

Aufgabe 1:

e)

Dynamic scheduling:

	1 Thread	2 Threads	4 Threads	8 Threads	16 Threads
Serial	0.523s	0.501s	0.5014s	0.499s	0.508s
Parallel	0.526s	0.263s	0.138s	0.102s	0.091s

f)

Static scheduling:

	1 Thread	2 Threads	4 Threads	8 Threads	16 Threads
Sequenziell	0.503s	0.508s	0.507s	0.513s	0.507s
Parallel	0.634s	0.560s	0.486s	0.451s	0.249s

The static scheduling is slower for the parallelization since it can't react to load imbalances between threads. The distribution of load is done once at the beginning of the loop and can't be changed later, possibly leading to idling threads. Without static scheduling the distribution is done dynamically at runtime and can react accordingly to load imbalances, so the threads get a more evenly distributed load.

Aufgabe 2:

a) + b)

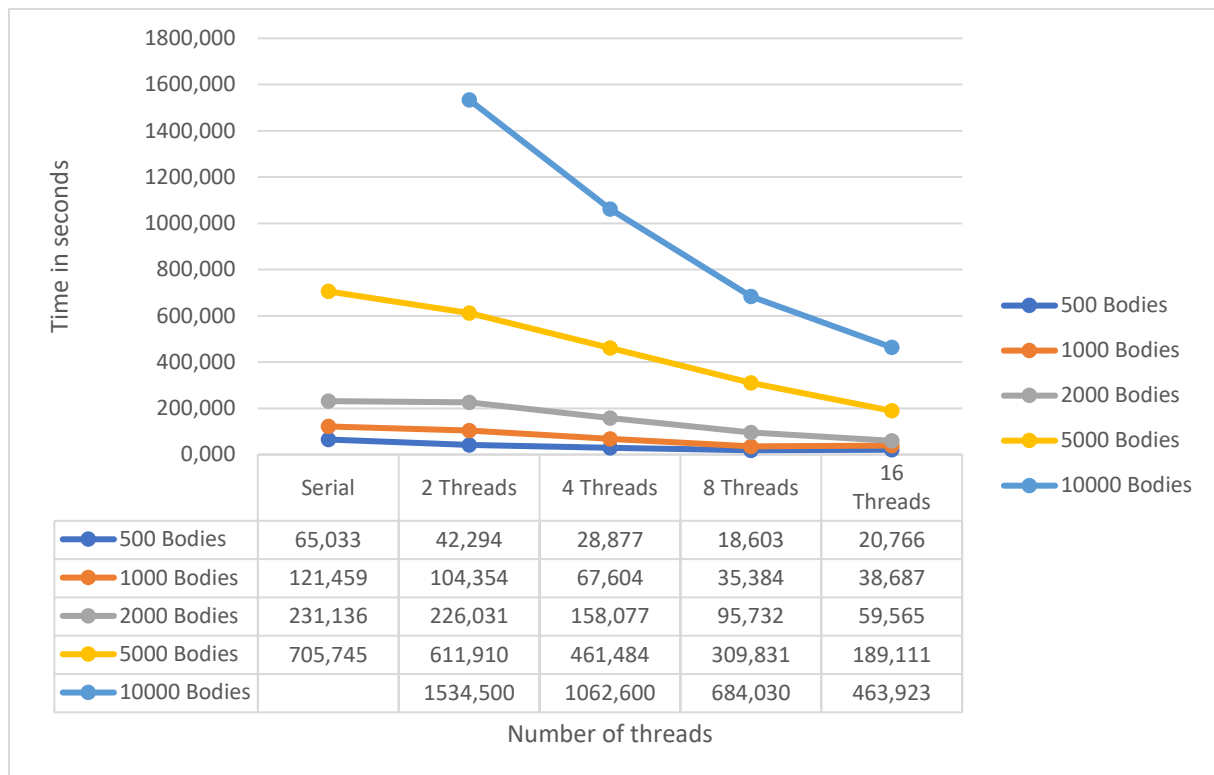
	1 Thread	2 Threads	4 Threads	8 Threads
Serial	1.814s	-	-	-
Parallel	1.946s	1.947s	1.948s	1.949s
Parallel (optimized)	2.444s	1.074s	0.586s	0.398s

In our first design for parallelization, we called `daxpy_par` not in parallel and our parallelization in `daxpy_par` itself was realized using `#pragma omp task`.

While trying to optimize our code, we realized our error of calling `daxpy_par` in serial and changed it to a parallel call, using a `#pragma omp parallel-section` and the `#pragma omp single-construct`, so the call gets made only once and by a single thread.

Aufgabe 3:

e)



Parallelization only makes sense after reaching 1000 bodies or more, since the runtime can be reduced by a significant amount. Everything below 1000 bodies is sped up a little, but not as effectively as with more bodies.

But as the graph shows with a higher number of bodies the saved time is increased by a large amount.

Our table is missing a value for the serial calculation of 10000 bodies, since it took over 30 minutes to complete.