power_system_optimization

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Optimization of a power system 1

Student: Bruno Kiyoshi Ynumaru; Prof. Eduardo Camponogara

In this exercise, you will have the opportunity to approximate a nonlinear problem as a MILP by means of piecewise-linear models. The power system has 3 buses as depicted in Fig. 1. Buses 1 and 3 have generation units, whereas bus 2 is a power consumer. This Figures also gives the maximum power generation (\bar{P}_{gi}) and the power consumption (\bar{P}_{di}) of each bus i, under low and high demand. The properties of the transmission lines appear in Table 1, in pu using a 100 MVA basis, are indicated in the Figure. The parameters are the resistance $r_{i,j}$, the reactance $x_{i,j}$ and the number of lines installed between buses i and j.

Line	$r_{i,j}$ (pu)	$x_{i,j}$ (pu)	ni,j
1-2	0.030	0.23	2
1-3	0.035	0.25	1
2-3	0.025	0.20	1

A simplified model is adopted for the transmission network, in which:

•Lines and transformers are represented by their series impedances in per unit:

$$z_{i,j} = r_{i,j} + jx_{i,j}(1)$$

where rij is the resistance and xij is the reactance of line (i; j).

- Voltage magnitudes are fixed at 1:0 pu.
- Reactive power balance is supposed to be satisfied.

With these assumptions, active power flows are expressed as

$$p.flowi \rightarrow j: P_{i,j} = g_{i,j} - (g_{i,j}cos\theta_{i,j} + b_{i,j}sin\theta_{i,j})(2a)$$

$$p.flowj \rightarrow i: P_{j,i} = g_{i,j} - (g_{i,j}cos\theta_{i,j} - b_{i,j}sin\theta_{i,j})(2b)$$

where gij and b_{ij} are, respectively, the series conductance and series susceptance of line (i, j), $\theta_{i,j} = (\theta_i - \theta_j)$ and θ_i is the voltage angle of bus i.

Conductance and susceptance are calculated as follows

$$g_{i,j} = \frac{r_{i,j}}{(r_{i,j}^2 + x_{i,j}^2)}$$
$$b_{i,j} = -\frac{x_{i,j}}{(r_{i,j}^2 + x_{i,j}^2)}$$

The power injected into bus i is defined as
$$P_i = \sum_{j \in N_i} n_{i,j} P_{i,j} = \sum_{j \in N_i} n_{i,j} [g_{i,j} - (g_{i,j} cos\theta_{i,j} + b_{i,j} sin\theta_{i,j}])](3)$$

where N_i is the set of neighboring buses of bus i. To ensure energy conservation, the following equations must also be satisfied

$$Pg_i = P\bar{d}_i + P_i(4)$$

Aiming to minimize the power loss in transmission, the power-flow optimization problem could be solved:

$$\begin{aligned} \min \sum_{i \in N} |P_i| \\ s.t : Pg_i &= P\overline{d}_i + P_i, \\ P_i &= \sum_{j \in N_i} n_{i,j} P_{i,j}, \\ 0 &\leq Pg_i \leq P\overline{g}_i, \\ \theta_i &\in [\frac{-\pi}{2}, \frac{\pi}{2}, i \in N], \\ P_{i,j} &= g_{i,j} - (g_{i,j} cos\theta_{i,j} + b_{i,j} sin\theta_{i,j}), \\ \theta_{i,j} &= \theta_i - \theta_j, \\ \theta_{i,i} &\in [-\pi, \pi], i \in N, j \in N_i \end{aligned}$$

Tasks:

- Reformulate the power-flow optimization problem in MILP using the following piecewise-linear models: CC and SOS2.
- Implement the models in AMPL, choosing a suitable number of breakpoints to induce a good approximation of the power-flow equations. You may plot the piecewise linear approximations for $\sin \theta_{i,j}$ and $\cos \theta_{i,j}$ in order to show the degree of approximation.
- Solve the problem for the low and high power demand cases. Present and illustrate the solutions.

1.1 Optimization problem solution using Gurobi

```
[1]: import gurobipy as gp
  from gurobipy import GRB, Model
  import pandas as pd
  import matplotlib.pyplot as plt
  import numpy as np
  import math
  from itertools import combinations
  pd.set_option("display.max_columns", None)
  pd.set_option('display.max_rows', None)
```

1.2 Generate data points

```
[2]: n_points = 15
    theta_array = np.linspace(-math.pi, math.pi, n_points)
    cos_array = np.cos(theta_array)
    sin_array = np.sin(theta_array)
    plt.figure()
```

```
plt.scatter(theta_array,cos_array)
plt.scatter(theta_array,sin_array)
plt.plot(theta_array,cos_array,label="f(x)=cos(x)")
plt.plot(theta_array,sin_array,label="f(x)=sin(x)")
plt.title("sin and cos functions")
plt.xlabel(r'$\theta$')
plt.ylabel(r'$\theta$')
plt.ylabel(r'$f(\theta)$')
plt.legend()
plt.grid(which="both")
plt.show()
```

sin and cos functions 1.00 f(x) = cos(x) $f(x)=\sin(x)$ 0.75 0.50 0.25 0.00 -0.25-0.50-0.75-1.00-2 -10 2 -3 1 θ

```
[3]: n_busses = 3
bus_set = [i for i in range(1,n_busses + 1)]
print(bus_set)
```

[1, 2, 3]

```
[4]: # Create dictionaries containing the data provided in problem statement

Pd_dict_high = {bus_set[0]:1.0,bus_set[1]:3.5,bus_set[2]:5.0} # Power demand -

→ high

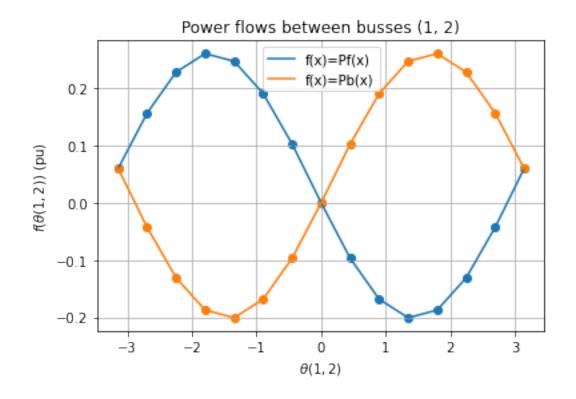
Pd_dict_low = {bus_set[0]:1.0,bus_set[1]:2.0,bus_set[2]:3.0} # Power demand - low

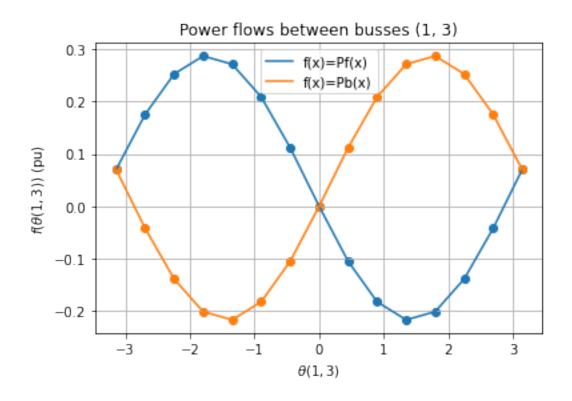
Pgmax_dict = {bus_set[0]:7.0,bus_set[1]:0.0,bus_set[2]:4.0} # Max power

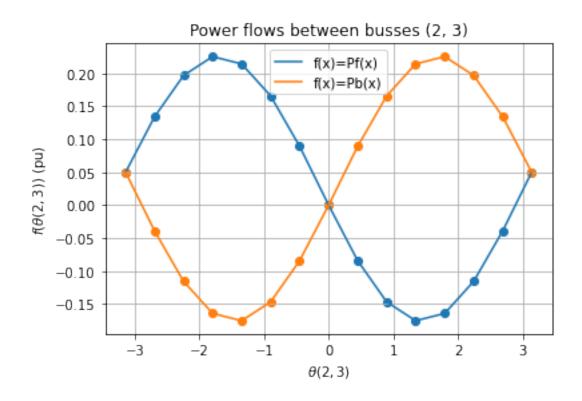
→ generation
```

```
print(f'Pd_dict_high={Pd_dict_high}')
     print(f'Pd_dict_low={Pd_dict_low}')
     print(f'Pgmax_dict={Pgmax_dict}')
    Pd_dict_high={1: 1.0, 2: 3.5, 3: 5.0}
    Pd_dict_low={1: 1.0, 2: 2.0, 3: 3.0}
    Pgmax_dict={1: 7.0, 2: 0.0, 3: 4.0}
[5]: b_combs = combinations(bus_set,2) # connections between busses
     b_combs = list(b_combs)
     print(f"bus pairs:{b_combs}")
    bus pairs: [(1, 2), (1, 3), (2, 3)]
[6]: # More data from problem statement
     r_dict = {b_combs[0]:0.030, b_combs[1]:0.035, b_combs[2]:0.025}
     x_dict = \{b_combs[0]: 0.23, b_combs[1]: 0.25, b_combs[2]: 0.20\}
     n_dict = {b_combs[0]:2, b_combs[1]:1, b_combs[2]:1}
     print(f'r_dict={r_dict}')
     print(f'x_dict={x_dict}')
     print(f'n_dict={n_dict}')
     # Calculate z values and assign values to a dict:
     z = lambda r, x : r + x*1j
     z_dict = {pair:z(r_dict[pair], x_dict[pair]) for pair in b_combs}
     print(f'z_dict={z_dict}')
    r_dict=\{(1, 2): 0.03, (1, 3): 0.035, (2, 3): 0.025\}
    x_dict=\{(1, 2): 0.23, (1, 3): 0.25, (2, 3): 0.2\}
    n_dict=\{(1, 2): 2, (1, 3): 1, (2, 3): 1\}
    z_{dict}=\{(1, 2): (0.03+0.23j), (1, 3): (0.035+0.25j), (2, 3): (0.025+0.2j)\}
[7]: # Calculate q and b values and assign to dict:
     g = lambda r, x: r / (r**2+x**2)
     b = lambda r, x: -x / (r**2+x**2)
     g_dict = {pair:g(r_dict[pair], x_dict[pair]) for pair in b_combs}
     b_dict = {pair:b(r_dict[pair], x_dict[pair]) for pair in b_combs}
     print(f'g_dict={g_dict}')
     print(f'b_dict={b_dict}')
    g_{\text{dict}}=\{(1, 2): 0.5576208178438662, (1, 3): 0.5492349941153394, (2, 3):
    0.6153846153846153}
    b_dict={(1, 2): -4.275092936802974, (1, 3): -3.9231071008238523, (2, 3):
    -4.9230769230769225}
[8]: # power flow (P) has different values for forwards (f-Pij) and backwards (b-Pji)
      \rightarrow directions:
     Pf = lambda g,b,theta: (g - (g*np.cos(theta) + b*np.sin(theta))) # Pij
```

```
Pb = lambda g,b,theta: (g - (g*np.cos(theta) - b*np.sin(theta))) # Pji
    Pf_dict = {pair:Pf(r_dict[pair], x_dict[pair], theta_array) for pair in b_combs}
    print(f'Pf_dict={Pf_dict}')
    Pb_dict = {pair:Pb(r_dict[pair], x_dict[pair], theta_array) for pair in b_combs}
    print(f'Pb_dict={Pb_dict}')
    0.24755779,
           0.19111655, 0.10276419, 0.
                                       , -0.09682233, -0.16852594,
          -0.20090905, -0.18755779, -0.13111655, -0.04276419, 0.06
                       , 0.17500485, 0.25228001, 0.28652021, 0.27094375,
    3): array([ 0.07
           0.20863573, 0.11193702, 0. , -0.10500485, -0.18228001,
          -0.21652021, -0.20094375, -0.13863573, -0.04193702, 0.07
                      , 0.13430097, 0.19695354, 0.22554861, 0.21442256,
    3): array([ 0.05
                                            , -0.08430097, -0.14695354,
           0.16577905, 0.08925253, 0.
          -0.17554861, -0.16442256, -0.11577905, -0.03925253, 0.05
    Pb_dict={(1, 2): array([ 0.06 , -0.04276419, -0.13111655, -0.18755779,
    -0.20090905,
                                            , 0.10276419, 0.19111655,
          -0.16852594, -0.09682233, 0.
           0.24755779, 0.26090905, 0.22852594, 0.15682233, 0.06
                                                                    ]), (1,
                        , -0.04193702, -0.13863573, -0.20094375, -0.21652021,
    3): array([ 0.07
                                            , 0.11193702, 0.20863573,
          -0.18228001, -0.10500485, 0.
           0.27094375, 0.28652021, 0.25228001, 0.17500485, 0.07
                        , -0.03925253, -0.11577905, -0.16442256, -0.17554861,
    3): array([ 0.05
          -0.14695354, -0.08430097, 0.
                                            , 0.08925253, 0.16577905,
           0.21442256, 0.22554861, 0.19695354, 0.13430097, 0.05
                                                                    1)}
[9]: for k, bc in enumerate(b_combs):
        plt.figure()
        plt.scatter(theta_array,Pf_dict[bc])
        plt.scatter(theta_array,Pb_dict[bc])
        plt.plot(theta_array,Pf_dict[bc],label="f(x)=Pf(x)")
        plt.plot(theta_array,Pb_dict[bc],label="f(x)=Pb(x)")
        plt.title(f"Power flows between busses {bc}")
        plt.xlabel(fr'$\theta{bc}$')
        plt.ylabel(fr'$f(\theta{bc})$ (pu)')
        plt.legend()
        plt.grid(which="both")
        plt.show()
```







1.3 Piecewise linear reformulations and solving

1.3.1 Convex-combination - CC

In convex combination approximations, the dependent variable is given by a linear combination of two consecutive points from the available data: For a given pair of buses (i, j), the CC piecewise linear reformulation is:

$$\begin{aligned} &(i,j) \in \{1,\ldots,N\}^2, i \neq j \\ &Givens^{(i,j)} : \{(\theta_{k=0}^{(i,j)}, P_{k=0}^{(i,j)}), \ldots, (\theta_{(M-1)}^{(i,j)}, P_{(M-1)}^{(i,j)})\} \\ &\theta^{(i,j)} = \sum_{k=0}^{M-1} \lambda_k^{(i,j)} \theta_k^{(i,j)} \\ &P^{(i,j)} = \sum_{k=0}^{M-1} \lambda_k^{(i,j)} P_k^{(i,j)} \\ &\lambda_k^{(i,j)} \geq 1, k = 0, \ldots, (M-1) \\ &1 = \sum_{k=0}^{M-1} \lambda_k^{(i,j)} \\ &1 = \sum_{k=1}^{M-1} \lambda_k^{(i,j)} \\ &\lambda_k^{(i,j)} \in \{0,1\}, k = 1, \ldots, (M-1) \\ &\lambda_0^n \leq z_1^{(i,j)} \\ &\lambda_{(M-1)}^{(i,j)} \leq z_{(M-1)}^{(i,j)} \\ &\lambda_k^{(i,j)} \leq z_k^{(i,j)} + z_{k+1}, k = 1, \ldots, (M-1) \\ &z_k^{(i,j)} = 1 \text{ if } P^{(i,j)} \in [P_{k-1}^{(i,j)}, P_k^{(i,j)}] \end{aligned}$$

 $z_k^{(i,j)} = 1 \text{ if } P^{(i,j)} \in [P_{k-1}^{(i,j)}, P_k^{(i,j)}]$ Where M is the number of available data points for bus pair (i,j) and N is the number of buses in the system.

1.3.2 Convex Combination in Gurobi

```
[10]: cc = Model()
cc.Params.LogFile = "cc_log.txt"

# each bus i is in a certain theta
thetai_vars = cc.addVars(bus_set, lb=-math.pi/2, ub=math.pi/2, vtype=GRB.

—CONTINUOUS, name="thetai")

# power generated in each bus i, constrained by values given in problem statement
Pgi_vars = cc.addVars(bus_set, lb=0,ub=Pgmax_dict,vtype=GRB.CONTINUOUS,
—name="Pgi")
cc.update()
print([(f"Pg{Pgi}",Pgi_vars[Pgi].ub) for Pgi in Pgi_vars])
# Pgi_vars = cc.addVars(bus_set, lb=0,vtype=GRB.CONTINUOUS, name="Pgi") # This
—would be a relaxation
```

```
# total power flow into each bus i
Pi_vars = cc.addVars(bus_set, vtype=GRB.CONTINUOUS, name="Pi")
# auxiliary variables which represents each |Pi|
Pi_abs_vars = cc.addVars(bus_set, vtype=GRB.CONTINUOUS, name="Pi_abs")
lambda_vars = gp.tupledict() # 1 value per data interval per pair ((n_points-1)_
\rightarrow * len(b_combs))
z_vars = gp.tupledict() # 1 value per data point per pair (n_points *_
\rightarrow len(b_combs))
lag_vars = gp.tupledict() # 1 value per pair (len(b_combs))
Pf_vars = gp.tupledict() # 1 value per pair (len(b_combs))
Pb_vars = gp.tupledict() # 1 value per pair (len(b_combs))
data_indexes = range(n_points)
for pair in b_combs:
   # create lambdas for current pair
   lambda_vars_ = cc.addVars(data_indexes, lb=0.0, vtype=GRB.CONTINUOUS,_
 cc.addConstr(gp.quicksum(lambda_vars_)==1)
   lambda_vars[pair] = lambda_vars_
    \# z variables indicate in which piece of the piecewise linear function the
 →decision variable is
    # create z variables for current pair
   z_vars_ = cc.addVars(data_indexes[1:], vtype=GRB.BINARY, name=f"z{pair}") #__
 →note that first index is removed
   cc.addConstr(gp.quicksum(z_vars_)==1)
   z_vars[pair] = z_vars_
   cc.addConstr(lambda_vars_[0] <= z_vars_[1]) # ensure first lambda = 0 if_{\square}
 →decision variable outside of first piece
   cc.addConstr(lambda_vars_[n_points-1] <= z_vars_[n_points-1]) # ensure last_
 →lambda =0 if decision variable outside of last piece
   for i in range(1,n_points-1):
       →if decision variable not in any of the neighboring pieces
    # create lag variable for current pair
   lag_var = cc.addVar(vtype=GRB.CONTINUOUS, name=f"lag{pair}")
   cc.addConstr(lag_var==(gp.quicksum([lambda_vars_[i]*theta_array[i] for i in_
 →data_indexes])), name=f"lag{pair} calculation")
   lag_vars[pair] = lag_var
```

```
# create power flow variable for current pair
         Pf_data = Pf_dict[pair] # power flows calculated before for current pair_
  \hookrightarrow (Pij)
         Pf_var = cc.addVar(vtype=GRB.CONTINUOUS, name=f"Pf{pair}") # Power flow
  →variable for current pair
         cc.addConstr(Pf_var==(gp.quicksum([lambda_vars_[i]*Pf_data[i] for i in_
  →data_indexes])), name=f"Pf{pair} calculation")
         Pf_vars[pair] = Pf_var
          # create power flow variable for current pair, reverse
         Pb_data = Pb_dict[pair] # power flows calculated before for current pair_
  \hookrightarrow (Pij)
         Pb_var = cc.addVar(vtype=GRB.CONTINUOUS, name=f"Pb{pair}") # Power flow_
  →variable for current pair
         cc.addConstr(Pb_var==(gp.quicksum([lambda_vars_[i]*Pb_data[i] for i in_
  →data_indexes])), name=f"Pb{pair} calculation")
         Pb_vars[pair] = Pb_var
         # not quite necessary, but create theta for each individual bus
         i = pair[0]
         j = pair[1]
         cc.addConstr(lag_var==thetai_vars[i]-thetai_vars[j],__

¬name=f"thetas_i=({pair})")
cc.update()
for bus in bus_set:
          # energy conservation constraint
          # calculate power inflow at each bus
         print(f"Power inflow at bus {bus}:")
         Pi_value = 0
         for pair in b_combs:
                   if bus == pair[0]: # bus is i in pair (i,j), power inflow at i is Pb
                             inflow = Pb_vars[pair]
                   elif bus == pair[1]: # bus is j in pair (i, j), power inflow at i is Pf
                             inflow = Pf_vars[pair]
                   else:
                             inflow = 0
                   Pi_value += n_dict[pair] * inflow
         print(Pi_value)
         Pi_injected_constr = cc.addConstr(Pi_vars[bus]==Pi_value)
          # en_cons_constr = cc.
  \rightarrow addConstr(Pgi\_vars[bus] == Pd\_dict\_low[bus] + Pi\_vars[bus], f"Energy balance_{\sqcup} + Pi\_vars[bus] + Pi\_vars[b
   \hookrightarrow \{bus\}''\}
```

```
en_cons_constr = cc.addConstr(Pgi_vars[bus] == Pd_dict_high[bus] + Pi_vars[bus], ___
       abs_constr = cc.addGenConstrAbs(Pi_abs_vars[bus], Pi_vars[bus], name="ABS")
          cc.update()
          print(Pi_injected_constr)
      cc.setObjective(gp.quicksum(Pi_abs_vars))
      cc.update()
      # cc.display()
     Set parameter Username
     Academic license - for non-commercial use only - expires 2022-05-20
     Set parameter LogFile to value "cc_log.txt"
     [('Pg1', 7.0), ('Pg2', 0.0), ('Pg3', 4.0)]
     Power inflow at bus 1:
     <gurobi.LinExpr: 2.0 Pb(1, 2) + Pb(1, 3)>
     <gurobi.Constr R63>
     Power inflow at bus 2:
     <gurobi.LinExpr: 2.0 Pf(1, 2) + Pb(2, 3)>
     <gurobi.Constr R65>
     Power inflow at bus 3:
     <gurobi.LinExpr: Pf(1, 3) + Pf(2, 3)>
     <gurobi.Constr R67>
[11]: cc.optimize()
     Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
     Thread count: 2 physical cores, 4 logical processors, using up to 4 threads
     Optimize a model with 69 rows, 108 columns and 375 nonzeros
     Model fingerprint: 0xd6415f2b
     Model has 3 general constraints
     Variable types: 66 continuous, 42 integer (42 binary)
     Coefficient statistics:
                        [4e-02, 3e+00]
       Matrix range
       Objective range [1e+00, 1e+00]
       Bounds range
                        [1e+00, 7e+00]
                        [1e+00, 5e+00]
       RHS range
     Presolve removed 0 rows and 3 columns
     Presolve time: 0.00s
     Explored 0 nodes (0 simplex iterations) in 0.02 seconds (0.00 work units)
     Thread count was 1 (of 4 available processors)
     Solution count 0
```

```
Best objective -, best bound -, gap -
[12]: cc.getVars()
[12]: [<gurobi.Var thetai[1]>,
       <gurobi.Var thetai[2]>,
       <gurobi.Var thetai[3]>,
       <gurobi.Var Pgi[1]>,
       <gurobi.Var Pgi[2]>,
       <gurobi.Var Pgi[3]>,
       <gurobi.Var Pi[1]>,
       <gurobi.Var Pi[2]>,
       <gurobi.Var Pi[3]>,
       <gurobi.Var Pi_abs[1]>,
       <gurobi.Var Pi_abs[2]>,
       <gurobi.Var Pi_abs[3]>,
       <gurobi.Var lambdas(1, 2)[0]>,
       <gurobi.Var lambdas(1, 2)[1]>,
       <gurobi.Var lambdas(1, 2)[2]>,
       <gurobi.Var lambdas(1, 2)[3]>,
       <gurobi.Var lambdas(1, 2)[4]>,
       <gurobi.Var lambdas(1, 2)[5]>,
       <gurobi.Var lambdas(1, 2)[6]>,
       <gurobi.Var lambdas(1, 2)[7]>,
       <gurobi.Var lambdas(1, 2)[8]>,
       <gurobi.Var lambdas(1, 2)[9]>,
       <gurobi.Var lambdas(1, 2)[10]>,
       <gurobi.Var lambdas(1, 2)[11]>,
       <gurobi.Var lambdas(1, 2)[12]>,
       <gurobi.Var lambdas(1, 2)[13]>,
       <gurobi.Var lambdas(1, 2)[14]>,
       <gurobi.Var z(1, 2)[1]>,
       <gurobi.Var z(1, 2)[2]>,
       <gurobi.Var z(1, 2)[3]>,
       <gurobi.Var z(1, 2)[4]>,
       <gurobi.Var z(1, 2)[5]>,
       <gurobi.Var z(1, 2)[6]>,
       \langle gurobi.Var z(1, 2)[7] \rangle
       <gurobi.Var z(1, 2)[8]>,
       <gurobi.Var z(1, 2)[9]>,
       <gurobi.Var z(1, 2)[10]>,
       <gurobi.Var z(1, 2)[11]>,
       <gurobi.Var z(1, 2)[12]>,
       <gurobi.Var z(1, 2)[13]>,
       <gurobi.Var z(1, 2)[14]>,
```

Model is infeasible

```
<gurobi.Var lag(1, 2)>,
<gurobi.Var Pf(1, 2)>,
<gurobi.Var Pb(1, 2)>,
<gurobi.Var lambdas(1, 3)[0]>,
<gurobi.Var lambdas(1, 3)[1]>,
<gurobi.Var lambdas(1, 3)[2]>,
<gurobi.Var lambdas(1, 3)[3]>,
<gurobi.Var lambdas(1, 3)[4]>,
<gurobi.Var lambdas(1, 3)[5]>,
<gurobi.Var lambdas(1, 3)[6]>,
<gurobi.Var lambdas(1, 3)[7]>,
<gurobi.Var lambdas(1, 3)[8]>,
<gurobi.Var lambdas(1, 3)[9]>,
<gurobi.Var lambdas(1, 3)[10]>,
<gurobi.Var lambdas(1, 3)[11]>,
<gurobi.Var lambdas(1, 3)[12]>,
<gurobi.Var lambdas(1, 3)[13]>,
<gurobi.Var lambdas(1, 3)[14]>,
<gurobi.Var z(1, 3)[1]>,
<gurobi.Var z(1, 3)[2]>,
<gurobi.Var z(1, 3)[3]>,
<gurobi.Var z(1, 3)[4]>,
<gurobi.Var z(1, 3)[5]>,
\leq (1, 3)[6]
<gurobi.Var z(1, 3)[7]>,
<gurobi.Var z(1, 3)[8]>,
<gurobi.Var z(1, 3)[9]>,
<gurobi.Var z(1, 3)[10]>,
<gurobi.Var z(1, 3)[11]>,
<gurobi.Var z(1, 3)[12]>,
<gurobi.Var z(1, 3)[13]>,
<gurobi.Var z(1, 3)[14]>,
<gurobi.Var lag(1, 3)>,
<gurobi.Var Pf(1, 3)>,
<gurobi.Var Pb(1, 3)>,
<gurobi.Var lambdas(2, 3)[0]>,
<gurobi.Var lambdas(2, 3)[1]>,
<gurobi.Var lambdas(2, 3)[2]>,
<gurobi.Var lambdas(2, 3)[3]>,
<gurobi.Var lambdas(2, 3)[4]>,
<gurobi.Var lambdas(2, 3)[5]>,
<gurobi.Var lambdas(2, 3)[6]>,
<gurobi.Var lambdas(2, 3)[7]>,
<gurobi.Var lambdas(2, 3)[8]>,
<gurobi.Var lambdas(2, 3)[9]>,
<gurobi.Var lambdas(2, 3)[10]>,
<gurobi.Var lambdas(2, 3)[11]>,
```

```
<gurobi.Var lambdas(2, 3)[12]>,
<gurobi.Var lambdas(2, 3)[13]>,
<gurobi.Var lambdas(2, 3)[14]>,
<gurobi.Var z(2, 3)[1]>,
<gurobi.Var z(2, 3)[2]>,
<gurobi.Var z(2, 3)[3]>,
<gurobi.Var z(2, 3)[4]>,
<gurobi.Var z(2, 3)[5]>,
<gurobi.Var z(2, 3)[6]>,
<gurobi.Var z(2, 3)[7]>,
<gurobi.Var z(2, 3)[8]>,
<gurobi.Var z(2, 3)[9]>,
<gurobi.Var z(2, 3)[10]>,
<gurobi.Var z(2, 3)[11]>,
<gurobi.Var z(2, 3)[12]>,
<gurobi.Var z(2, 3)[13]>,
<gurobi.Var z(2, 3)[14]>,
<gurobi.Var lag(2, 3)>,
<gurobi.Var Pf(2, 3)>,
<gurobi.Var Pb(2, 3)>]
```

1.3.3 Special Ordered Set of Variables Type 2 - SOS2

$$\begin{split} (i,j) &\in \{1,\dots,N\}^2, i \neq j \\ Givens^{(i,j)} &: \{(\theta_{k=0}^{(i,j)}, P_{k=0}^{(i,j)}), \dots, (\theta_{(M-1)}^{(i,j)}, P_{(M-1)}^{(i,j)})\} \\ \theta^{(i,j)} &= \sum_{k=0}^{M-1} \lambda_k^{(i,j)} \theta_k^{(i,j)} \\ P^{(i,j)} &= \sum_{k=0}^{M-1} \lambda_k^{(i,j)} P_k^{(i,j)} \\ \lambda_k^{(i,j)} &\geq 0, k = 0, \dots, (M-1) \\ 1 &= \sum_{k=0}^{M-1} \lambda_k^{(i,j)} \\ \{\lambda_k^{(i,j)}\}_{k=0}^{(M-1)} &\in \text{SOS2} \end{split}$$

Where **SOS2** (Special Ordered Set of type 2) is the set of sets that comply to the following criteria: At most 2 elements are positive.

 $\lambda_{k}^{(i,j)} \in [0,+\infty], k = 0,...,M-1$

In the case 2 elements in the set are positive, they must be consecutive in the ordered set.

 $z_k^{(i,j)} \in \{0,1\}, k=0,...,M-1 \\ \lambda_k^{(i,j)} \leq z_k, k=0,...,M-1 \\ \sum_{k=0}^{M-1} z_k \leq 2 \\ z_k^{(i,j)} + z_l^{(i,j)} \leq 1, l \in \{k+2,...,M-1\}$

1.3.4 Special Ordered Set of Variables Type 2 in Gurobi

```
[13]: sos2 = Model()
sos2.Params.LogFile = "sos2_log.txt"
# each bus i is in a certain theta
thetai_vars = sos2.addVars(bus_set, lb=-math.pi/2, ub=math.pi/2, vtype=GRB.
→CONTINUOUS, name="thetai")

# power generated in each bus i, constrained by values given in problem statement
Pgi_vars = sos2.addVars(bus_set, lb=0,ub=Pgmax_dict,vtype=GRB.CONTINUOUS,___
→name="Pgi")
sos2.update()
print([(f"Pg{Pgi}",Pgi_vars[Pgi].ub) for Pgi in Pgi_vars])
# Pgi_vars = sos2.addVars(bus_set, lb=0,vtype=GRB.CONTINUOUS, name="Pgi") # This___
→would be a relaxation
```

```
# total power flow into each bus i
Pi_vars = sos2.addVars(bus_set, vtype=GRB.CONTINUOUS, name="Pi")
# auxiliary variables which represents each |Pi|
Pi_abs_vars = sos2.addVars(bus_set, vtype=GRB.CONTINUOUS, name="Pi_abs")
lambda_vars = gp.tupledict() # 1 value per data interval per pair ((n_points-1)_
\rightarrow * len(b_combs)
z_vars = gp.tupledict() # 1 value per data point per pair (n_points *_
\rightarrow len(b_combs))
lag_vars = gp.tupledict() # 1 value per pair (len(b_combs))
Pf_vars = gp.tupledict() # 1 value per pair (len(b_combs))
Pb_vars = gp.tupledict() # 1 value per pair (len(b_combs))
data_indexes = range(n_points)
for pair in b_combs:
    # create lambdas for current pair
    lambda_vars_ = sos2.addVars(data_indexes, lb=0.0, vtype=GRB.CONTINUOUS,_u
 →name=f"lambdas{pair}")
    sos2.addConstr(gp.quicksum(lambda_vars_)==1)
    lambda_vars[pair] = lambda_vars_
    z_vars_ = sos2.addVars(data_indexes, vtype=GRB.BINARY, name=f"z{pair}")
    sos2.addConstr(gp.quicksum(z_vars_)<=2)</pre>
    z_vars[pair] = z_vars_
    for k in range(0,n_points):
        sos2.addConstr(lambda_vars_[k] <= z_vars_[k])</pre>
        for 1 in range(k+2,n_points):
            sos2.addConstr(lambda_vars_[k]+z_vars_[l]<=1)</pre>
    # create lag variable for current pair
    lag_var = sos2.addVar(vtype=GRB.CONTINUOUS, name=f"lag{pair}")
    sos2.addConstr(lag_var==(gp.quicksum([lambda_vars_[i]*theta_array[i] for iu
 →in data_indexes])), name=f"lag{pair} calculation")
    lag_vars[pair] = lag_var
    # create power flow variable for current pair
    Pf_data = Pf_dict[pair] # power flows calculated before for current pair_
 \hookrightarrow (Pij)
    Pf_var = sos2.addVar(vtype=GRB.CONTINUOUS, name=f"Pf{pair}") # Power flow_
 →variable for current pair
    sos2.addConstr(Pf_var==(gp.quicksum([lambda_vars_[i]*Pf_data[i] for i in_
 →data_indexes])), name=f"Pf{pair} calculation")
```

```
Pf_vars[pair] = Pf_var
    # create power flow variable for current pair, reverse
    Pb_data = Pb_dict[pair] # power flows calculated before for current pair_
 \hookrightarrow (Pij)
    Pb_var = sos2.addVar(vtype=GRB.CONTINUOUS, name=f"Pb{pair}") # Power flow
 →variable for current pair
    sos2.addConstr(Pb_var==(gp.quicksum([lambda_vars_[i]*Pb_data[i] for i in_
 →data_indexes])), name=f"Pb{pair} calculation")
    Pb_vars[pair] = Pb_var
    # not quite necessary, but create theta for each individual bus
    i = pair[0]
    j = pair[1]
    sos2.addConstr(lag_var==thetai_vars[i]-thetai_vars[j],__

¬name=f"thetas_i=({pair})")
sos2.update()
for bus in bus_set:
    # energy conservation constraint
    # calculate power inflow at each bus
    print(f"Power inflow at bus {bus}:")
    Pi_value = 0
    for pair in b_combs:
        if bus == pair[0]: # bus is i in pair (i,j), power inflow at i is Pb
            inflow = Pb_vars[pair]
        elif bus == pair[1]: # bus is j in pair (i,j), power inflow at i is Pf
            inflow = Pf_vars[pair]
        else:
            inflow = 0
        Pi_value += n_dict[pair] * inflow
   print(Pi_value)
    Pi_injected_constr = sos2.addConstr(Pi_vars[bus]==Pi_value)
    # en_cons_constr = sos2.
 →addConstr(Pqi_vars[bus] == Pd_dict_low[bus] + Pi_vars[bus], f"Energy balance
 \rightarrow {bus} }")
    en_cons_constr = sos2.
 →addConstr(Pgi_vars[bus] == Pd_dict_high[bus] + Pi_vars[bus], f"Energy balance_
 →{bus}")
    abs_constr = sos2.addGenConstrAbs(Pi_abs_vars[bus], Pi_vars[bus], name="ABS")
    sos2.update()
    print(Pi_injected_constr)
```

```
sos2.setObjective(gp.quicksum(Pi_abs_vars))
      sos2.update()
      # sos2.display()
     Set parameter LogFile to value "sos2_log.txt"
     [('Pg1', 7.0), ('Pg2', 0.0), ('Pg3', 4.0)]
     Power inflow at bus 1:
     <gurobi.LinExpr: 2.0 Pb(1, 2) + Pb(1, 3)>
     <gurobi.Constr R336>
     Power inflow at bus 2:
     <gurobi.LinExpr: 2.0 Pf(1, 2) + Pb(2, 3)>
     <gurobi.Constr R338>
     Power inflow at bus 3:
     <gurobi.LinExpr: Pf(1, 3) + Pf(2, 3)>
     <gurobi.Constr R340>
[14]: sos2.optimize()
     Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
     Thread count: 2 physical cores, 4 logical processors, using up to 4 threads
     Optimize a model with 342 rows, 111 columns and 885 nonzeros
     Model fingerprint: 0x36dcab36
     Model has 3 general constraints
     Variable types: 66 continuous, 45 integer (45 binary)
     Coefficient statistics:
       Matrix range
                        [4e-02, 3e+00]
       Objective range [1e+00, 1e+00]
       Bounds range
                        [1e+00, 7e+00]
       RHS range
                        [1e+00, 5e+00]
     Presolve removed 0 rows and 3 columns
     Presolve time: 0.00s
     Explored 0 nodes (0 simplex iterations) in 0.02 seconds (0.00 work units)
     Thread count was 1 (of 4 available processors)
     Solution count 0
     Model is infeasible
     Best objective -, best bound -, gap -
```

1.3.5 Using Gurobi built-in PWL constraints

```
[15]: m = Model()
      m.Params.LogFile = "m_log.txt"
      # each bus i is in a certain theta
      thetai_vars = m.addVars(bus_set, lb=-math.pi/2, ub=math.pi/2, vtype=GRB.
       →CONTINUOUS, name="thetai")
      # power generated in each bus i, constrained by values given in problem statement
      Pgi_vars = m.addVars(bus_set, lb=0,ub=Pgmax_dict,vtype=GRB.CONTINUOUS,_
       →name="Pgi")
      m.update()
      print([(f"Pg{Pgi}",Pgi_vars[Pgi].ub) for Pgi in Pgi_vars])
      # Pqi_vars = m.addVars(bus_set, lb=0,vtype=GRB.CONTINUOUS, name="Pqi") # Thisu
       →would be a relaxation
      # total power flow into each bus i
      Pi_vars = m.addVars(bus_set, vtype=GRB.CONTINUOUS, name="Pi")
      # auxiliary variables which represents each |Pi|
      Pi_abs_vars = m.addVars(bus_set, vtype=GRB.CONTINUOUS, name="Pi_abs")
      lambda_vars = gp.tupledict() # 1 value per data interval per pair ((n_points-1)_
       \rightarrow* len(b_combs))
      z_vars = gp.tupledict() # 1 value per data point per pair (n_points *_
      \rightarrow len(b_combs))
      lag_vars = gp.tupledict() # 1 value per pair (len(b_combs))
      Pf_vars = gp.tupledict() # 1 value per pair (len(b_combs))
      Pb_vars = gp.tupledict() # 1 value per pair (len(b_combs))
      data_indexes = range(n_points)
      pwlff = {}
      pwlfb = \{\}
      for pair in b_combs:
          Pf_vars[pair] = m.addVar(vtype=GRB.CONTINUOUS, name=f"Pf{pair}")
          Pb_vars[pair] = m.addVar(vtype=GRB.CONTINUOUS, name=f"Pb{pair}")
          lag_vars[pair] = m.addVar(vtype=GRB.CONTINUOUS, name=f"lag{pair}")
          pwlff[pair] = m.addGenConstrPWL(lag_vars[pair], Pf_vars[pair], theta_array,__
       →Pf_dict[pair], f"Pf(lag) pair {pair}")
          pwlfb[pair] = m.addGenConstrPWL(lag_vars[pair], Pb_vars[pair], theta_array,__
       →Pb_dict[pair], f"Pb(lag) pair {pair}")
          # not quite necessary, but create theta for each individual bus
          i = pair[0]
          j = pair[1]
```

```
m.addConstr(lag_vars[pair] == thetai_vars[i] - thetai_vars[j],__
 →name=f"thetas_i=({pair})")
m.update()
for bus in bus_set:
    # energy conservation constraint
    # calculate power inflow at each bus
    print(f"Power inflow at bus {bus}:")
    Pi_value = 0
    for pair in b_combs:
        if bus == pair[0]: # bus is i in pair (i,j), power inflow at i is Pb
             inflow = Pb_vars[pair]
        elif bus == pair[1]: # bus is j in pair (i,j), power inflow at i is Pf
            inflow = Pf_vars[pair]
        else:
             inflow = 0
        Pi_value += n_dict[pair] * inflow
    print(Pi_value)
    Pi_injected_constr = m.addConstr(Pi_vars[bus] == Pi_value)
    # en_cons_constr = m.addConstr(Pgi_vars[bus] == Pd_dict_low[bus] + Pi_vars[bus], __
 \rightarrow f "Energy balance {bus}")
    en_cons_constr = m.addConstr(Pgi_vars[bus] == Pd_dict_high[bus] + Pi_vars[bus],_u
 abs_constr = m.addGenConstrAbs(Pi_abs_vars[bus], Pi_vars[bus], name="ABS")
    m.update()
    print(Pi_injected_constr)
m.setObjective(gp.quicksum(Pi_abs_vars))
m.update()
# m.display()
Set parameter LogFile to value "m_log.txt"
[('Pg1', 7.0), ('Pg2', 0.0), ('Pg3', 4.0)]
Power inflow at bus 1:
<gurobi.LinExpr: 2.0 Pb(1, 2) + Pb(1, 3)>
<gurobi.Constr R3>
Power inflow at bus 2:
<gurobi.LinExpr: 2.0 Pf(1, 2) + Pb(2, 3)>
<gurobi.Constr R5>
Power inflow at bus 3:
<gurobi.LinExpr: Pf(1, 3) + Pf(2, 3)>
```

```
<gurobi.Constr R7>
```

```
[16]: m.optimize()
     Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64)
     Thread count: 2 physical cores, 4 logical processors, using up to 4 threads
     Optimize a model with 9 rows, 21 columns and 24 nonzeros
     Model fingerprint: 0x70ab9279
     Model has 9 general constraints
     Variable types: 21 continuous, 0 integer (0 binary)
     Coefficient statistics:
                         [1e+00, 2e+00]
       Matrix range
       Objective range
                         [1e+00, 1e+00]
                         [2e+00, 7e+00]
       Bounds range
       RHS range
                         [1e+00, 5e+00]
                         [0e+00, 3e+00]
       PWLCon x range
       PWLCon y range
                         [0e+00, 3e-01]
     Presolve removed 0 rows and 3 columns
     Presolve time: 0.00s
     Explored 0 nodes (0 simplex iterations) in 0.02 seconds (0.00 work units)
     Thread count was 1 (of 4 available processors)
     Solution count 0
     Model is infeasible
     Best objective -, best bound -, gap -
[17]: m.getVars()
[17]: [<gurobi.Var thetai[1]>,
       <gurobi.Var thetai[2]>,
       <gurobi.Var thetai[3]>,
       <gurobi.Var Pgi[1]>,
       <gurobi.Var Pgi[2]>,
       <gurobi.Var Pgi[3]>,
       <gurobi.Var Pi[1]>,
       <gurobi.Var Pi[2]>,
       <gurobi.Var Pi[3]>,
       <gurobi.Var Pi_abs[1]>,
       <gurobi.Var Pi_abs[2]>,
       <gurobi.Var Pi_abs[3]>,
       <gurobi.Var Pf(1, 2)>,
       <gurobi.Var Pb(1, 2)>,
       <gurobi.Var lag(1, 2)>,
       <gurobi.Var Pf(1, 3)>,
       <gurobi.Var Pb(1, 3)>,
       <gurobi.Var lag(1, 3)>,
```