THE AMERICAN UNIVERSITY IN CAIRO

School of Sciences and Engineering

CSCE 3304-01 Digital Design II

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Fall 2022

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Algorithm Overview

The simulated annealing procedure is an optimization technique that simulates the gradual cooling of metals, which is characterized by a gradual decrease in the atomic motions that lower the density of lattice defects until a lowest-energy state is obtained. Similar to this, the simulated annealing algorithm provides a new possible solution (or neighbor of the present state) to the issue under consideration by changing the current state in accordance with a preset criterion at each virtual annealing temperature. The Metropolis criteria is then used to determine if the new state should be accepted, and this process is repeated until convergence. The metropolis is calculated in our project by raising e to the negative of the difference between the proposed wire length and the current wire length over the current temperature.

The simulated annealing is an optimization algorithm that indicates that randomization is included into the search process. Because of this, the technique works well for nonlinear objective functions, unlike other local search algorithms.It adjusts a single solution and scans the relatively local region of the search space until the local optima is found, much like the stochastic hill climbing local search algorithm. It may accept less desirable alternatives as the current working solution, unlike the hill climbing algorithm.

Simulated Annealing vs. Greedy algorithm

The fundamental difference between greedy search and simulated annealing is that, whereas greedy search always selects the best proposal, simulated annealing has a chance of rejecting it and selecting a worse one . By leaving the local optimum, this aids the algorithm's

search for a global optimum. Temperature and other factors are only a supplemental benefit (or drawback) of SA.

Simulated annealing algorithm has the option to first discover the region for the global optima, escape the local optima, then hill climb to the optima itself. The likelihood of accepting poorer solutions starts high at the beginning of the search and lowers with the progress of the search.

Implementation

The first part of the program is the parsing of the text files in order to extract the needed relevant information for the rest of the program to work. Firstly the user enters the name of the file they want to parse. Secondly, the regex library is used to extract all the digits from the first line of the program, and that allows us to get the number of nets, cells, and the dimensions of our board. The program then initialises a board where are all elements are '---' with the dimensions that were extracts from the txt file using the initialisearray() function. The program then iterates over every line, and extracts the components that need to be place onto the board, while also removing unwanted white spaces and line terminators. A component in the program is represented as object with the following attributes:

1. Value: This holds the identifier of the componet
2. Row: This holds the row that the component is in
3. Col: This holds the column that the component is in
4. Netindex: This holds the set of all the nets where this component is located

The program then randomly generates two indices for our rows and columns, and proceeds to place the components from the generated list onto the board, and assigning values

to the object attributes, while checking that the location of the placement is a valid location, where a '---' symbol exists, denoting that this point on the board is an empty location that has not had a component placed on it

The program than proceeds to calculate the initial distance on the random initial board that was generated. It does this by calling the calcdistance function. The calcdistance function takes the list that indicates how the components are connected, and the list of objects, and caluclates the half perimeter distance of a rectangle that has the elements that form the net in question. This gives us the total wire length between the elements in that one specific connection. A loop is created that loops over all the connections in our list, and the half perimeter distance is calculated for each of them. The sum of all those values gives us the initial total wire length of our board

The next step in the program is the annealing algorithim, denoted by the thermal_an() function. The function takes the board, the connection list, the initial wire length, the number of nets, and number of cells. The function then calculates t_initial and t_final, as well as the number of moves. The program then proceeds to go into a while loop, on the condition that current temperature >final temperature, and does the following:

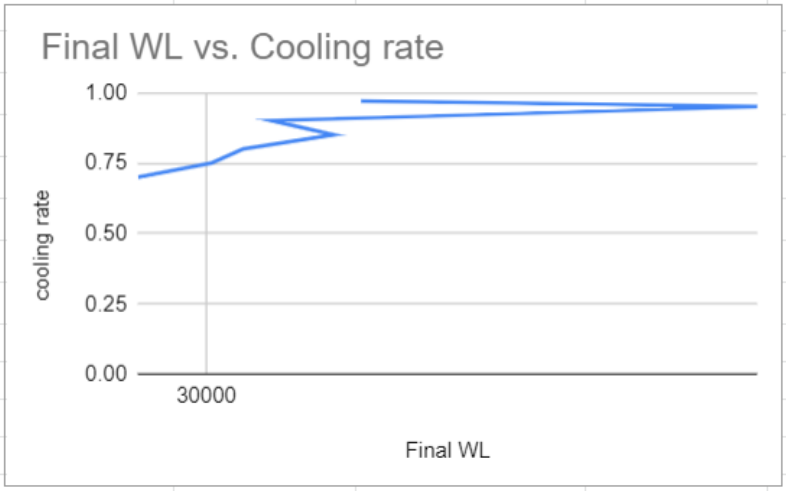
1. Swaps two random components in our board
2. Calculates the new wire length for the component that we swapped
3. Calculates the delta_l difference between initial wire length and wire length after the swap
4. If delta_l is negative, it is accepted, or it is rejected with probability 1-exp(delta_L/temperatures)
5. We then check the number of moves against the number of iterations. If they are equal iterations are reset, and the temperature=temperature*0.95

6. This is done until the condition of the while loop is met, after which the program prints out the final placement and the final wire length of the board

Cooling rate vs. TWL graphs.

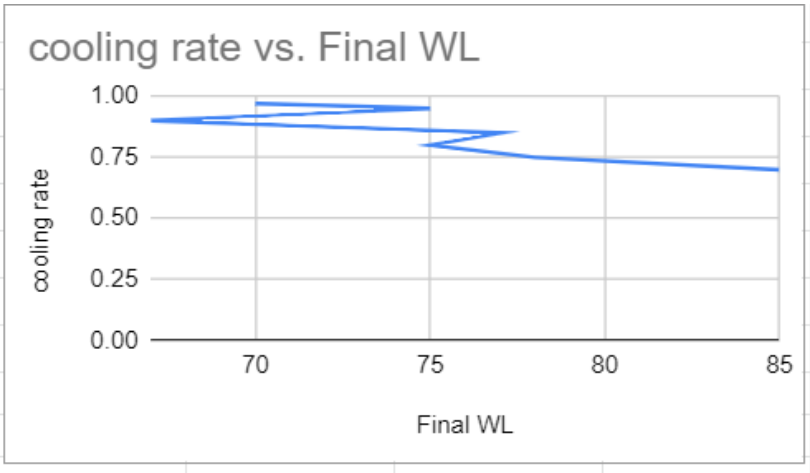
T3

Final WL	cooling rate
30065	0.7
29995	0.75
29965	0.8
29879	0.85
29938	0.9
29480	0.95
29853	0.97



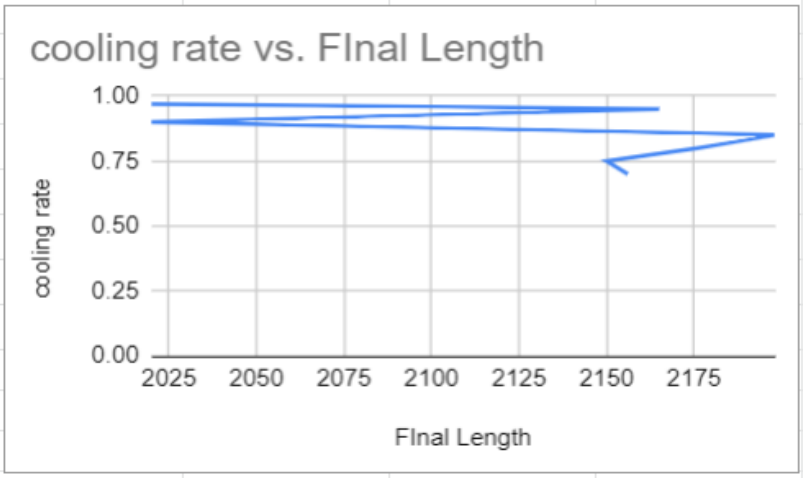
D1

Final WL	cooling rate
85	0.7
78	0.75
75	0.8
77	0.85
67	0.9
75	0.95
70	0.97



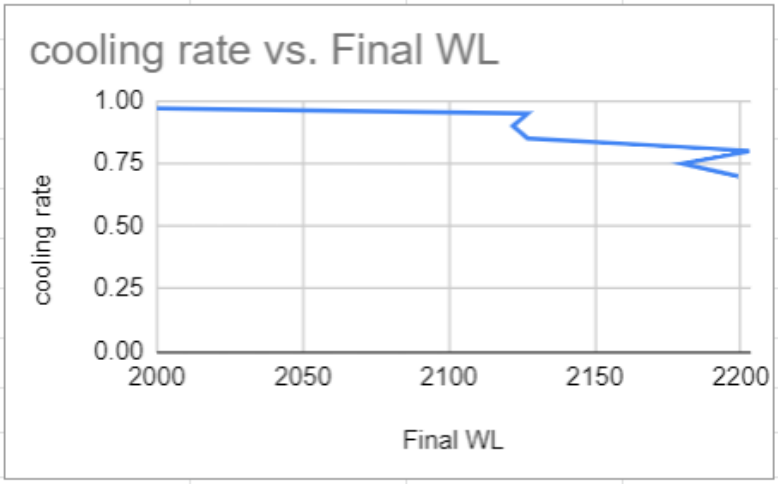
D2

FInal Length	cooling rate
2156	0.7
2150	0.75
2176	0.8
2198	0.85
2020	0.9
2165	0.95
2020	0.97



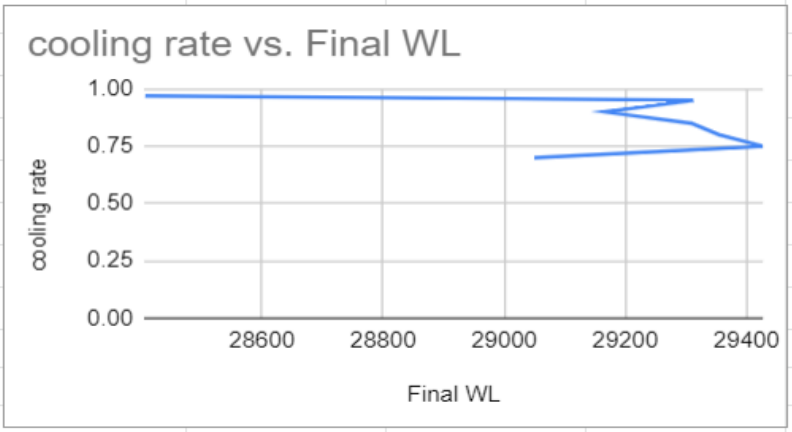
D3

Final WL	cooling rate
2199	0.7
2180	0.75
2203	0.8
2127	0.85
2122	0.9
2127	0.95
2000	0.97



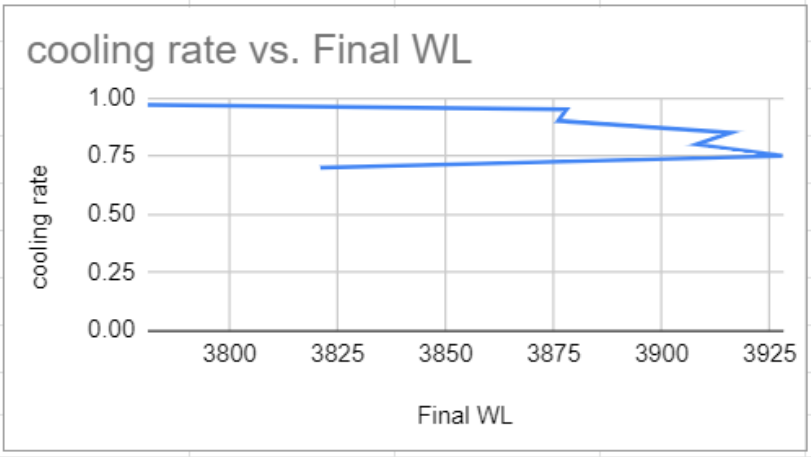
T2

Final WL	cooling rate
29050	0.7
29427	0.75
29355	0.8
29309	0.85
29166	0.9
29312	0.95
28407	0.97



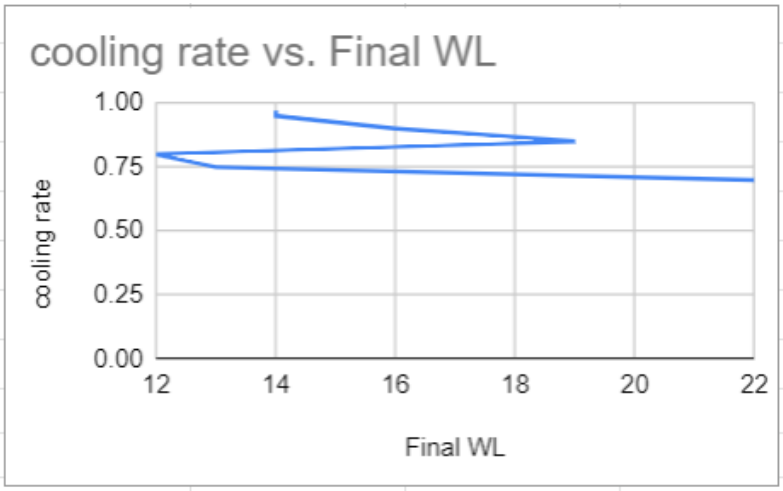
T1

Final WL	cooling rate
3821	0.7
3928	0.75
3908	0.8
3916	0.85
3876	0.9
3878	0.95
3781	0.97



D1

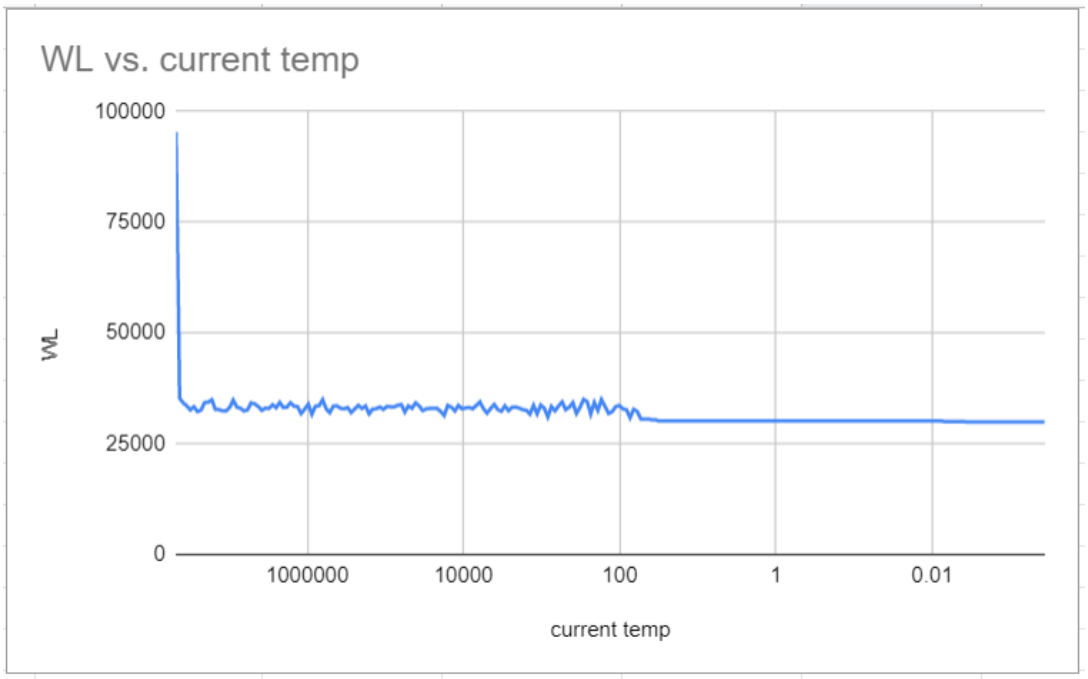
Final WL	cooling rate
22	0.7
13	0.75
12	0.8
19	0.85
16	0.9
14	0.95
14	0.97



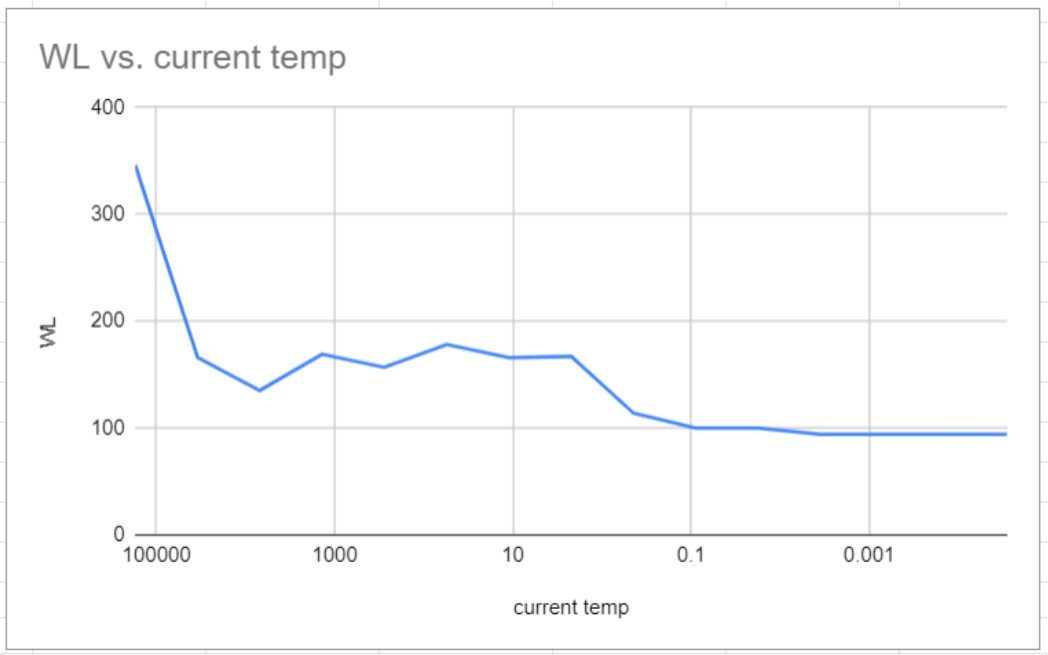
Due to the way the probability is calculated when the temperature is higher, it is more likely that the algorithm accepts a worse solution. This promotes Exploration of the search space and allows the algorithm to more likely travel down a sub-optimal path to potentially find a global maximum. When the temperature is lower, the algorithm is less likely or will not accept a worse solution. This promotes Exploitation which means that once the algorithm is in the right search space, there is no need to search other sections of the search space and should instead try to converge and find the global maximum. Therefore, by increasing the rate of cooling down the temperature then decreases, thus the wire length decreases as well.

Temperature vs. TWL graphs

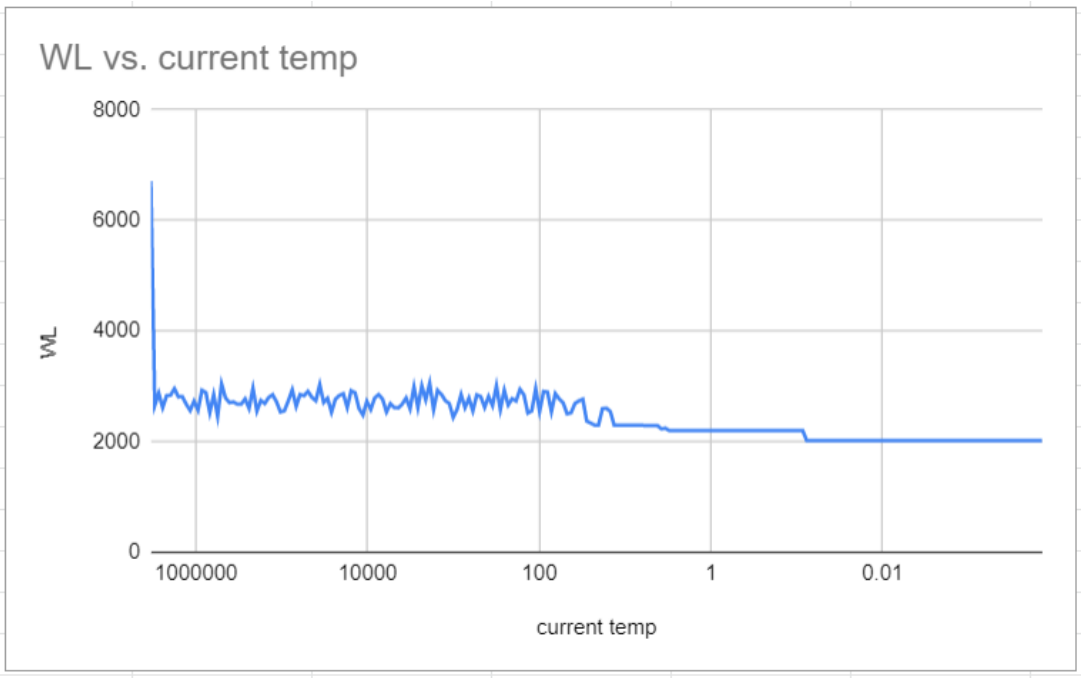
T3



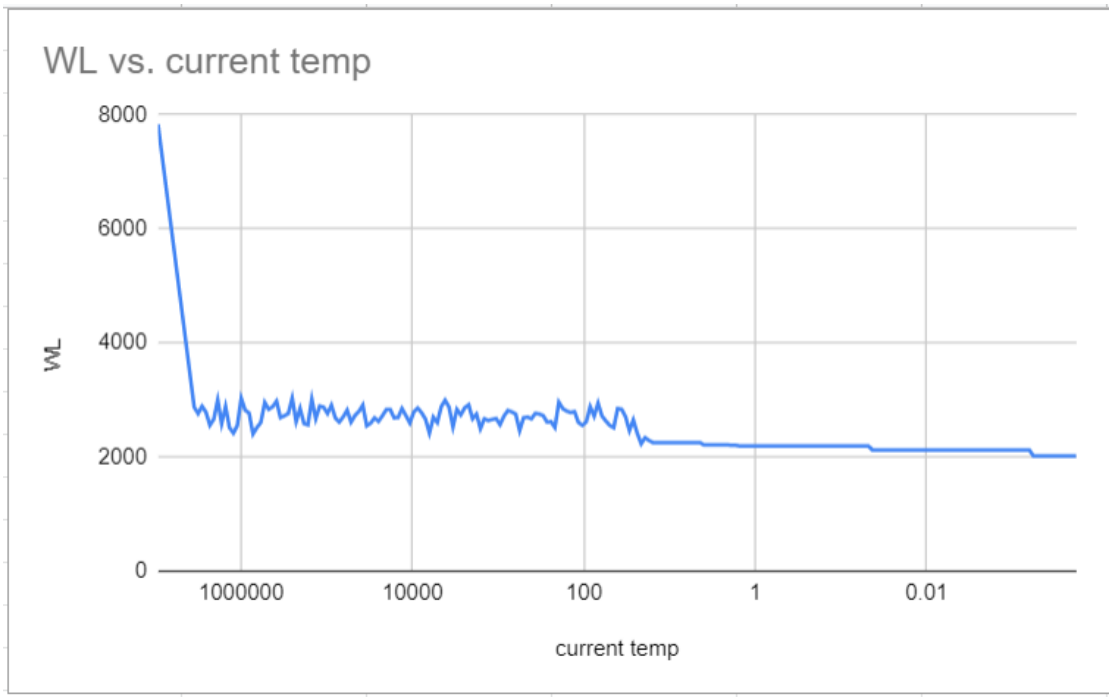
D1


WL vs. current temp
400
300
200
100
0
WL
100000
1000
10
0.1
0.001
current temp

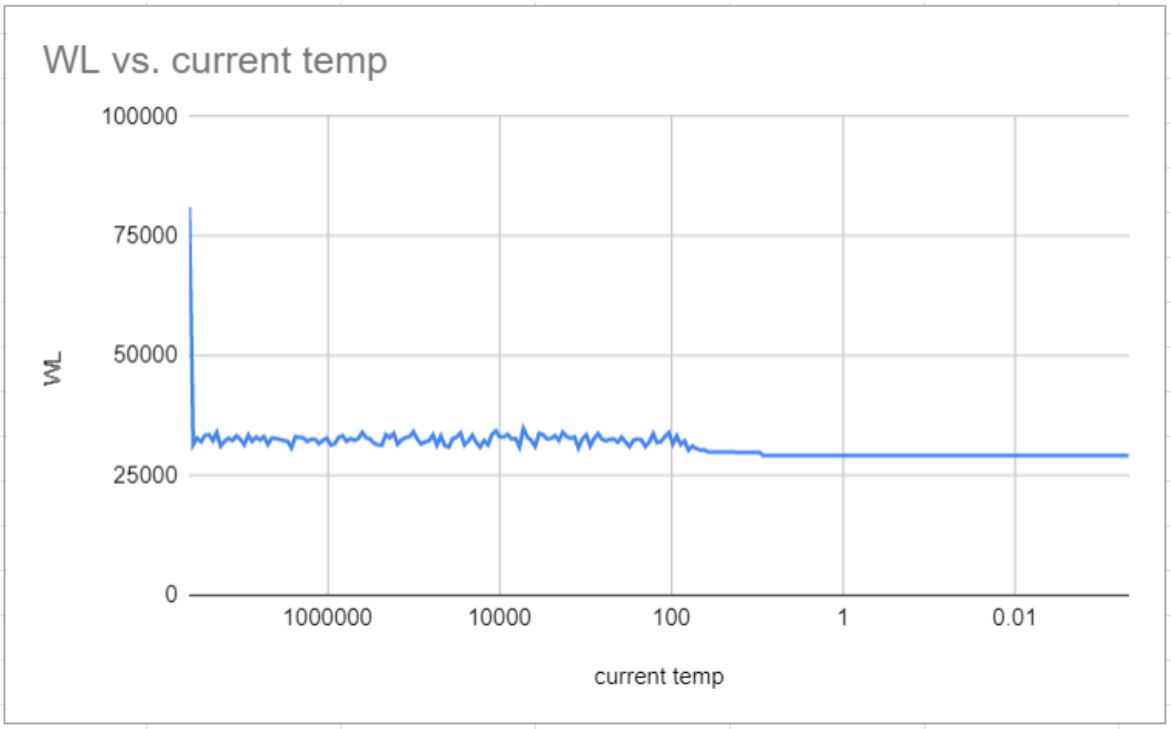
D2


WL vs. current temp
8000
6000
4000
2000
0
WL
1000000
10000
100
1
0.01
current temp

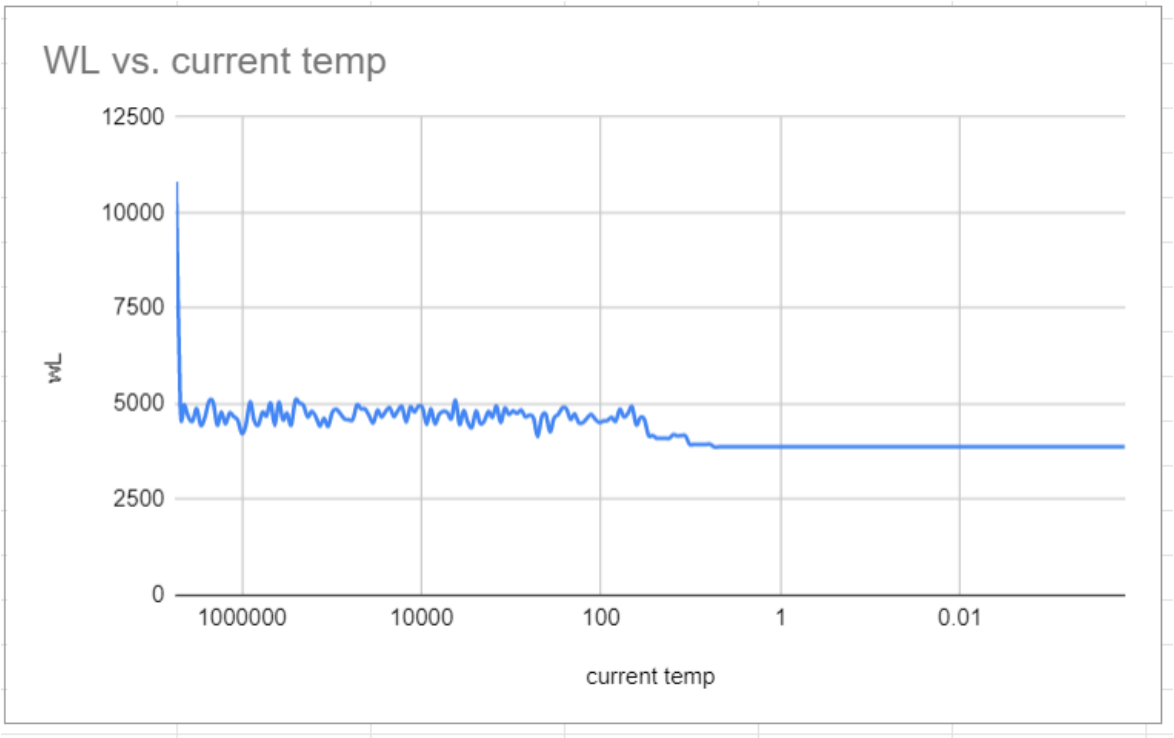
D3


WL vs. current temp
8000
6000
4000
2000
0
WL
1000000
10000
100
1
0.01
current temp

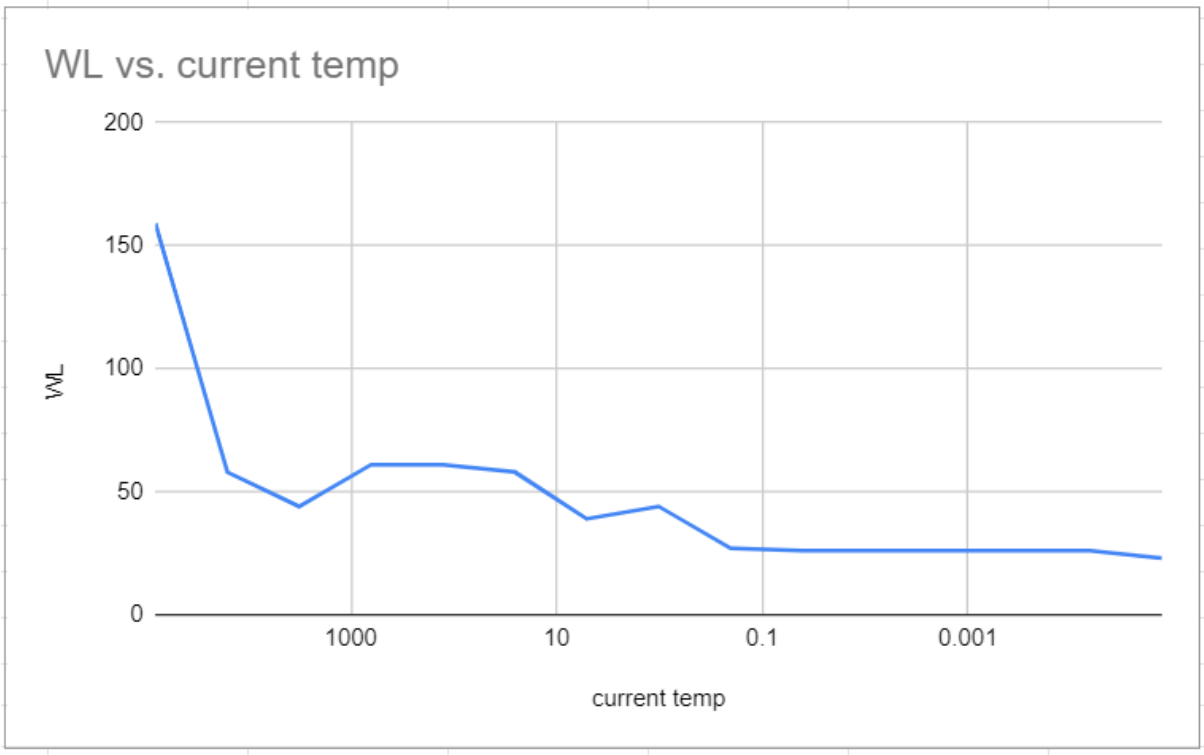
T2


WL vs. current temp
100000
75000
50000
25000
0
WL
1000000
10000
100
1
0.01
current temp

T1


WL vs. current temp
12500
10000
7500
5000
2500
0
WL
1000000
10000
100
1
0.01
current temp

D0


WL vs. current temp
200
150
100
50
0
WL
1000
10
0.1
0.001
current temp

Here we can see a general trend in all of the seven samples when the current temperature decreases the total wire length also decreases. according to the algorithm, it can raise the temperature by setting the annealing parameter to a lower value than the current iteration. The slower the rate of temperature decrease, the better the chances are of finding an optimal solution, but the longer the run time. We reversed the graph and used a log scale for enhancing the visibility of the graph. In all of the graphs, there is a significant decrease from the initial value which insures the quality of the optimization and signifies the lower tendency to be in a local minimum.