.79    19334.28
```

Next, we report the total amount of material falling under each uncertainty score by year of construction.

[34]:
```python
f = lambda x: x.split('_')[-1].split('.')[0] #Select only the uncertainty score.
print('Average amount of material used per building, by year and uncertainty␣
 ↪score (%)')
result = pd.concat([df['Construction Date'],df[[c for c in df.columns if 'kg'␣
 ↪in c]].groupby(f,axis=1).sum()],axis=1).groupby('Construction Date').mean()
for k,v in result.iterrows():
    result.loc[k,:] = v/v.sum()
display(result.round(2))
```

```
Average amount of material used per building, by year and uncertainty score (%)

                      1     2     3     4
Construction Date
1913               0.85  0.08  0.00  0.07
1917               0.75  0.14  0.00  0.11
1969               0.50  0.37  0.00  0.13
1988               0.97  0.00  0.03  0.00
2007               0.97  0.00  0.03  0.00
2009               0.97  0.00  0.03  0.00
2011               0.94  0.03  0.03  0.00
2016               0.95  0.02  0.03  0.00
2017               0.97  0.00  0.03  0.00
2018               0.97  0.00  0.03  0.00
2019               0.96  0.04  0.00  0.00
2020               0.80  0.10  0.00  0.10
2021               0.78  0.09  0.00  0.13
```

5 4. Material Intensity

We can easily calculate material intensity by dividing takeoffs which are measured in kilograms by the `Gross Floor Area`:

[35]:
```python
kilogram_columns = [d for d in df.columns if 'kg' in d]
df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
```

```
[36]: kilogram_columns = [d for d in df.columns if 'kg' in d]
df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
f = lambda x: name_map[re.split('[_\.\ ]',x)[1][0:3]]
pd.concat([df[headings[1:]],df_mi[kilogram_columns].groupby(f,axis=1).
 ↪sum()],axis=1)[df['Building Type'] == 'SND']
```

```
[36]:    Country City Quality / Stage of Data  Construction Date Building Type  \
     0        CA  TOR                    00IFC               2021           SND
     1        CA  TOR                    00IFC               2021           SND
     2        CA  TOR                    00IFC               2021           SND
     3        CA  TOR                    00IFC               2021           SND
     6        CA  TOR                    00IFC               2021           SND
     7        CA  TOR                    00IFC               2021           SND
     8        CA  TOR                    00IFC               2021           SND
     9        CA  TOR                    00IFC               2021           SND
     12       CA  TOR                    00IFC               2021           SND
     13       CA  TOR                    00IFC               2021           SND
     14       CA  TOR                    00IFC               2021           SND
     15       CA  TOR                    00IFC               2021           SND
     18       CA  TOR                    00IFC               2021           SND
     19       CA  TOR                    00IFC               2021           SND
     20       CA  TOR                    00IFC               2020           SND
     21       CA  TOR                    00IFC               2021           SND
     22       CA  TOR                    00IFC               2021           SND
     24       CA  TOR                    00IFC               2021           SND
     25       CA  TOR                    00IFC               2021           SND
     27       CA  TOR                    00IFC               2021           SND
     28       CA  TOR                    00IFC               2021           SND
     30       CA  TOR                    00IFC               2021           SND
     31       CA  TOR                    00IFC               2021           SND
     32       CA  TOR                    00IFC               2020           SND
     34       CA  TOR                    00IFC               2021           SND
     35       CA  TOR                    00IFC               2021           SND
     36       CA  TOR                    00IFC               2021           SND
     37       CA  TOR                    00IFC               2020           SND
     38       CA  TOR                    00IFC               2021           SND
     40       CA  TOR                    00IFC               2021           SND
     42       CA  TOR                    00IFC               2021           SND
     43       CA  TOR                    00IFC               2021           SND
     44       CA  TOR                    00IFC               2021           SND
     45       CA  TOR                    00IFC               2021           SND
     46       CA  TOR                    00IFC               2021           SND
     48       CA  TOR                    00IFC               2020           SND
     49       CA  TOR                    00IFC               2021           SND

         Gross Floor Area  Conveying  Exterior Horizontal Enclosures  \
     0             521.18        0.0                       11.137992
```

1	389.24	0.0	5.461939
2	411.64	0.0	3.786074
3	269.56	0.0	6.503479
6	445.99	0.0	11.933511
7	438.45	0.0	12.707195
8	714.07	0.0	12.865930
9	343.24	0.0	4.300619
12	226.89	0.0	12.424245
13	611.73	0.0	5.140200
14	343.44	0.0	6.494467
15	613.38	0.0	13.090524
18	178.38	0.0	9.782438
19	323.80	0.0	9.824569
20	837.56	0.0	13.521848
21	587.86	0.0	6.949783
22	568.21	0.0	12.754287
24	294.84	0.0	3.650542
25	496.77	0.0	5.352985
27	643.30	0.0	11.769043
28	701.61	0.0	11.799093
30	378.70	0.0	5.522739
31	324.16	0.0	5.361174
32	533.53	0.0	8.494907
34	423.03	0.0	11.102019
35	328.16	0.0	10.234937
36	421.59	0.0	12.223172
37	628.59	0.0	10.408758
38	464.51	0.0	4.118745
40	346.14	0.0	11.787081
42	891.97	0.0	10.710312
43	525.61	0.0	18.918490
44	502.87	0.0	6.014586
45	379.18	0.0	6.169302
46	549.65	0.0	11.310711
48	393.82	0.0	16.116861
49	648.14	0.0	9.684756

	Exterior Vertical Enclosures	Foundations	…	Interior Finishes	\
0	136.939623	335.649367	…	6.202080	
1	69.018253	281.318698	…	4.491260	
2	101.450370	464.462195	…	3.030369	
3	188.215196	255.359136	…	2.920482	
6	61.325975	295.116668	…	4.539900	
7	130.552921	269.468463	…	4.767511	
8	104.310510	276.917123	…	4.898301	
9	210.632241	283.893850	…	6.753884	
12	186.668275	261.874926	…	4.154604	

13	102.332008	343.714248	…	5.577869
14	147.104280	424.099610	…	5.729880
15	156.986570	298.537712	…	5.763898
18	112.523711	371.149916	…	7.549843
19	186.570501	148.769711	…	3.384055
20	91.689386	317.583491	…	5.017694
21	94.557055	428.185321	…	4.710543
22	83.789887	255.012975	…	5.714419
24	127.856507	261.274626	…	3.601363
25	89.883144	251.725837	…	4.321980
27	83.949693	156.365248	…	5.765195
28	53.418023	266.164355	…	5.728781
30	164.214896	403.602589	…	7.221059
31	190.512918	377.853541	…	4.906090
32	68.518430	309.062696	…	4.971297
34	154.072547	243.607664	…	3.227528
35	184.202156	388.744353	…	1.765491
36	158.716507	424.443503	…	3.247311
37	136.076590	369.744859	…	4.180593
38	151.068033	412.845205	…	5.465049
40	146.479339	287.564257	…	5.764737
42	213.677214	245.205806	…	5.194042
43	109.529933	498.010299	…	5.835201
44	91.481074	278.679758	…	2.978621
45	172.418003	391.303861	…	4.323340
46	127.866168	266.468237	…	4.819176
48	140.069509	188.980245	…	7.801305
49	131.118584	347.187490	…	3.705203

	Plumbing	Site Improvements	Slabs-On-Grade	Special Construction	\
0	0.0	0.0	273.972401	0.0	
1	0.0	0.0	192.874465	0.0	
2	0.0	0.0	170.733356	0.0	
3	0.0	0.0	124.186526	0.0	
6	0.0	0.0	153.061618	0.0	
7	0.0	0.0	211.910108	0.0	
8	0.0	0.0	266.709576	0.0	
9	0.0	0.0	138.510228	0.0	
12	0.0	0.0	129.263543	0.0	
13	0.0	0.0	165.513154	0.0	
14	0.0	0.0	129.532248	0.0	
15	0.0	0.0	166.414337	0.0	
18	0.0	0.0	223.398638	0.0	
19	0.0	0.0	158.178114	0.0	
20	0.0	0.0	143.282268	0.0	
21	0.0	0.0	237.918968	0.0	
22	0.0	0.0	199.364347	0.0	

24	0.0	0.0	131.174185	0.0
25	0.0	0.0	242.284758	0.0
27	0.0	0.0	152.407914	0.0
28	0.0	0.0	169.419640	0.0
30	0.0	0.0	179.868896	0.0
31	0.0	0.0	132.696247	0.0
32	0.0	0.0	135.390288	0.0
34	0.0	0.0	147.458950	0.0
35	0.0	0.0	128.887840	0.0
36	0.0	0.0	147.225241	0.0
37	0.0	0.0	186.334547	0.0
38	0.0	0.0	145.273403	0.0
40	0.0	0.0	139.821081	0.0
42	0.0	0.0	138.994603	0.0
43	0.0	0.0	139.646277	0.0
44	0.0	0.0	182.059329	0.0
45	0.0	0.0	158.446049	0.0
46	0.0	0.0	154.805714	0.0
48	0.0	0.0	198.860705	0.0
49	0.0	0.0	199.209464	0.0

	Subgrade Enclosures	Substructure Interior \
0	9.652903	7.521547
1	6.851955	11.871041
2	11.298572	8.277288
3	4.351465	20.070275
6	9.478642	5.575509
7	4.218921	1.817270
8	8.902623	25.192687
9	9.601245	7.744759
12	3.818403	9.532825
13	7.722754	6.168162
14	9.135529	5.601240
15	4.868508	9.004152
18	0.000000	8.758309
19	4.617006	11.946436
20	7.131170	8.875410
21	7.959752	9.098153
22	6.339651	11.209887
24	7.469048	3.895085
25	9.448689	4.154656
27	0.000000	11.506782
28	11.919460	8.789598
30	7.509119	10.575300
31	5.073992	8.309600
32	8.867868	13.435344
34	0.000000	10.013415

35	4.762839	19.086997
36	9.538939	12.833857
37	6.039206	7.143042
38	9.071017	12.485838
40	7.568785	12.011677
42	4.540919	10.725241
43	6.720435	8.275280
44	6.092739	10.878686
45	9.489156	13.750663
46	6.042229	8.345960
48	6.057127	5.861907
49	7.221222	8.240307

	Substructure Related Activities	Superstructure	Water And Gas Mitigation
0	0.0	30.228003	0.0
1	0.0	26.271523	0.0
2	0.0	23.756286	0.0
3	0.0	30.396721	0.0
6	0.0	39.906513	0.0
7	0.0	39.907474	0.0
8	0.0	38.291591	0.0
9	0.0	35.370538	0.0
12	0.0	35.355314	0.0
13	0.0	33.388004	0.0
14	0.0	39.370016	0.0
15	0.0	40.958564	0.0
18	0.0	63.006044	0.0
19	0.0	36.597047	0.0
20	0.0	28.734226	0.0
21	0.0	37.457583	0.0
22	0.0	36.265538	0.0
24	0.0	30.389475	0.0
25	0.0	43.728928	0.0
27	0.0	35.393414	0.0
28	0.0	39.408113	0.0
30	0.0	82.392236	0.0
31	0.0	46.380703	0.0
32	0.0	25.469871	0.0
34	0.0	35.666107	0.0
35	0.0	49.284461	0.0
36	0.0	34.035382	0.0
37	0.0	47.065025	0.0
38	0.0	37.921434	0.0
40	0.0	27.740220	0.0
42	0.0	29.045531	0.0
43	0.0	33.265489	0.0
44	0.0	37.265275	0.0

45	0.0	46.860447	0.0
46	0.0	31.152827	0.0
48	0.0	49.899420	0.0
49	0.0	38.021046	0.0

[37 rows x 21 columns]

[37]:
```
master_format_convert = {v:k for k,v in {
    'Concrete':'03',
    'Masonry':'04',
    'Metals':'05',
    'WoodPlasticsAndComposites':'06',
    'ThermalAndMoistureProtection':'07',
    'Finishes':'09',
    'Openings':'08',
    'Earthwork':'31',
    'ExteriorImprovements':'32'
}.items() }
```

[38]:
```
f = lambda x: master_format_convert[re.split('[_\.\ ]',x)[4]]
toplot = pd.concat([df[headings[1:]],df_mi[kilogram_columns].groupby(f,axis=1).
 ↪sum()],axis=1).sort_values(['Building Type'])
```

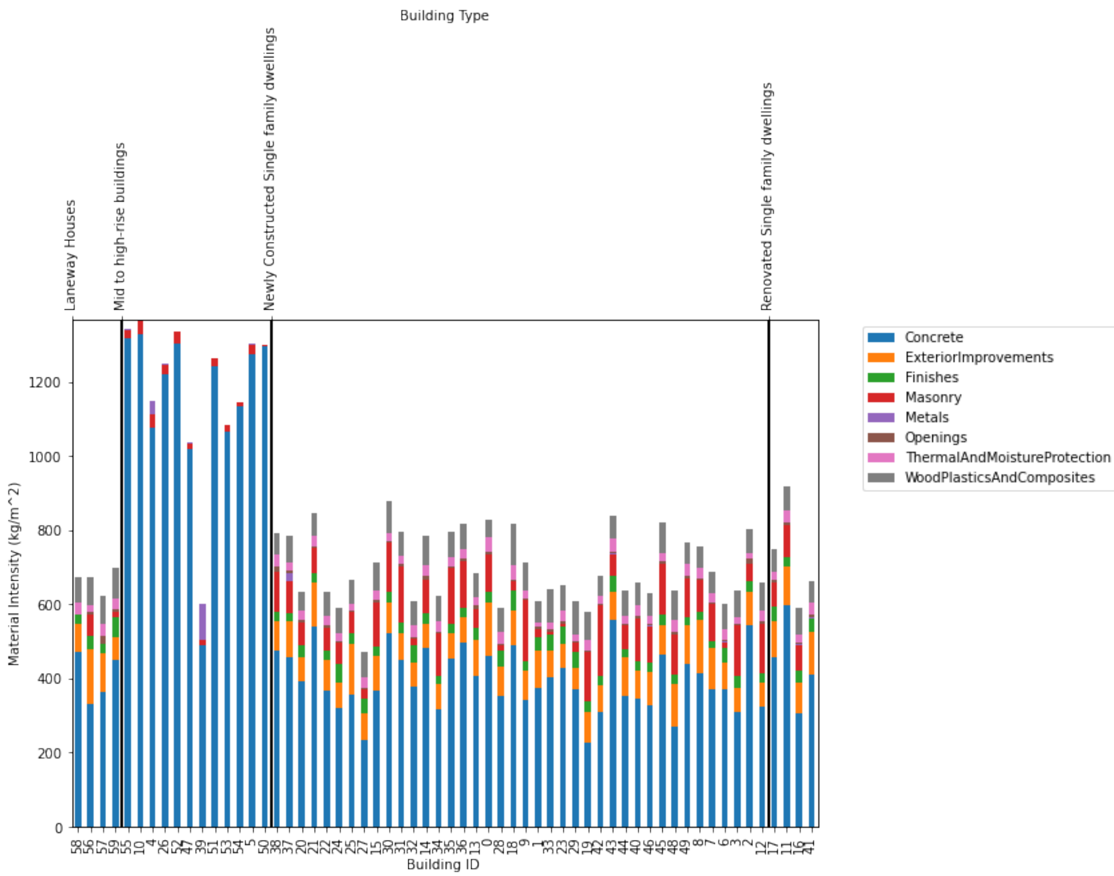
[39]:
```
building_type_map = {
    'APB':'Mid to high-rise buildings',
    'EDU':'Mid to high-rise buildings',
    'INS':'Mid to high-rise buildings',
    'MIX':'Mid to high-rise buildings',
    'OFF':'Mid to high-rise buildings',
    'SND':'Newly Constructed Single family dwellings',
    'SNR':'Renovated Single family dwellings',
    'SMD':'Newly Constructed Single family dwellings',
    'SMR':'Renovated Single family dwellings',
    'ADU':'Other',
    'SEC':'Other',
    'ROW':'Other',
    'LNW':'Laneway Houses'
}

toplot['Building Type'] = toplot['Building Type'].replace(building_type_map)
toplot = toplot.sort_values('Building Type')
```

[40]:
```
set(df['Building Type'].values)
```

[40]: {'APB', 'EDU', 'INS', 'LNW', 'MIX', 'OFF', 'SMD', 'SMR', 'SND', 'SNR'}

[41]:

```
fig, ax = plt.subplots(figsize=(10,7))

cols = toplot.columns[6:]
margin_bottom = np.zeros(len(toplot))

cmap = plt.get_cmap('tab10')

for num, col in enumerate(cols):
    values = toplot[col].values

    toplot[col].plot.bar(x='Year',y='Value', ax=ax, stacked=True,
                                    bottom = margin_bottom, color=cmap(num),␣
↪label=col)
    margin_bottom += values
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.ylabel('Material Intensity (kg/m^2)')
plt.xlabel('Building ID ')
ax2 = ax.twiny()
ax2.set_xlim(0, len(toplot))
ax2.set_xticks([k for k,v in enumerate(toplot['Building Type'].values) if v !=␣
↪toplot['Building Type'].values[k-1] or k==0])
for tick in ax2.get_xticklabels():
    tick.set_rotation(90)
ax2.set_xticklabels([v for k,v in enumerate(toplot['Building Type'].values) if␣
↪v != toplot['Building Type'].values[k-1] or k==0])
ax2.set_xlabel("Building Type")
plt.grid(color='black',linewidth=2)

plt.show()
```



[42]:
```
toplot['Total MI'] = toplot.iloc[:,6:].sum(axis=1)
```

[43]:
```
print('Mean Material Intensity:')
display(toplot.groupby('Building Type').mean().iloc[:,1:].round(2))
print('Std Dev Material Intensity:')
display(toplot.groupby('Building Type').std().iloc[:,1:].round(2))
```

```
Mean Material Intensity:

                                           Gross Floor Area  Concrete  \
Building Type
Laneway Houses                                       150.01    404.05
Mid to high-rise buildings                         38097.44   1148.05
Newly Constructed Single family dwellings            461.18    396.71
Renovated Single family dwellings                    277.06    442.97

                                           ExteriorImprovements  Finishes  \
Building Type
Laneway Houses                                            97.09     35.27
Mid to high-rise buildings                                 0.00      0.00
```

```
Newly Constructed Single family dwellings                 86.16     31.17
Renovated Single family dwellings                        100.30     33.64

                                           Masonry  Metals  Openings  \
Building Type
Laneway Houses                               17.83    0.26      9.62
Mid to high-rise buildings                   20.90   12.76      0.00
Newly Constructed Single family dwellings    83.77    0.96      5.99
Renovated Single family dwellings            55.31    0.74      5.84

                                           ThermalAndMoistureProtection  \
Building Type
Laneway Houses                                                    27.13
Mid to high-rise buildings                                         0.00
Newly Constructed Single family dwellings                         25.63
Renovated Single family dwellings                                 26.98

                                           WoodPlasticsAndComposites  Total MI
Building Type
Laneway Houses                                                 76.52    667.77
Mid to high-rise buildings                                      0.00   1181.71
Newly Constructed Single family dwellings                      68.82    699.22
Renovated Single family dwellings                              64.59    730.36
Std Dev Material Intensity:
                                           Gross Floor Area  Concrete  \
Building Type
Laneway Houses                                        62.86     66.88
Mid to high-rise buildings                         26125.17    233.16
Newly Constructed Single family dwellings            168.17     82.14
Renovated Single family dwellings                    117.28    120.26

                                           ExteriorImprovements  Finishes  \
Building Type
Laneway Houses                                            37.25     13.46
Mid to high-rise buildings                                 0.00      0.00
Newly Constructed Single family dwellings                 22.30      9.40
Renovated Single family dwellings                         12.94      6.38

                                           Masonry  Metals  Openings  \
Building Type
Laneway Houses                               27.54    0.52      9.08
Mid to high-rise buildings                    9.92   28.07      0.00
Newly Constructed Single family dwellings    49.26    3.35      2.21
Renovated Single family dwellings            37.88    0.86      1.43

                                           ThermalAndMoistureProtection  \
Building Type
```

```
Laneway Houses                                                     7.80
Mid to high-rise buildings                                         0.00
Newly Constructed Single family dwellings                          6.14
Renovated Single family dwellings                                  5.44

                                           WoodPlasticsAndComposites  Total MI
Building Type
Laneway Houses                                                  6.94     30.87
Mid to high-rise buildings                                      0.00    212.39
Newly Constructed Single family dwellings                      11.58     95.96
Renovated Single family dwellings                               6.55    140.02
```

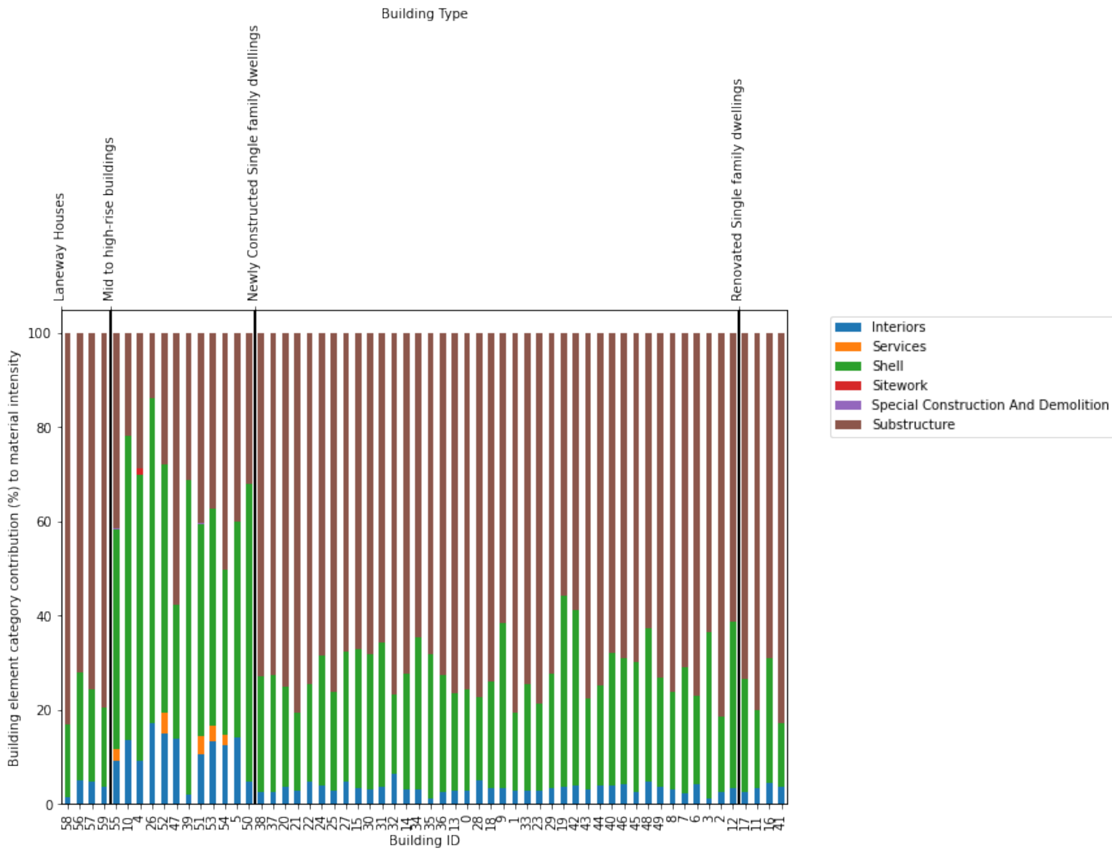
[44]:

```python
df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
```

[45]:

```python
df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
df_mi = df_mi.div(df_mi.sum(axis=1),axis=0) * 100
f = lambda x: name_map[re.split('[_\.\ ]',x)[1][0]]
toplot = pd.concat([df[headings[1:]],df_mi[kilogram_columns].groupby(f,axis=1).
 ↪sum()],axis=1).sort_values('Building Type')
toplot['Building Type'] = toplot['Building Type'].replace(building_type_map)
toplot = toplot.sort_values('Building Type')
fig, ax = plt.subplots(figsize=(10,7))

cols = toplot.columns[6:]
margin_bottom = np.zeros(len(toplot))

cmap = plt.get_cmap('tab10')

for num, col in enumerate(cols):
    values = toplot[col].values

    toplot[col].plot.bar(x='Year',y='Value', ax=ax, stacked=True,
                                    bottom = margin_bottom, color=cmap(num),␣
 ↪label=col)
    margin_bottom += values
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xlabel('Building ID')
plt.ylabel('Building element category contribution (%) to material intensity')

ax2 = ax.twiny()
ax2.set_xlim(0, len(toplot))
ax2.set_xticks([k for k,v in enumerate(toplot['Building Type'].values) if v !=␣
 ↪toplot['Building Type'].values[k-1] or k==0])
for tick in ax2.get_xticklabels():
    tick.set_rotation(90)
ax2.set_xticklabels([v for k,v in enumerate(toplot['Building Type'].values) if␣
 ↪v != toplot['Building Type'].values[k-1] or k==0])
```

```python
ax2.set_xlabel("Building Type")
plt.grid(color='black',linewidth=2)
plt.show()
```



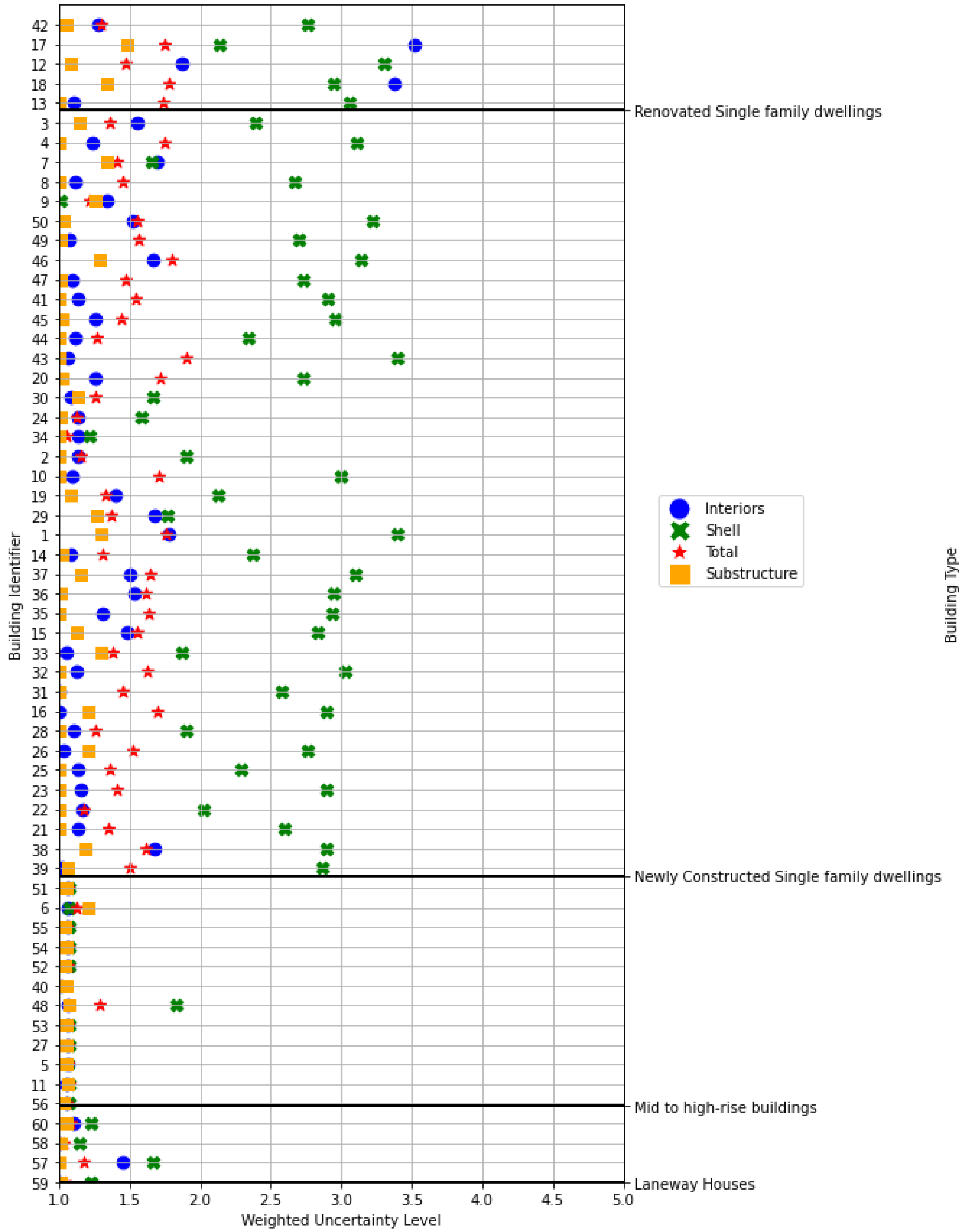
[46]:
```python
f = lambda x: name_map[re.split('[_\.\ ]',x)[1][0]] + '/' + re.split('[_\.\
 ↪]',x)[-1]
toplot = df_mi[kilogram_columns].groupby(f,axis=1).sum()
```

[47]:
```python
df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
df_mi = df_mi.div(df_mi.sum(axis=1),axis=0)
f = lambda x: name_map[re.split('[_\.\ ]',x)[1][0]] + '/' + re.split('[_\.\
 ↪]',x)[-1]
toplot = df_mi[kilogram_columns].groupby(f,axis=1).sum()
for i in range(1,5):
    toplot[f'Total/{i}'] = 0
for k,v in toplot.iteritems():
    toplot[f'Total/{k.split("/")[1]}'] += v
toplot_out = deepcopy(toplot)
for k,v in toplot.iteritems():
```

```
    toplot_out[k] = (v/toplot[[c for c in toplot.columns if k.split('/')[0] in␣
↪c]].sum(axis=1)) * int(k.split('/')[1])
f = lambda x: x.split('/')[0]
toplot_out = pd.concat([df['Building Type'],toplot_out.groupby(f,axis=1).
↪sum()],axis=1).sort_values('Building Type')
toplot_out = toplot_out.reset_index()
toplot_out['index'] += 1
toplot_out['index'] = toplot_out['index'].astype('str')
```

[48]:
```
# toplot_out = toplot_out[toplot_out['Building Type'].isin(types_to_keep)]
toplot_out['Building Type'] = toplot_out['Building Type'].
↪replace(building_type_map)
toplot_out = toplot_out.sort_values('Building Type')
```

[49]:
```
from matplotlib.lines import Line2D
fig, ax = plt.subplots(figsize=(7,15))
ax.set_xlim(1,5)
ax.set_ylim(0,len(toplot_out))
# ax.set_yticks(toplot_out['index'])
handles = []
for v,m,c in␣
↪[('Interiors','o','blue'),('Shell','X','green'),('Total','*','red'),('Substructure','s','or
↪
    ax.scatter(x=toplot_out[v].values,y=toplot_out['index'].values, marker=m,␣
↪color=c, s=75)
    handles.append(
        Line2D([0], [0], marker=m, color='w', label=v,
                              markerfacecolor=c, markersize=15)
    )
plt.legend(handles=handles,bbox_to_anchor=(1.05, 0.5), loc='lower left')
plt.ylabel('Building Identifier')
plt.xlabel('Weighted Uncertainty Level')
plt.grid()
ax2 = ax.twinx()
ax2.set_ylim(0, len(toplot_out))
ax2.set_yticks([k-1.5 for k,v in enumerate(toplot_out['Building Type'].values)␣
↪if v != toplot_out['Building Type'].values[k-1] or k==0])
# for tick in ax2.get_yticklabels():
#     tick.set_rotation(90)
ax2.set_yticklabels([v for k,v in enumerate(toplot_out['Building Type'].values)␣
↪if v != toplot_out['Building Type'].values[k-1] or k==0])
ax2.set_ylabel("Building Type")


plt.grid(color='black',linewidth=2)
```




```
[50]: toplot_out
```

```
[50]:    index                     Building Type  Interiors  Services  \
      11    59                    Laneway Houses   1.000000  0.000000
```

10	57	Laneway Houses	1.448192	0.000000
9	58	Laneway Houses	1.000000	0.000000
8	60	Laneway Houses	1.106514	0.000000
0	56	Mid to high-rise buildings	1.055282	1.063345
15	11	Mid to high-rise buildings	1.053931	1.000000
14	5	Mid to high-rise buildings	1.062126	0.000000
13	27	Mid to high-rise buildings	1.057465	1.000000
12	53	Mid to high-rise buildings	1.056937	1.063339
6	48	Mid to high-rise buildings	1.064117	0.000000
5	40	Mid to high-rise buildings	1.003158	0.000000
4	52	Mid to high-rise buildings	1.059125	1.063345
3	54	Mid to high-rise buildings	1.058893	1.063560
2	55	Mid to high-rise buildings	1.060142	1.063635
1	6	Mid to high-rise buildings	1.064886	1.000000
7	51	Mid to high-rise buildings	1.061145	1.000000
46	39	Newly Constructed Single family dwellings	1.022510	0.000000
39	38	Newly Constructed Single family dwellings	1.677158	0.000000
40	21	Newly Constructed Single family dwellings	1.129914	0.000000
41	22	Newly Constructed Single family dwellings	1.164362	0.000000
42	23	Newly Constructed Single family dwellings	1.158614	0.000000
43	25	Newly Constructed Single family dwellings	1.129050	0.000000
44	26	Newly Constructed Single family dwellings	1.029460	0.000000
45	28	Newly Constructed Single family dwellings	1.105249	0.000000
47	16	Newly Constructed Single family dwellings	1.000773	0.000000
55	31	Newly Constructed Single family dwellings	1.000711	0.000000
49	32	Newly Constructed Single family dwellings	1.126565	0.000000
50	33	Newly Constructed Single family dwellings	1.052470	0.000000
51	15	Newly Constructed Single family dwellings	1.482589	0.000000
52	35	Newly Constructed Single family dwellings	1.304223	0.000000
53	36	Newly Constructed Single family dwellings	1.530154	0.000000
54	37	Newly Constructed Single family dwellings	1.504454	0.000000
38	14	Newly Constructed Single family dwellings	1.084267	0.000000
56	1	Newly Constructed Single family dwellings	1.783909	0.000000
48	29	Newly Constructed Single family dwellings	1.673890	0.000000
37	19	Newly Constructed Single family dwellings	1.403578	0.000000
29	10	Newly Constructed Single family dwellings	1.093928	0.000000
35	2	Newly Constructed Single family dwellings	1.135291	0.000000
16	34	Newly Constructed Single family dwellings	1.137204	0.000000
17	24	Newly Constructed Single family dwellings	1.133368	0.000000
18	30	Newly Constructed Single family dwellings	1.082719	0.000000
20	20	Newly Constructed Single family dwellings	1.258605	0.000000
21	43	Newly Constructed Single family dwellings	1.065774	0.000000
22	44	Newly Constructed Single family dwellings	1.114970	0.000000
23	45	Newly Constructed Single family dwellings	1.259042	0.000000
36	41	Newly Constructed Single family dwellings	1.133974	0.000000
25	47	Newly Constructed Single family dwellings	1.088947	0.000000
24	46	Newly Constructed Single family dwellings	1.669508	0.000000

27	49	Newly Constructed Single family dwellings	1.075363	0.000000
28	50	Newly Constructed Single family dwellings	1.526666	0.000000
30	9	Newly Constructed Single family dwellings	1.340940	0.000000
31	8	Newly Constructed Single family dwellings	1.113892	0.000000
32	7	Newly Constructed Single family dwellings	1.696426	0.000000
33	4	Newly Constructed Single family dwellings	1.232972	0.000000
34	3	Newly Constructed Single family dwellings	1.554259	0.000000
26	13	Newly Constructed Single family dwellings	1.098557	0.000000
58	18	Renovated Single family dwellings	3.371953	0.000000
19	12	Renovated Single family dwellings	1.868511	0.000000
57	17	Renovated Single family dwellings	3.523878	0.000000
59	42	Renovated Single family dwellings	1.275307	0.000000

	Shell	Sitework	Special Construction And Demolition	Substructure \
11	1.222478	0.000000	0.000000	1.009743
10	1.667883	0.000000	0.000000	1.005174
9	1.139704	0.000000	0.000000	1.007530
8	1.229146	0.000000	0.000000	1.046766
0	1.073363	0.000000	1.000000	1.033361
15	1.074135	1.065811	0.000000	1.060777
14	1.060001	1.065088	0.000000	1.054245
13	1.072925	0.000000	0.000000	1.046992
12	1.070630	0.000000	1.069459	1.048509
6	1.834375	0.000000	0.000000	1.069459
5	1.003376	0.000000	0.000000	1.049684
4	1.069581	0.000000	1.065274	1.043075
3	1.069970	1.063345	0.000000	1.056689
2	1.070633	1.063345	0.000000	1.041937
1	1.069540	0.000000	0.000000	1.207878
7	1.072911	0.000000	0.000000	1.052481
46	2.868481	0.000000	0.000000	1.057930
39	2.899588	0.000000	0.000000	1.180799
40	2.596013	0.000000	0.000000	1.004987
41	2.023583	0.000000	0.000000	1.000000
42	2.900097	0.000000	0.000000	1.004738
43	2.286621	0.000000	0.000000	1.000304
44	2.760160	0.000000	0.000000	1.205806
45	1.902957	0.000000	0.000000	1.001697
47	2.891919	0.000000	0.000000	1.202004
55	2.576590	0.000000	0.000000	1.005355
49	3.024183	0.000000	0.000000	1.000000
50	1.866082	0.000000	0.000000	1.295051
51	2.831209	0.000000	0.000000	1.121468
52	2.938528	0.000000	0.000000	1.004000
53	2.948675	0.000000	0.000000	1.013934
54	3.096763	0.000000	0.000000	1.149482
38	2.375985	0.000000	0.000000	1.023681

56	3.400587	0.000000	0.000000	1.295789
48	1.772127	0.000000	0.000000	1.262282
37	2.129471	0.000000	0.000000	1.082723
29	2.994000	0.000000	0.000000	1.005093
35	1.903168	0.000000	0.000000	1.000307
16	1.219179	0.000000	0.000000	1.003856
17	1.584751	0.000000	0.000000	1.008351
18	1.662132	0.000000	0.000000	1.132094
20	2.731786	0.000000	0.000000	1.020715
21	3.396133	0.000000	0.000000	1.005594
22	2.341648	0.000000	0.000000	1.000000
23	2.953420	0.000000	0.000000	1.020065
36	2.905343	0.000000	0.000000	1.002057
25	2.729139	0.000000	0.000000	1.009751
24	3.135893	0.000000	0.000000	1.283675
27	2.700480	0.000000	0.000000	1.013980
28	3.220079	0.000000	0.000000	1.027128
30	1.012868	0.000000	0.000000	1.258398
31	2.671444	0.000000	0.000000	1.000182
32	1.652987	0.000000	0.000000	1.336877
33	3.110887	0.000000	0.000000	1.004190
34	2.394424	0.000000	0.000000	1.146312
26	3.060873	0.000000	0.000000	1.005552
58	2.946027	0.000000	0.000000	1.342662
19	3.306551	0.000000	0.000000	1.082720
57	2.139931	0.000000	0.000000	1.480406
59	2.763229	0.000000	0.000000	1.056058

	Total
11	1.042436
10	1.178813
9	1.033101
8	1.079606
0	1.054691
15	1.068445
14	1.058603
13	1.066705
12	1.062100
6	1.287491
5	1.017895
4	1.057521
3	1.063310
2	1.054738
1	1.124455
7	1.065816
46	1.497711
39	1.618485

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40   1.345816
41   1.172773
42   1.408989
43   1.358821
44   1.525532
45   1.256196
47   1.695451
55   1.455347
49   1.621240
50   1.375711
51   1.552619
52   1.638589
53   1.613443
54   1.645604
38   1.304323
56   1.762540
48   1.372842
37   1.331187
29   1.704715
35   1.153032
16   1.055995
17   1.118378
18   1.259561
20   1.719237
21   1.900427
22   1.261910
23   1.438017
36   1.544942
25   1.476667
24   1.803159
27   1.563390
28   1.555498
30   1.210574
31   1.448962
32   1.410980
33   1.751883
34   1.356512
26   1.738281
58   1.777552
19   1.475825
57   1.744405
59   1.294809
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