project3

July 10, 2017

1 Project 3

1.1 Abstract

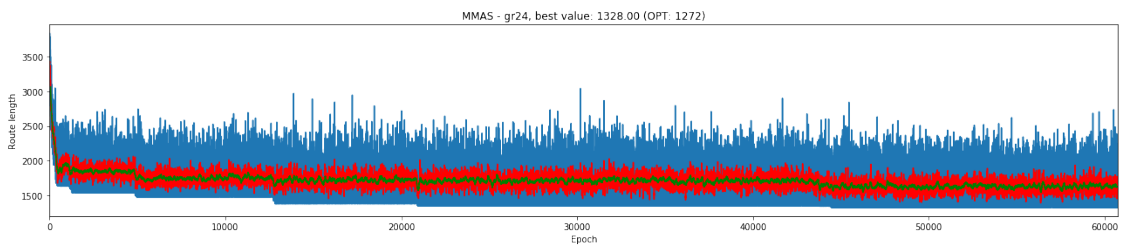
- We wrote our own tsp parser module due to the fact the available packages are not working for all tsp files
  - We tried: https://github.com/tsartsaris/TSPLIB-python-parser
- You can find the MMAS algorithm in `algorithm.py`. It's just the basic implementation as described in the exercise sheet.
- We document our results in this jupyter notebook:
  1. Test MMAS using the initial parameters
     - gr24 problem
     - Comparing $\beta = 0$ with $\beta = 4$
  2. Parameter tuning for all five parameters
     - gr48 problem
     - Grid search
     - Test resulting parameter setting on three different problems (gr24, gr48, gr96)
  3. Collect the extra credits
     - We found the optimal solution for dantzig42
     - We found a solution for kroB100 being less than 1 % worse than the optimum
     - We found a solution for dsj1000 being less than 30 % worse than the optimum
     - We found a solution for d18512 being less than 50 % worse than the optimum
- The problems are downloaded from http://elib.zib.de/pub/mp-testdata/tsp/tsplib/tsp/
- In our plots we use three different colors:
  1. Blue: The actual results of each epoch
  2. Red: The running mean of the results (window size: 10)
  3. Green: The running mean of the results (window size: 100)

In [2]:
```
import numpy as np
import tsp_parser
import algorithms as algo
import viz
import utils
from matplotlib import pyplot as plt
```

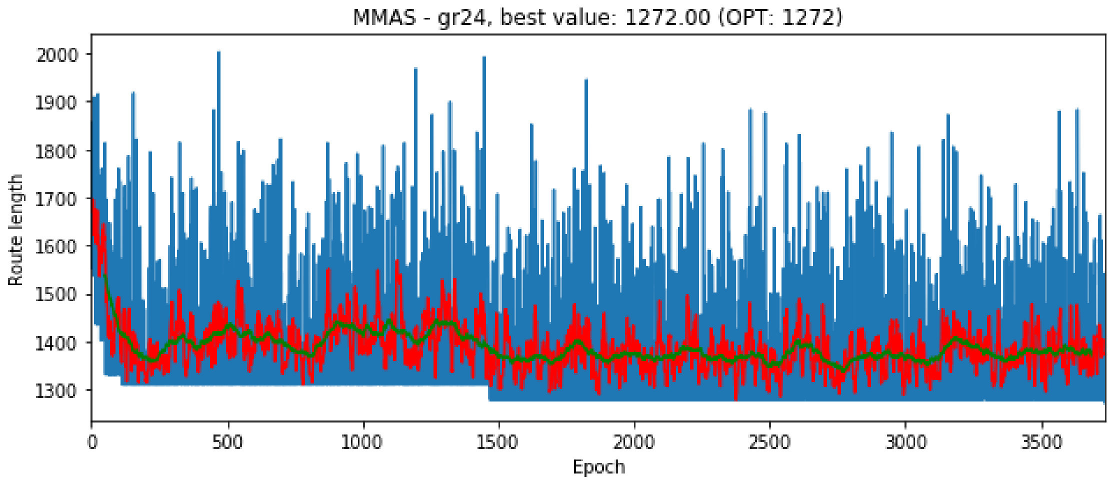
```
%matplotlib inline
```

2 Test MMAS using the initial parameters

```
In [2]: gr24_problem = tsp_parser.load_problem('data/gr24')

In [96]: np.random.seed(0)  # Always produce the same random decisions (for debugging)
         mmas = algo.MMAS(gr24_problem, wall_clock_time=10*60)  # Run for 10 minutes
         mmas()

Stopped after 10.01 minutes

Out[96]: (1328,
          array([23, 11,  3,  0, 15, 10,  2, 17, 21, 16, 18, 14,  1, 19, 12,  8, 22,
                 13,  9,  4, 20,  7,  6,  5]))
```




```
In [97]: np.random.seed(0)
         mmas = algo.MMAS(gr24_problem, wall_clock_time=10*60, beta=4)
         mmas()

Stopped after 0.74 minutes

Out[97]: (1272,
          array([ 7, 20,  4,  9, 16, 21, 17, 18, 14,  1, 19, 13, 12,  8, 22,  3, 11,
                  0, 15, 10,  2,  6,  5, 23]))
```



1. Without heuristic information: 1328
2. With $\beta = 4$: 1272 [7 20 4 9 16 21 17 18 14 1 19 13 12 8 22 3 11 0 15 10 2 6 5 23]
3. We found the same solution but shifted and with 0-based IDs
4. Without β we didn't find the solution within the 10 minutes. Using β it took only ~45 seconds finding the optimal solution.

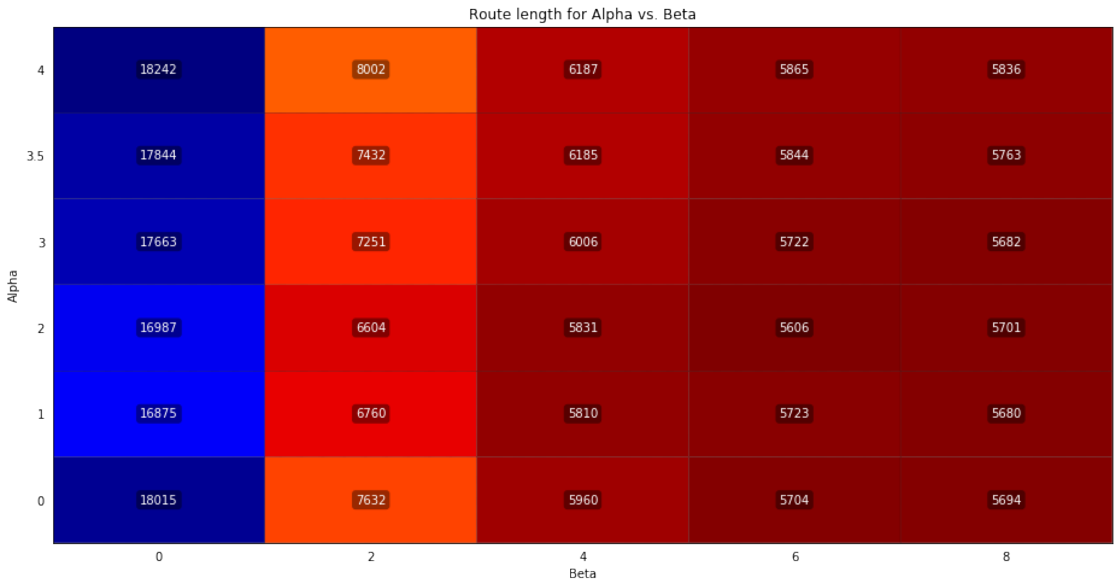
3 Parameter tuning

In [8]:
```
# Take a harder example so it will be actually hard to find the best solution
gr48_problem = tsp_parser.load_problem('data/gr48')
gr96_problem = tsp_parser.load_problem('data/gr96')
print('Best solution for gr48: {}'.format(gr48_problem['opt']))
```

```
Best solution for gr48: 5046
```

In [175]:
```
alphas=[0, 1, 2, 3, 3.5, 4]
betas=[0, 2, 4, 6, 8]
opt_params, costs = utils.grid_search(gr48_problem, alphas=alphas,
                                      betas=betas, runtime=1, tries=20)
print('alpha={} beta={} rho={:.4f} tau_min={:.4f} tau_max={:.4f}'.format(*opt_params))
utils.plot_parameter_heatmap(costs, (alphas, 'Alpha'), (betas, 'Beta'))
```

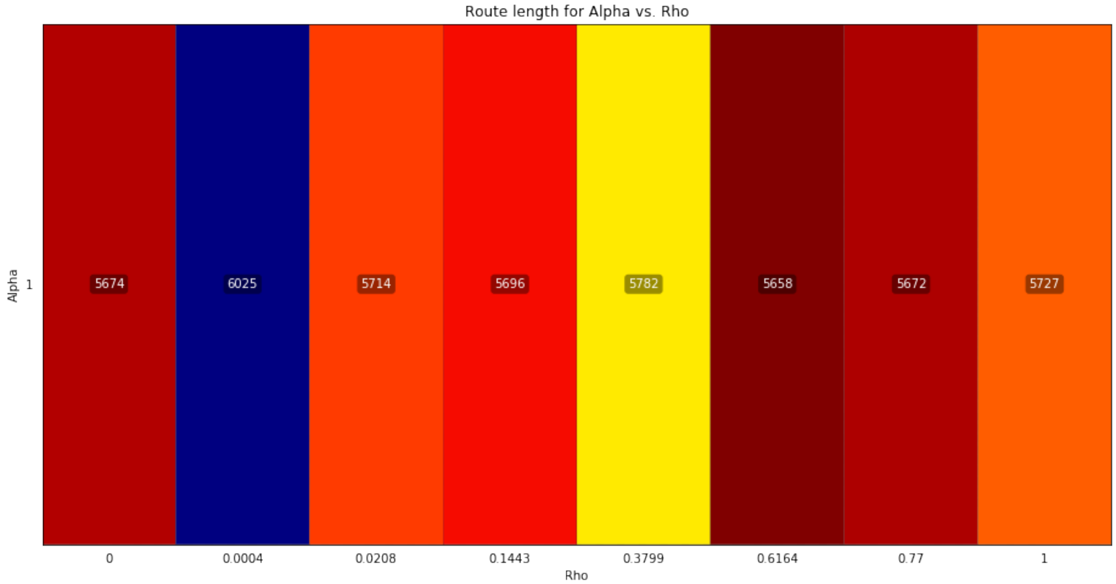
```
alpha=2 beta=6 rho=0.0208 tau_min=0.0004 tau_max=47.9792
```



In [206]:
```
opt_alpha = 1
opt_beta = 6
```

In [212]:
```
alphas=[opt_alpha]
n = gr48_problem['dimension']
rhos=[round(x, 4) for x in [0, 1/n**2, 1/n, 1/n**0.5, 1/n**0.25, 1/n**0.125, 1/n**0.06
opt_params, costs = utils.grid_search(gr48_problem, alphas=alphas,
                                      betas=[opt_beta], rhos=rhos, runtime=1, tries=10
print('alpha={} beta={} rho={:.4f} tau_min={:.4f} tau_max={:.4f}'.format(*opt_params))
utils.plot_parameter_heatmap(costs, (alphas, 'Alpha'), (rhos, 'Rho'))
```

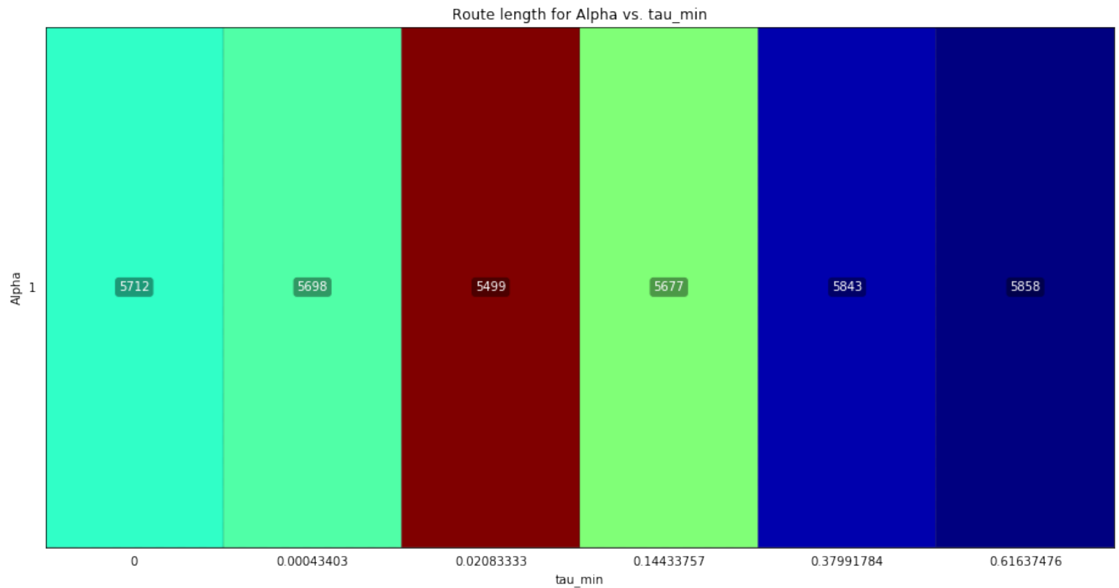
```
alpha=1 beta=6 rho=0.6164 tau_min=0.0004 tau_max=47.9792
```




```
In [3]: opt_rho = lambda n: 1/n**0.25
```

```
In [214]: alphas=[opt_alpha]
          n = gr48_problem['dimension']
          # Applying a factor (e.g. 0,5 or 2) doesn't affect the results -> Change power value
          tau_mins=[round(x, 8) for x in [0, 1/n**2, 1/n, 1/n**0.5, 1/n**0.25, 1/n**0.125]]
          opt_params, costs = utils.grid_search(gr48_problem, alphas=alphas, betas=[opt_beta],
                                                rhos=[opt_rho(n)], tau_mins=tau_mins, runtime=2,
          print('alpha={} beta={} rho={:.4f} tau_min={:.4f} tau_max={:.4f}'.format(*opt_params))
          utils.plot_parameter_heatmap(costs, (alphas, 'Alpha'), (tau_mins, 'tau_min'))
```

```
alpha=1 beta=6 rho=0.3799 tau_min=0.0208 tau_max=47.9792
```

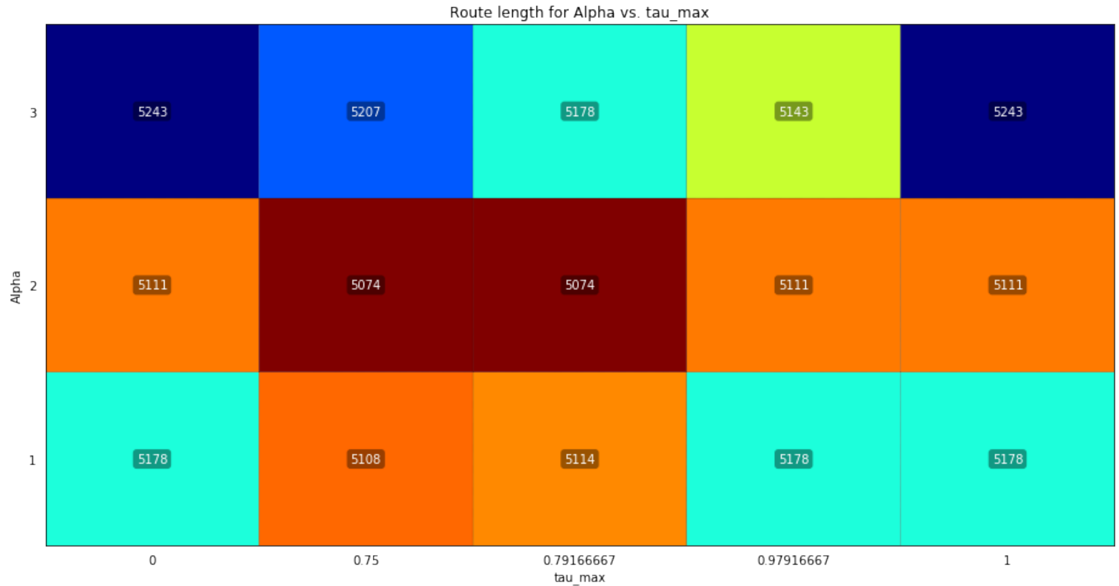



```
In [4]: opt_tau_min = lambda n: 1/n
```

Execute this parameter tuning with 5 minutes wall clock time (instead of 1 second) for parameters which influence the performance on the long run.

```
In [220]: alphas=[1, 2, 3]
          tau_maxs=[round(x, 8) for x in [0, 1-min(20, n/4)/n, 1-min(10, n/4)/n, 1-1/n, 1]]
          n = gr48_problem['dimension']
          opt_params, costs = utils.grid_search(gr48_problem, alphas=alphas, tau_maxs=tau_maxs,
                                                betas=[opt_beta], tau_mins=[opt_tau_min(n)], rho
          print('alpha={} beta={} rho={:.4f} tau_min={:.4f} tau_max={:.4f}'.format(*opt_params))
          utils.plot_parameter_heatmap(costs, (alphas, 'Alpha'), (tau_maxs, 'tau_max'))
```

```
alpha=2 beta=6 rho=0.3799 tau_min=0.0208 tau_max=0.7500
```



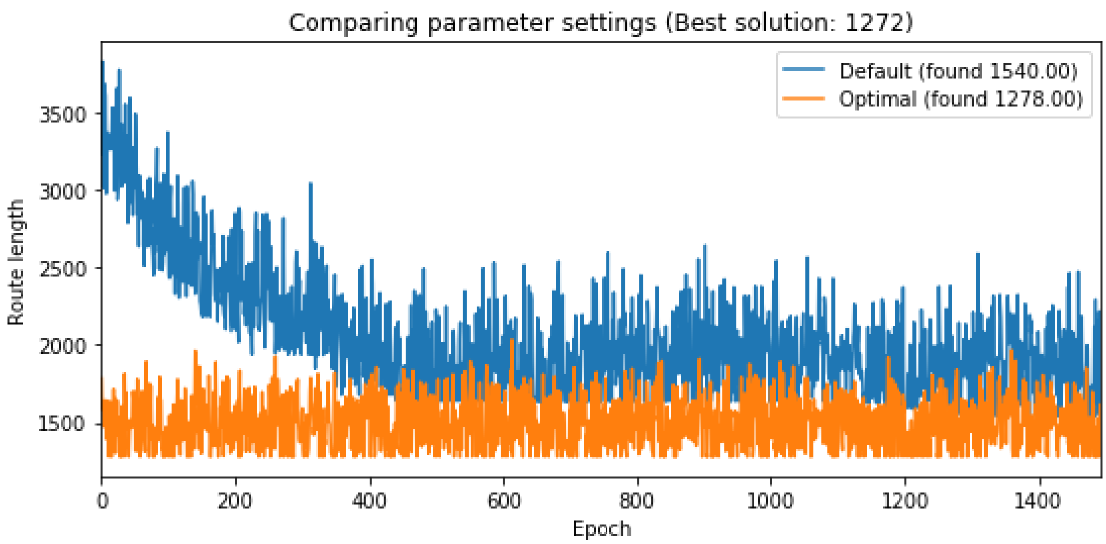

```
In [5]: opt_tau_max = lambda n: 1-min(20, n/4)/n
```

From now on we define our parameter setting using `utils.opt_setting(problem)` [containing the results of the parameter tuning]

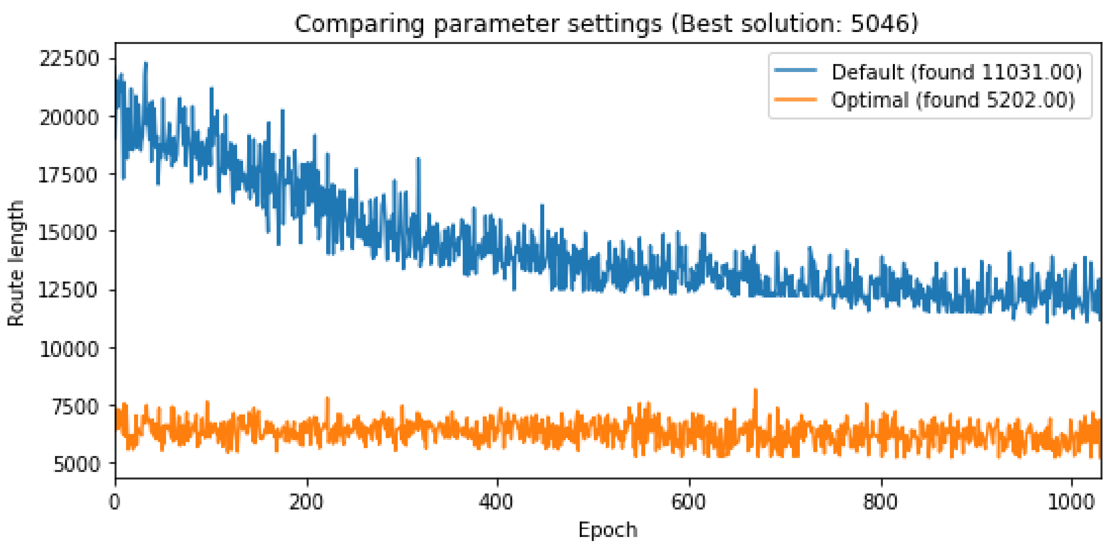
```
In [221]: # Evaluate best params on a short time interval
          print('gr24 - Compare parameter settings:')
          utils.evaluate_params(gr24_problem, utils.opt_setting(gr24_problem), runtime=10)
          print('gr48 - Compare parameter settings:')
          utils.evaluate_params(gr48_problem, utils.opt_setting(gr48_problem), runtime=20)
          print('gr96 - Compare parameter settings:')
          utils.evaluate_params(gr96_problem, utils.opt_setting(gr96_problem), runtime=40)

          # Run on simple, middle and big problem for 10 minutes to evaluate if we can improve t
          # Compare the default parameter with our parameters
          opt_setting = utils.opt_setting(gr24_problem)
          print('gr24 [Default params]:')
          algo.MMAS(gr24_problem, wall_clock_time=600)()
          print('gr24 [Optimal params]:')
          algo.MMAS(gr24_problem, wall_clock_time=600, **opt_setting)()

          opt_setting = utils.opt_setting(gr48_problem)
          print('gr48 [Default params]:')
          algo.MMAS(gr48_problem, wall_clock_time=600)()
          print('gr48 [Optimal params]:')
          algo.MMAS(gr48_problem, wall_clock_time=600, **opt_setting)()

          opt_setting = utils.opt_setting(gr96_problem)
```

```
print('gr96 [Default params]:')
algo.MMAS(gr96_problem, wall_clock_time=600)()
print('gr96 [Optimal params]:')
_ = algo.MMAS(gr96_problem, wall_clock_time=600, **opt_setting)()
```

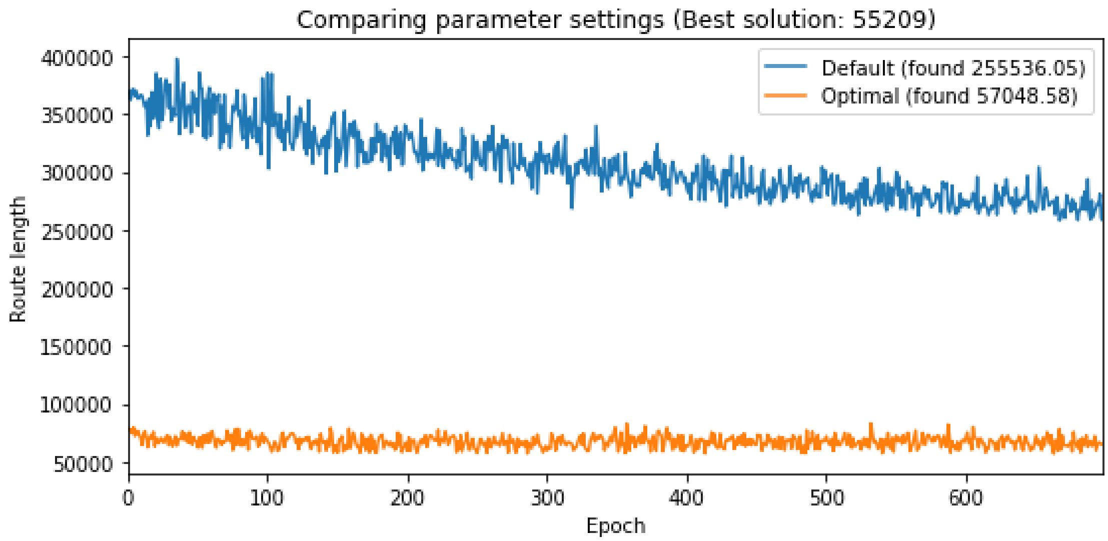
gr24 - Compare parameter settings:



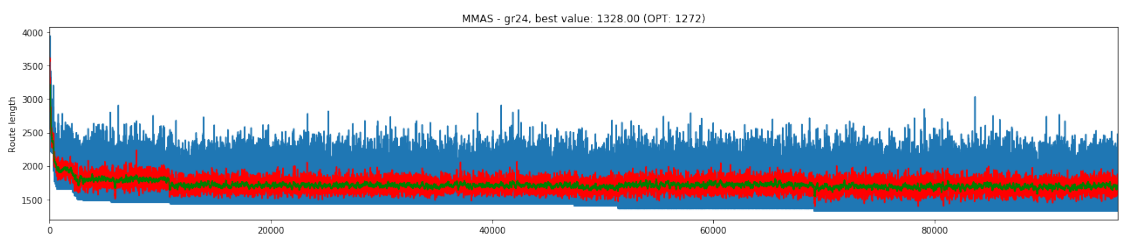
gr48 - Compare parameter settings:



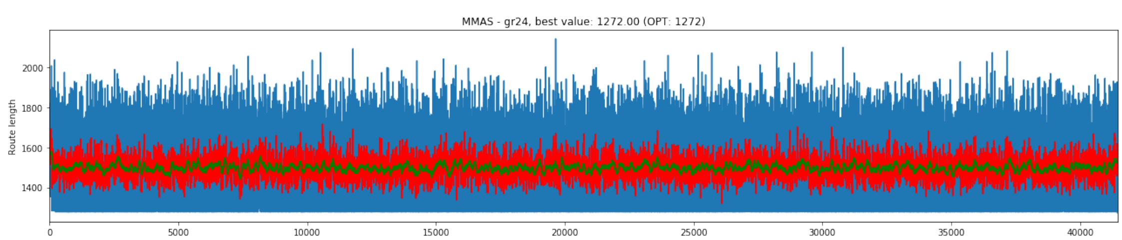
```
gr96 - Compare parameter settings:
```



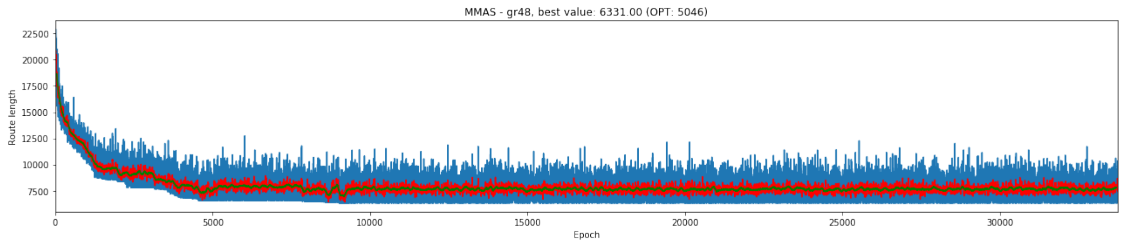

```
gr24 [Default params]:
Stopped after 10.00 minutes
```



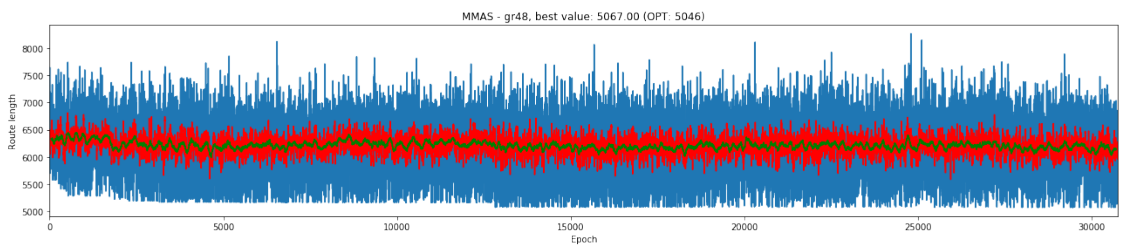

```
gr24 [Optimal params]:
Stopped after 4.68 minutes
```



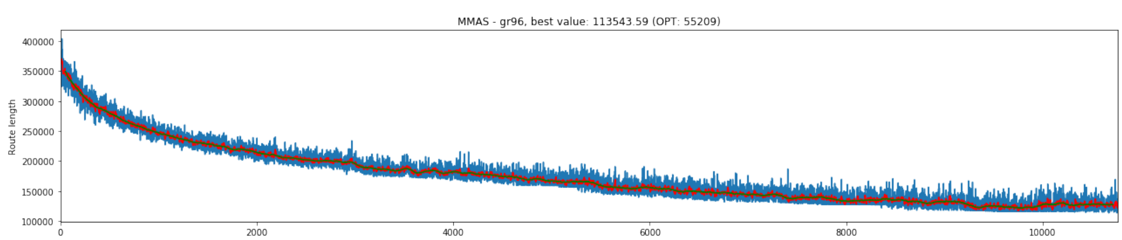
gr48 [Default params]:
Stopped after 10.00 minutes



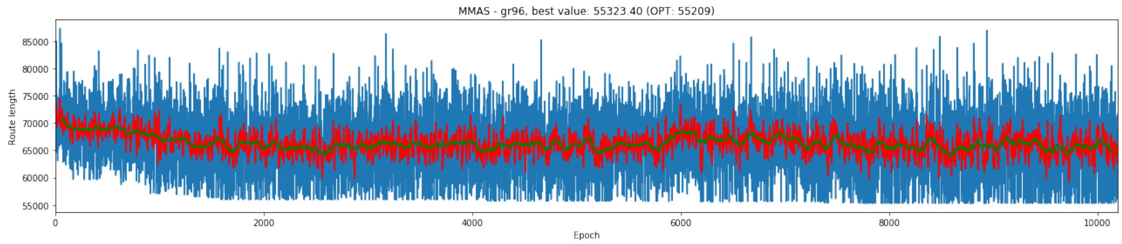
gr48 [Optimal params]:
Stopped after 10.00 minutes



gr96 [Default params]:
Stopped after 10.00 minutes



gr96 [Optimal params]:
Stopped after 10.00 minutes



Conclusion (Parameter tuning)

- We executed the algorithm for each setting with a different walltime. e.g. t_max and alpha will be important on long runs so it was executed over 5 minutes (instead of a few seconds)
- The performance of the algorithm strongly correlates with β. Good results always include a high value for β.
- To find the best parameters we would have to expand our search exponentially so we decided to find good parameters step by step
- Some of the parameters really depend on the size of the problem. We received different optimal parameters for ρ, τ_{min} and τ_{max} if we use gr24 instead of gr48.
- For ρ it looks like $n^{-\frac{1}{4}}$ is a good parameter (assuming that it has to depend on n)
- For τ_{min} it looks like n^{-2} is a good parameter (assuming that it has to depend on n)
- For τ_{max} it looks like $1 - \frac{min(20,\frac{n}{4})}{n}$ is a good parameter (assuming that it has to depend on n and is close to 1)
- Although we trained our parameters on a single problem we get much better results in three problems with different sizes
- Especially on the big problem (gr96) MMAS with our parameters found a much better solution which is actually very close to the optimal solution
- After the first execution of parameter tuning we got $\alpha = 3$ as part of a good parameter setting. After testing on different problems with 10 minutes wall clock time we saw that the algorithm gets stuck not far away from the optimal solution - even on a small problem where it should be able to find the optimal solution. After defining $\alpha = 1$ we executed the parameter tuning and the long time tests a second time and found better results.
- With these parameters on gr96 it's strongly fluctuating. Thus it's able to expand the search space and find good results.
- Resources
  - 2.3 GHz Intel Core i5
  - 2.5 GHz Intel Core i7

Parameters for further tests: $\beta = 8$, $\alpha = 1$, $\rho = n^{-\frac{1}{4}}$, $tau_{min} = n^{-2}$, $tau_{max} = 1 - \frac{min(20,\frac{n}{4})}{n}$

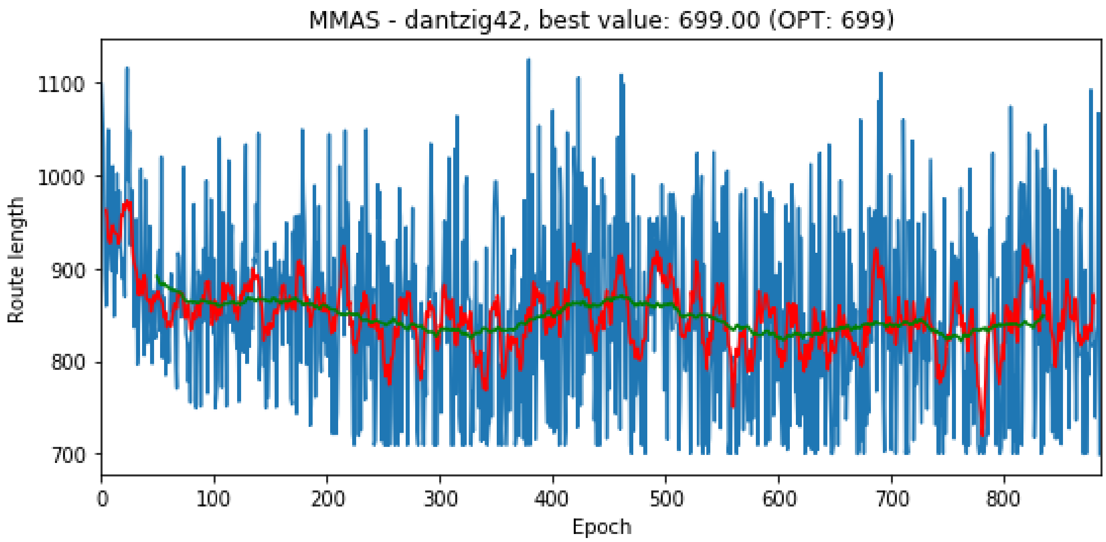
3.1 Collecting extra credtis

1.) "Solving an instance from TSPLib with at least 40 cities optimally":

```
In [20]: # Run dantzig42 for 60 minutes
         np.random.seed(0)
```

```
d42_problem = tsp_parser.load_problem('data/dantzig42')
opt_setting = utils.opt_setting(d42_problem)
mmas42 = algo.MMAS(d42_problem, wall_clock_time=60*60, **opt_setting)
route_length, route = mmas42()
if route_length == d42_problem['opt']:
    # Shift indizes to their original value
    print('We found the optimal route for d42:\nCosts = {} [optimum]\n{}'.format(
        route_length,
        ' '.join([str(x + 1) for x in route])))
```

```
Stopped after 0.31 minutes
We found the optimal route for d42:
Costs = 699 [optimum]
9 8 7 6 5 4 3 2 1 42 41 40 39 38 37 36 35 34 33 32 31 30 29 28 27 26 25 24 23 22 21 20 19 18 17
```



Notes:

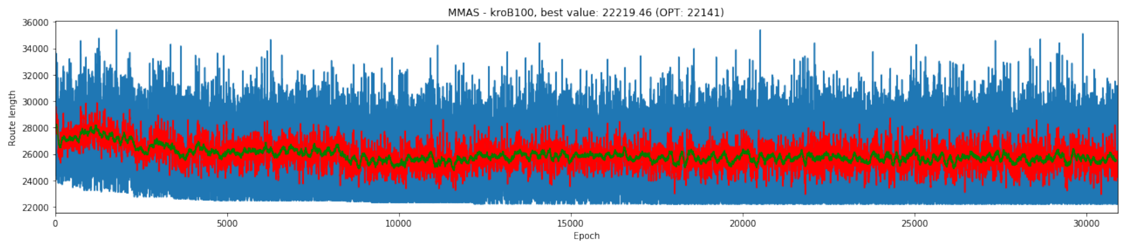
```
1. We found the optimal solution for the dantzig42 problem after executing our tuned MMAS for 20
2. Optimal solution:
    9 8 7 6 5 4 3 2 1 42 41 40 39 38 37 36 35 34 33 32 31 30 29 28 27 26 25 24 23 22 21 20 19 18
3. Before executing on this problem we failed getting the optimal solution for the problems gr48
```

2.) "Solving an instance from TSPLib with at least 100 cities at most 1% worse than the optimum tour length":

```
In [5]: # Run dantzig42 for 30 minutes
        np.random.seed(0)
        krob100_problem = tsp_parser.load_problem('data/kroB100')
        opt_setting = utils.opt_setting(krob100_problem)
```

```
    mmasb100 = algo.MMAS(krob100_problem, wall_clock_time=30*60, **opt_setting)
    route_length, route = mmasb100()
```

```
Stopped after 30.00 minutes
```



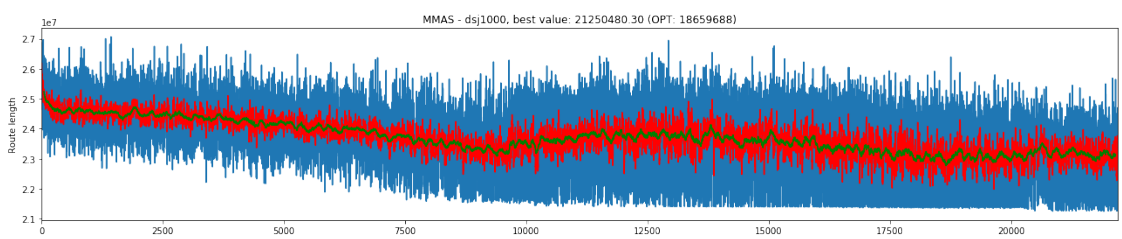
After 30 minutes: 22219.46
Optimum: 22141
$(22219.46 - 22141)/22141 = 0.0035$
We found a solution for the kroB100 problem which is only 0.35 % worse than the optimum. Before that we tried executing MMAS on kroA100 but only found a solution being 1.03% worse than the optimum.

3.) "Solving an instance from TSPLib with at least 1000 cities at most 30% worse than the optimum tour length":

```
In [3]: dsj1000_problem = tsp_parser.load_problem('data/dsj1000') # 1354
```

```
In [11]: np.random.seed(0)
         opt_setting = utils.opt_setting(dsj1000_problem)
         mmas = algo.MMAS(dsj1000_problem, wall_clock_time=60*60*9, **opt_setting)
         route_length, costs = mmas()
```

```
Stopped after 540.00 minutes
```



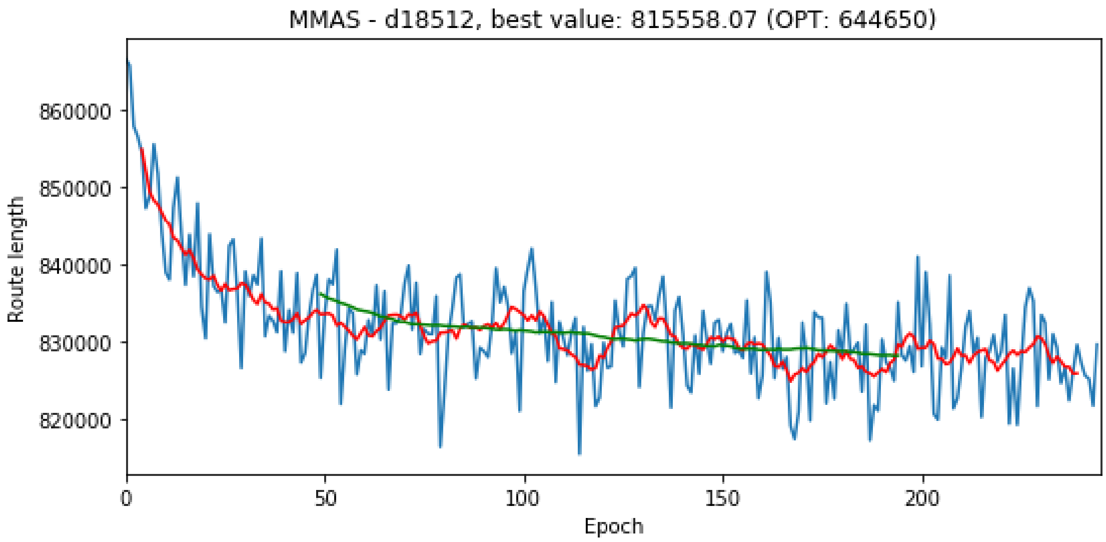
After 9h: 21250480.3
Optimum: 1859688
$(21250480.3 - 18659688)/18659688 = 0.1388$
We found a solution for the dsj1000 problem which is 13.88 % worse than the optimum

4.) "Being the team which solved the highest-number-of-cities instance from TSPLib at most 50% worse than the optimum tour length":

```
In [ ]: d18512_problem = tsp_parser.load_problem('data/d18512')
```

```
In [3]: np.random.seed(0)
        opt_setting = utils.opt_setting(d18512_problem)
        mmas18512 = algo.MMAS(d18512_problem, wall_clock_time=60*60*26, **opt_setting)
        route_length, costs = mmas18512()
```

```
Stopped after 1565.33 minutes
```



After 26 hours: 815558.07
Optimum: 644650
$(815558.07 - 644650)/644650 = 0.2651$
Notes:

```
1. We found a solution for the d18512 problem which is 26.51% worse than the optimum
2. We also tried running MMAS on the two bigger problems (pla85900 and pla33810) but our noteboo
3. Resources: i7-6700 CPU @ 3.40GHz
```