

Figure 1: Initial problem with 20 nodes

# C++ Parallel application for Traveling Salesman Problem resolution by genetic algorithm

Parallel and distributed system: paradigms and models  
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## Abstract

The aim of this project is to implement a genetic algorithm for the resolution of the Traveling Salesman Problem and to parallelize it with two different mechanisms:

- C++ standard threads and mutex
- Fastflow library

## 1 Problem description

The genetic algorithm mimic the natural evolution and selection. In order to do that, we need a population, a way to assign a probability about which elements

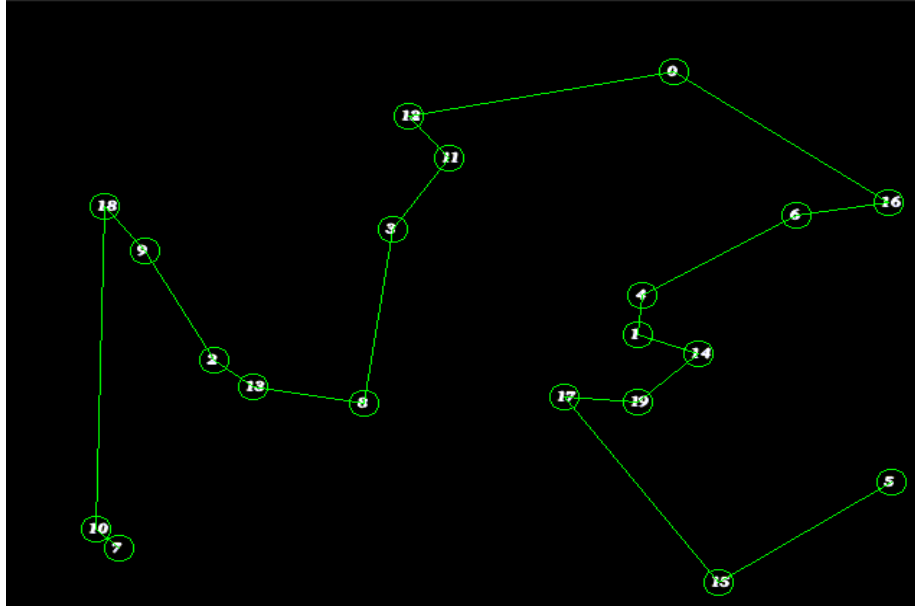


Figure 2: Solution found after some iterations

of the population will survive (and so will reproduce), how they reproduce and how a mutation can occur.

- **Population:** it is a matrix (vector of vector), where each row contains a sequence of number, and each number represent a node
- **Affinity:** for each element  $x$  is the probability that  $x$  will be selected for reproduction, and is calculated as the inverse of the path length, normalized w.r.t. all other elements in order to obtain a proper probability
- **Reproduction:** 2 paths A and B can create a new path C by generating 2 random numbers  $i$  and  $j$  and putting the subsequence  $B[i, j]$  in A
- **Mutation:** a mutation occurs with a certain probability to every generated path, and it is a random shuffle of two positions in the paths. The probability that a mutation does not occur is 0.9, which is a good trade-off (too high leads to casuality, too low leads to no evolution).

To calculate the length of each path, I use a random generated city, where for each node number we have the relative coordinates, picked up randomly in a window of size 640x480. It is possible to plot the city and the best solution found till that moment at runtime by compiling with **make compile-graph**, this is available only for the sequential version and has huge impact on the performance, but shows the correctness of the algorithm. This algorithm is not guaranteed to find the best solution of the problem, which is a NP problem, but can find a good starting point.

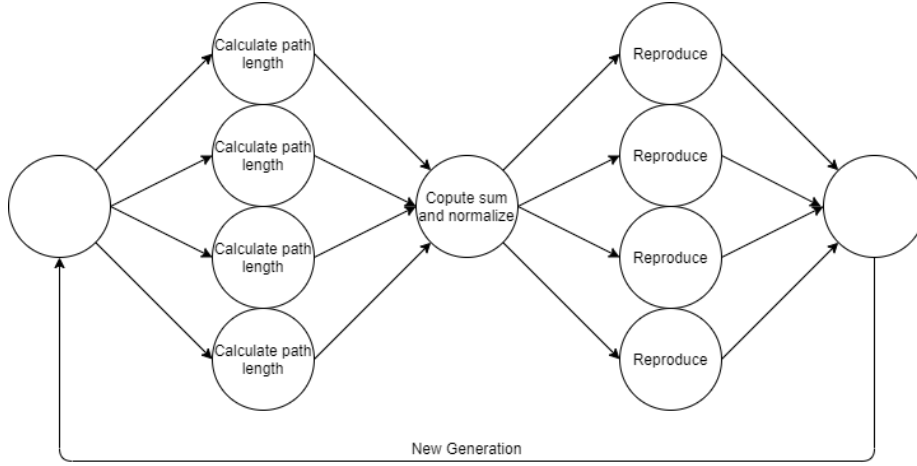


Figure 3: The first approach

## 2 A first approach

The first approach that I thought was a pipeline with feedback composed by a farm for calculating the length of each path, a collector to compute sum and to normalize each path length in order to obtain probability, and another farm for the reproduction stage. Each worker had its own chunk of the population/affinities to compute, and the fastflow version was implemented with a `parallelforreduce` to compute the sum while computing the length of each path, and a `parallelfor` to compute the new population. We also had some false sharing, due to the sharing of the population and affinities data structure and the modification of each worker on different part of it. This approach leads to a poor speedup, because we need to stop after the calculation of the length of each member of the population in order to compute the total sum to divide them and obtain a proper probability, which will be used to select best candidates in the reproduction stage. So the good news is that we are considering a big population and the crossover between each pair of it, but the bad news is that we need to synchronize each evolution phase. But we can think to a different solution, which drives us to the normal form: when the population is big, the probabilities are all small and not very different because the path lengths don't differ too much, if we assume to have more than one independent populations, we will not make the same computation as before because we are not considering anymore the possibility of crossover among each pair of the elements of the population, but our throughput will increase more rapidly, and we can expect a linear speedup.

### 3 The second approach

This approach is a simple farm over the task **evolve**, which is a composition of the two stages **calculate affinities** and **reproduce**. The service time of the farm is

$$\max T_{scheduler}, T_w/nw, T_{gatherer}$$

and the times of the scheduler and the gatherer are negligible, because the scheduler just starts the computation and the gatherer just selects the best result over the nw ones returned by the workers. So, by increasing the number of workers, I expect to see a linear speedup. My machine has 5 cores, so I also expect to have the **knee** at 5 workers. The heaviest data structure is the **population** one, which has dimension 0.8MB (4 byte(int) \* 20 \* 10000), while affinities has size 0.08MB (8byte(double) \* 10000) and city as a very small size around 320byte (8byte(double) \* 2 \* 20). My cpu has 3 caches L1, L2 and L3 of size respectively 9MB, 1.5MB and 350KB, so we also expect to have a superlinear speedup at a certain point due to the population data structure fitting in the L3 cache. I need to distinguish 2 cases because of I tried 2 different way to chose the elements that will be reproduced, and they give different performances. The results obtained locally are averaged on 3 runs, the results obtained on the remote machine are averaged on 5 runs.

#### 3.1 Pick

I create a function called pick candidate, that select one element considering the probabilities. This function cost  $O(n)$  in the worst case, where n is the populaton size, because it generate a random float and decrease it with the affinities untill it becomes negative, and then select the corresponding index. When we parallelize, we divide the population size with the number of worker, and this lead not only to less element of the population to generate for each worker, but also to a reduction of the time needed to generate each element, because of the  $O(n)$  of pick candidate. So we expect something like a double of the linear speedup, motivated not only by the hardware, but because of the way I implemented the logic code.

#### 3.2 Rand

The path length are not so different, so the affinities are almost all equal and the pick candidate function selects almost randomly the two elements of the population that will reproduce. Considering that pick candidate cost  $O(n)$  in the worst case, leading to difficultly predictable performance, I tried to replace it with a simple randomized selection of the two elements, with a cost of  $O(1)$ . In this way, we can expect a linear speedup because by increasing the number of workers, we only have less elements of the population to create, but the cost to create each one is always the same.

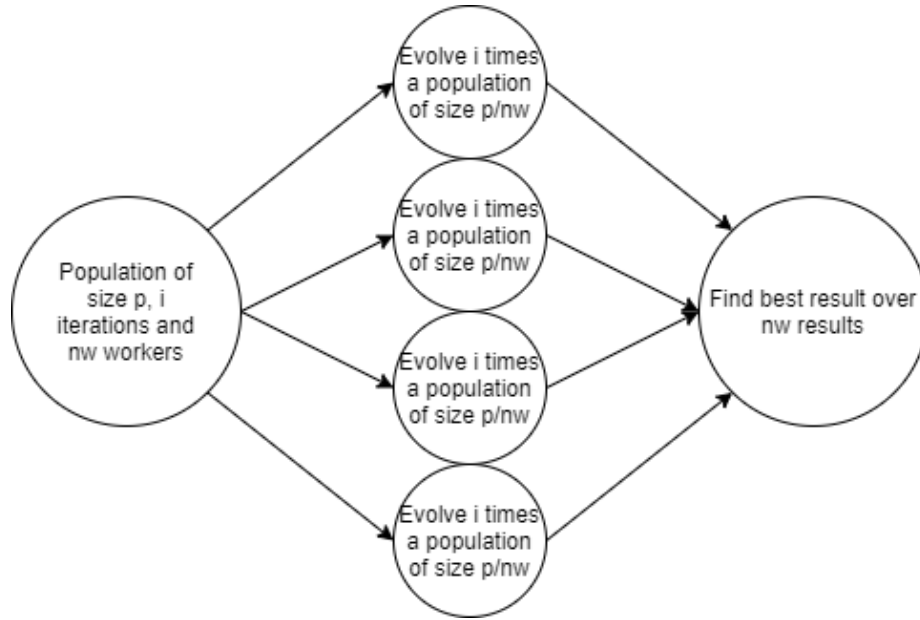


Figure 4: The second and final approach

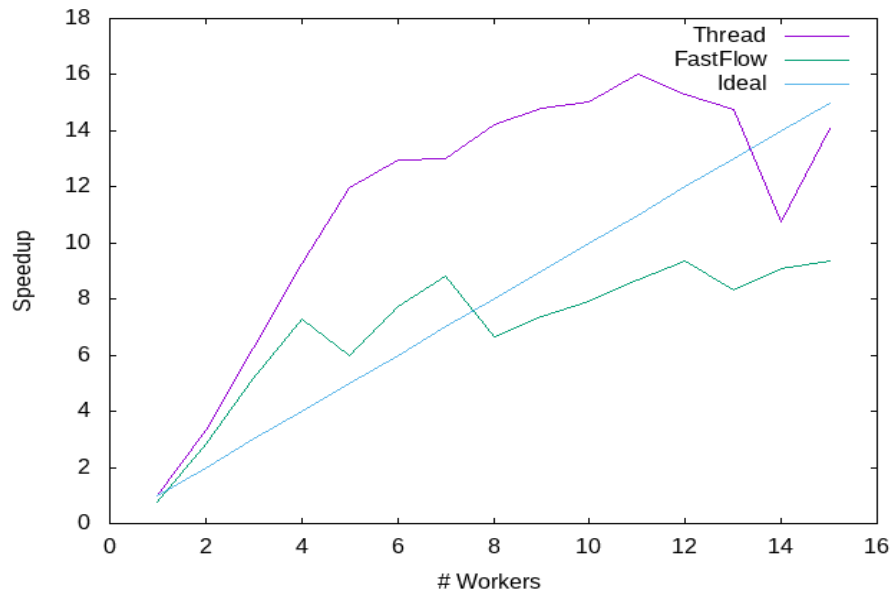


Figure 5: Local speedup using pick candidate with 20 nodes, 10000 elements of population and 1000 iterations

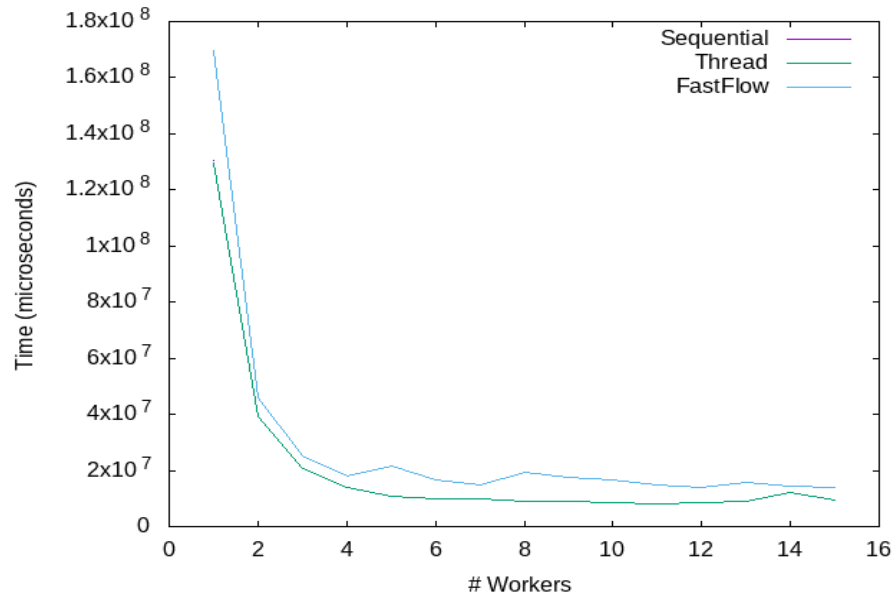


Figure 6: Local time using pick candidate with 20 nodes, 10000 elements of population and 1000 iterations

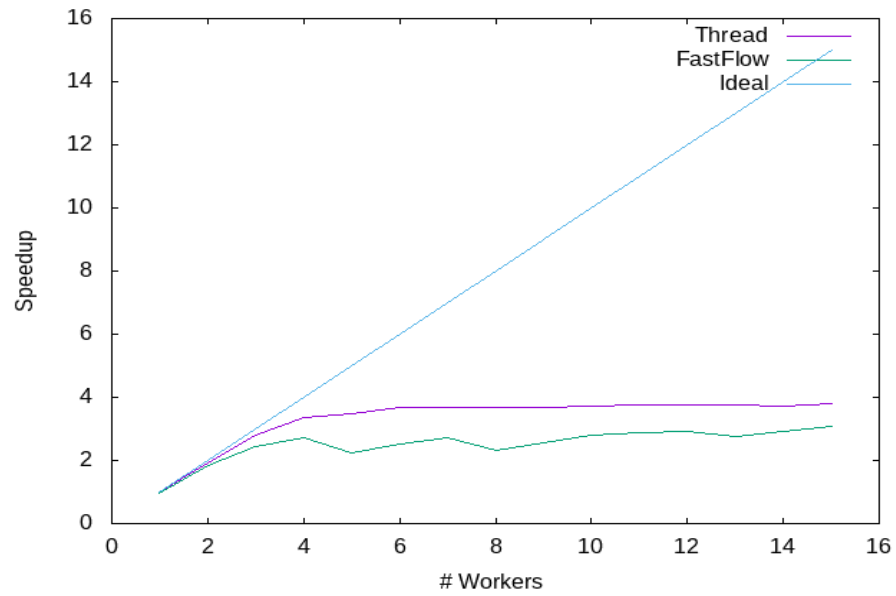


Figure 7: Local speedup using random selection with 20 nodes, 10000 elements of population and 1000 iterations

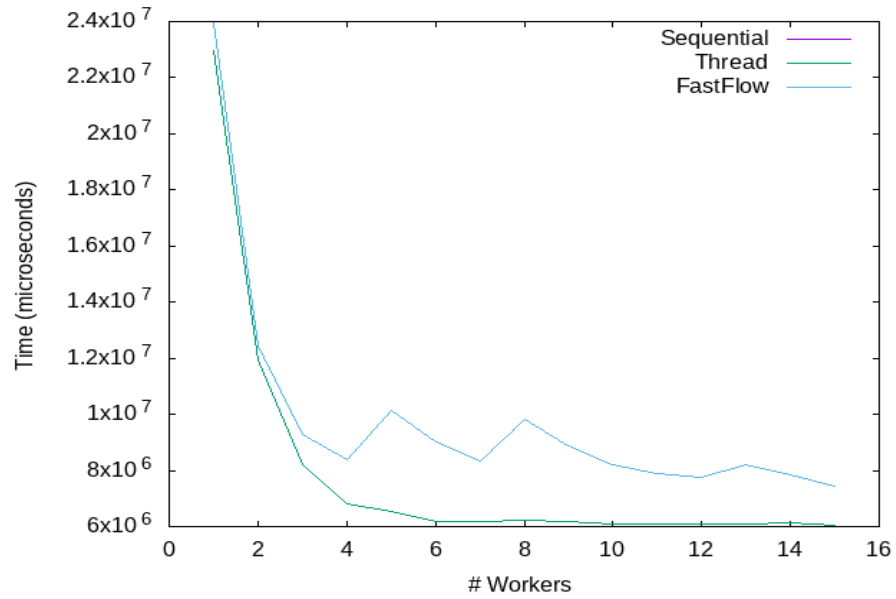


Figure 8: Local time using random selection with 20 nodes, 10000 elements of population and 1000 iterations

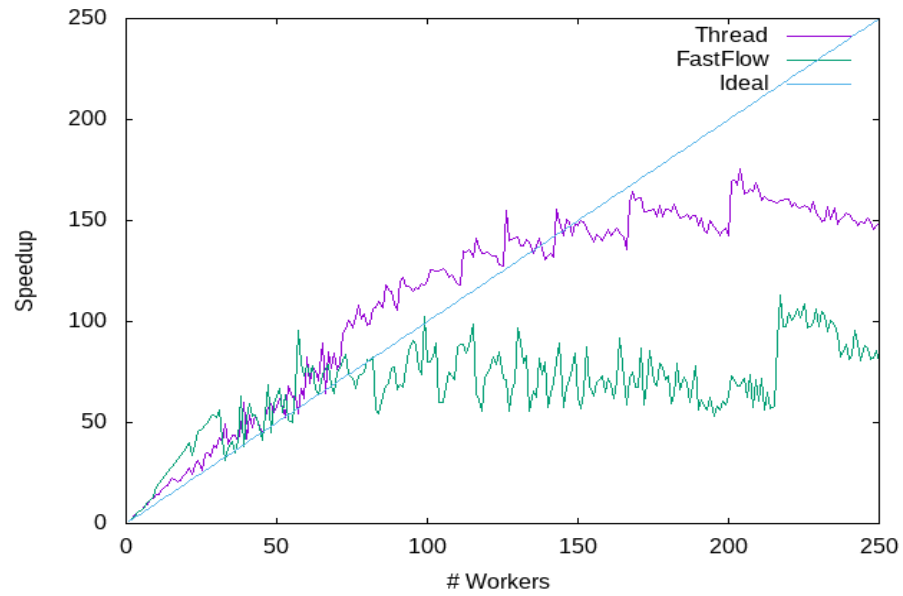


Figure 9: Remote speedup using pick candidate with 20 nodes, 1000 elements of population and 1000 iterations

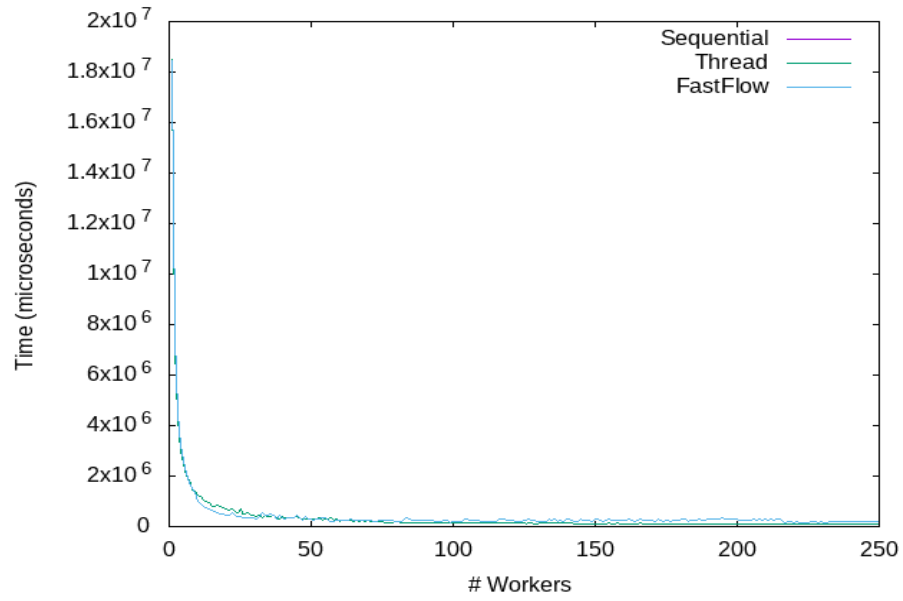


Figure 10: Remote time using pick candidate with 20 nodes, 1000 elements of population and 1000 iterations

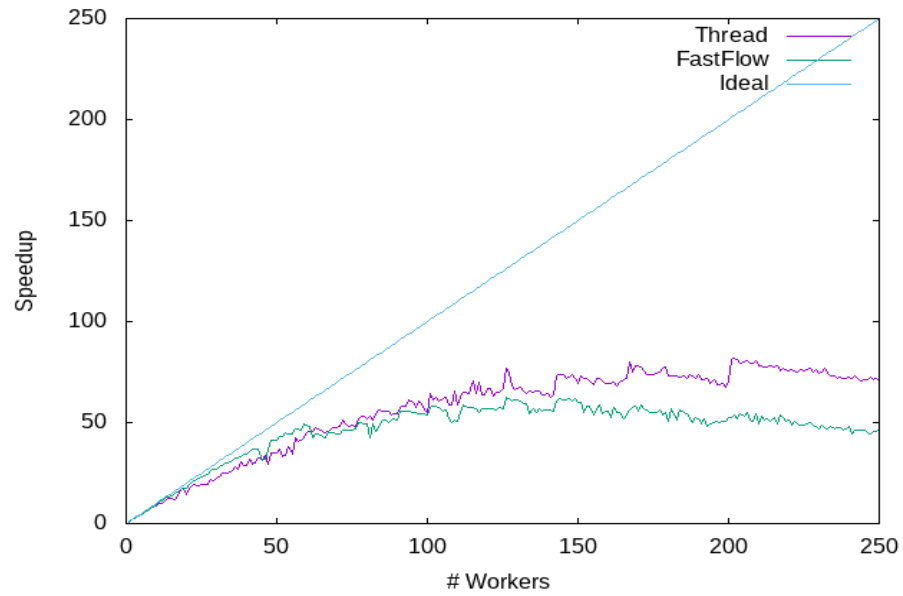


Figure 11: Remote speedup using random selection with 20 nodes, 1000 elements of population and 1000 iterations



Table 1: Expected service time, real service time, difference between the two (overhead) and relative overhead for local randomized solution with 20 nodes, 10000 size of population and 100 iterations (time in microseconds). My machine has 5 cores.

<b>nw</b>	<b>T(nw)</b>	<b>(T(1)/nw)</b>	<b>diff (overhead)</b>	<b>T(nw)/diff</b>
1	23334944	2341742	0	0%
2	11828148	11667472	160676	1.3%
3	7937058	7778314	158743	2%
4	6065433	5833736	231697	3.8%
5	5055524	4666988	388536	7.6%
6	4975386	3889157	1086229	21%
7	5210023	3333563	1876460	36%

## 4 Difficulties

At a certain point, I had a bottleneck in the remote machine that doesn't allow me to have a speedup higher than 3. I investigated this problem for days to find out that my bottleneck was caused by the **rand()** function. This, together with the pick candidate, made my development and my analysis a lot more difficult. To overcome this issue, i create the MyRandom class, which sets up the 3 different uniform distribution that I use in the program, that are [0, n\_nodes)(int), [0, pop\_size)(int) and [0, 1](double).

## 5 Other improvements

I always compile my code with the -O3 flag in order to make other optimizations, like vectorization, which occur in various places: when we push work in the farm of FastFlow, in the main loop of the Evolution node of FastFlow (basic block), the affinities normalization, in the main loop of the thread (basic block), in the normalization of the sequential part, in the loop that starts the thread, in the loop that generates the population. I tried to parallelize other part of the code, for example the random initialization of the city and of the population, but I didn't get enough improvements, so I removed it.

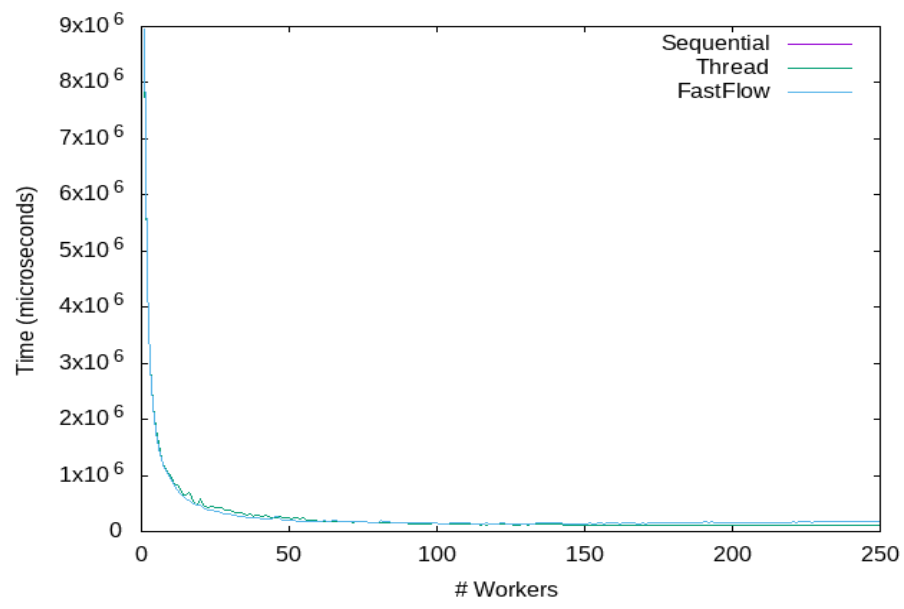


Figure 12: Remote time using random selection with 20 nodes, 1000 elements of population and 1000 iterations