Optimization result reporting:

**Dynamic Increasing of Low Mutation Ratio/Decreasing of High Crossover Ratio (ILM/DHC)** was found to be more effective with smaller populations (25 and 50 individuals), where higher mutation rates later in the search process introduced necessary diversity, helping the algorithm avoid local optima. **Dynamic Decreasing of High Mutation Ratio/Increasing of Low Crossover Ratio (DHM/ILC)** performed better with larger populations (200 and 400 individuals), where a higher crossover rate towards the end of the search allowed for the generation of stronger offspring, leveraging the diversity already present in the population (Hassanat et al., 2019).

The concept of dynamic crossover and mutation probability, helps the optimizer to perform xhigh exploration in earlier generation and and high exploitation later on, which would result in high diversity exploration in earlier phase and leads to optimal solution.

 **Mutation:** Introduces diversity by altering genes randomly in individuals, helping avoid premature convergence to suboptimal solutions.

 **Mutation**:

* Introduces random changes to individuals, allowing the algorithm to explore new regions of the search space.
* Helps in **exploration** by introducing diversity.
* Typically, a **mutation probability (Pm)** between **0.01–0.1** is used.

 **Crossover:** Combines features of parent solutions to create offspring, aiding in exploiting good solutions.

 **Crossover**:

* Combines the genetic material of two parent solutions to generate offspring.
* Helps in **exploitation** of the search space by combining existing good solutions.
* Usually, a **crossover probability (Pc)** of **0.6–0.9** is set.

***Starts with a high mutation rate (100%) and low crossover rate (0%). As the algorithm progresses, the mutation rate decreases, and the crossover rate increases linearly. By the end of the search, mutation is 0%, and crossover is 100%. Best suited for small populations where diversity is crucial early in the search process.***

***Starts with a low mutation rate and high crossover rate, the opposite of DHM/ILC. Mutation increases while crossover decreases as the search progresses. Works well with larger populations where diversity is naturally present, and focus shifts to exploiting existing solutions.***

**Dynamic crossover and mutation rates can be adjusted using linear functions over the number of generations:**

**Mutation rate, MR = LG/Gn, where LG is the current generation level nd Gn is the total number of generation**

**Crossover rate, CR = 1 – LG/Gn**

**This concept will avoid local optima, and helps in efficient search**

***Example for selection of mutationa and crossover weight value:***

*The values of mutation and crossover rates are calculated according to the generation level number. If the generation level is 500, the maximum generation is*=1600*, and the population size is*=100*, then the value of mutation and crossover rates according to the previous equations are:*

𝐿𝐺=500

𝐺𝑛=1600

𝑀𝑅=1−(500/1600)=0.69

𝑀=0.69∗100=69*individuals are to be mutated in generation level 500.*

*For Crossover rate:*𝐿𝐺=500,𝐺𝑛=1600*,*𝐶𝑅=(500/1600)=0.31

𝐶=0.31∗100=31*individual are to be used for the crossover process at generation level 500.*

Computing infrastructure used: Google colab T4 GPU

**Earth Model we choose:**

The WGS 84 datum surface is an [oblate spheroid](https://en.wikipedia.org/wiki/Oblate_spheroid) with equatorial radius *a* = 6378137 m at the equator and [flattening](https://en.wikipedia.org/wiki/Flattening) *f* = 1⁄298.257223563. The refined value of the WGS 84 [gravitational constant](https://en.wikipedia.org/wiki/Standard_gravitational_parameter) (mass of Earth's atmosphere included) is *GM* = 3.986004418×1014 m3/s2. The angular velocity of the Earth is defined to be *ω* = 72.92115×10−6 rad/s (Agency, 1987).

Our objective:

1. Minimize revisit time O\_1(x)
2. Maximize dwell time O\_2(x)

In **multi-objective optimization**, we need to minimize both objectives. However, since were trying to **maximize** the dwell time, we need to **transform** this into a **minimization** problem.

Mathematically,

* **Minimizing** O\_1(x): We want to minimize the revisit time directly.
* **Maximzing O-2(x): We want to maximize the dwell time. However, since DEAP’s optimizer minimizes by default, we must transform this into a minimization problem. To do that, we minimize the negative of dwell time:**

O\_2(x)\_maximizing = maximize O\_2(x). # dwell time

= minimize - O\_2(x)

The weights define whether to minimize or maximize an objective. (w1, w2) = (-1.0, -1.0) represents the fitness function as,

Fitness(x) = w1 \* O\_1(x) + w2 \* O\_2(x)

= -O\_1(x) + O\_2(x)

minimizing the fitness, results in minimization of revisit time and minimization of -ve of dwell time.

**Test1: NSGA3 optimizer, for best fit inclination angle and RAAN angle for the constellation of 3 plane and 4 satellite in each plane**

Number of objectives = 2, maximum cumulative dwell time and minimum cumulative revisit time of constellation

Fitness / evaluation function = -1 \* cumulative revisit time (CRT) -1 \* ( - cumulative dwell time (CDT))

Optimizing parameter = Inclination (i), and RAAN

Population size = 20,

NGen = 15

Number of plane = 3

Number of satellite per plane = 4

Fitness weight = (-1, -1)

Crossover weight = 0.7

Mutation weight = 0.2

**Result of Test 1:**

A graph with numbers and a blue dot

Description automatically generated

Figure1: final population fitness nsga3-20P15G

Best 5th individual (inclinations, raan) for each plane:

[[21.711890082943626, 84.1511867209388, 15.255350281208214], [168.27944861745772, 288.7786064367185, 223.71299670259702]]

Best fitness cumulative revisit time 75060.0 seconds and cumulative dwell time 9750.0 seconds

A graph with blue dots

Description automatically generated

Fig : Pareto front of NSGA-III

A map of the earth

Description automatically generated

Fig : resulted constellation of optimized using NSGA3 for 3plane 4 satellite per plane, constellation where genetic algorithms applied with population size 20 for 15 generation

Analysing the earlier batch experiment, We can expect the right plane to detect the area of our interest within the range as for inclination angle ranges from 0 to 90, and for RAAN angle ranges from 100 to 250 degrees.

**Test2: NSGA3 optimizer, for best fit inclination angle and raan angle for the constellation of 3 plane and 4 satellite in each plane with less population size 50, for 20 generation. Setting the crossover and mutation probability fixed and population size constant for all generation, that gives great diversity and exploration.**

Objectives: 2, maximum cumulative dwell time and minimum cumulative revisit time

Fitness / evaluation function = -1 \* cumulative revisit time (CRT) -1 \* ( - cumulative dwell time (CDT))

Population size = 50,

NGen = 20

Number of plane = 3

Number of satellite per plane = 4

Fitness weight = (-1, -1)

Crossover weight = 0.7

Mutation weight = 0.2

**Result of Test 2:**

[[165.03555591216696, 19.789844235792522, 168.37636452622212], [327.28347828763367, 109.2526412155637, 223.17197245577748]]

Best inclination and Raan angle for 3 planes

Inclination: [86.22229025577786, 87.01299475596664, 96.93082591770099]

Raan = [163.61694545224185, 141.80832178528414, 166.67088730999177]

Best fitness cumulative revisit time of 49320.0 seconds and cumulative dwell time of 2850.0 seconds when simulating for approximately 1 day.

Best fitness cumulative revisit time 34070.0 seconds and cumulative dwell time 11440.0 seconds

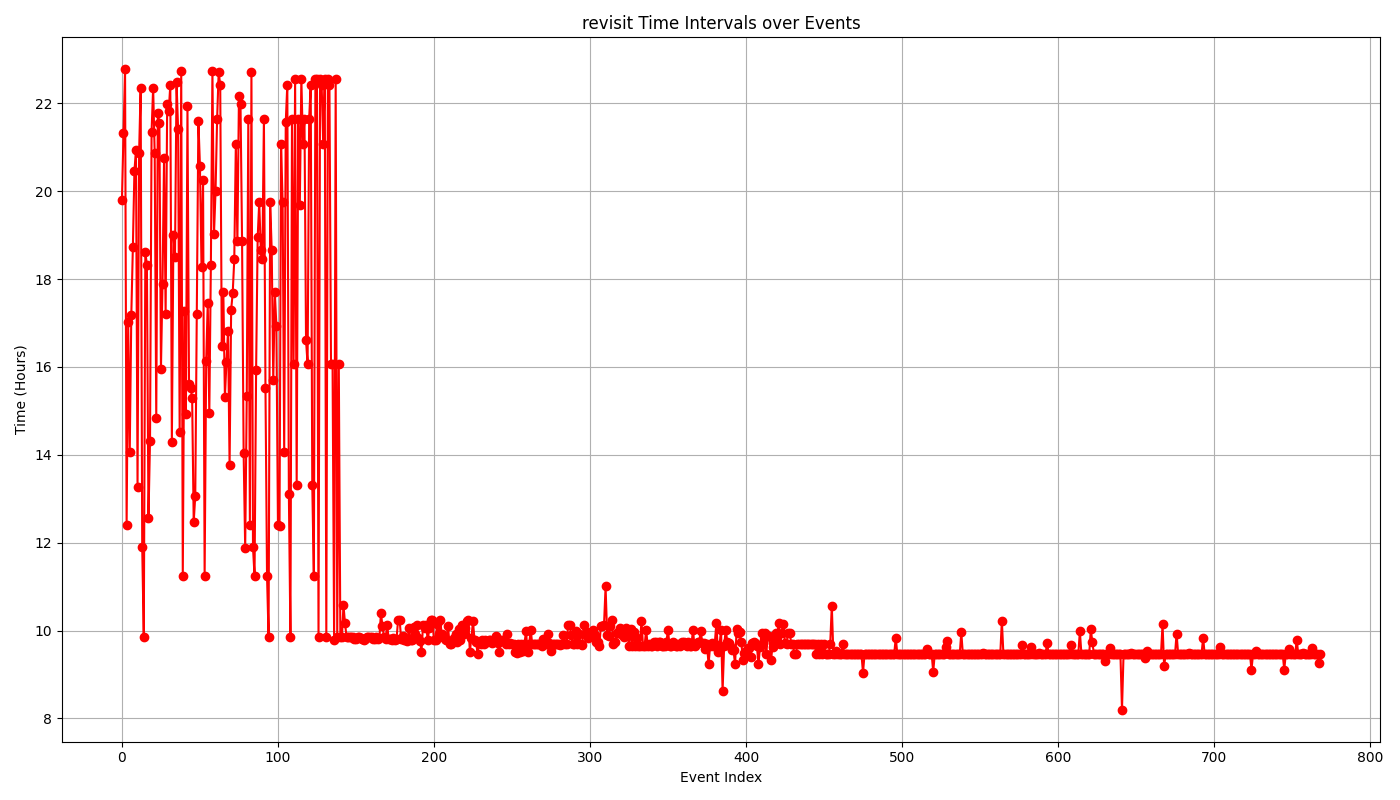


Fig. cummelative revisit time per individual in each generation

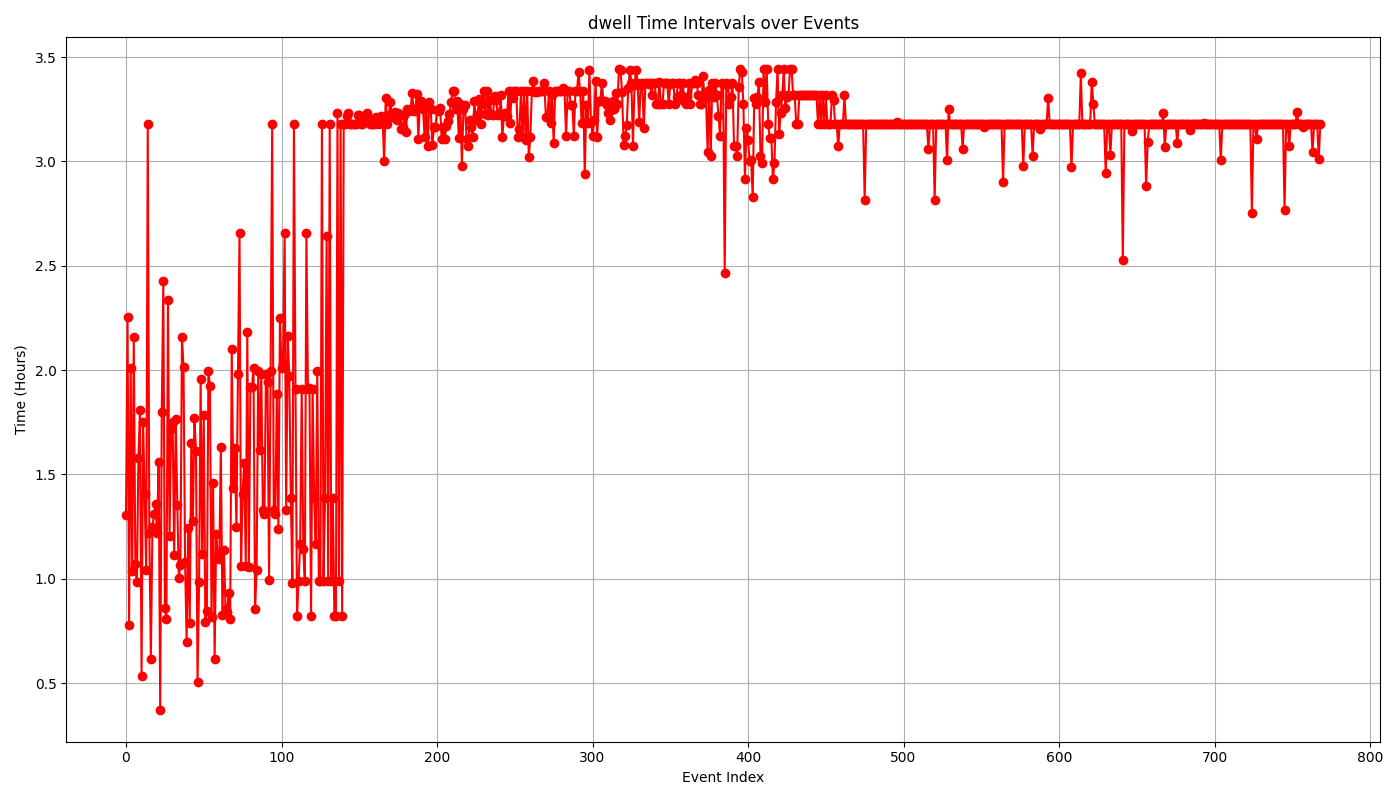
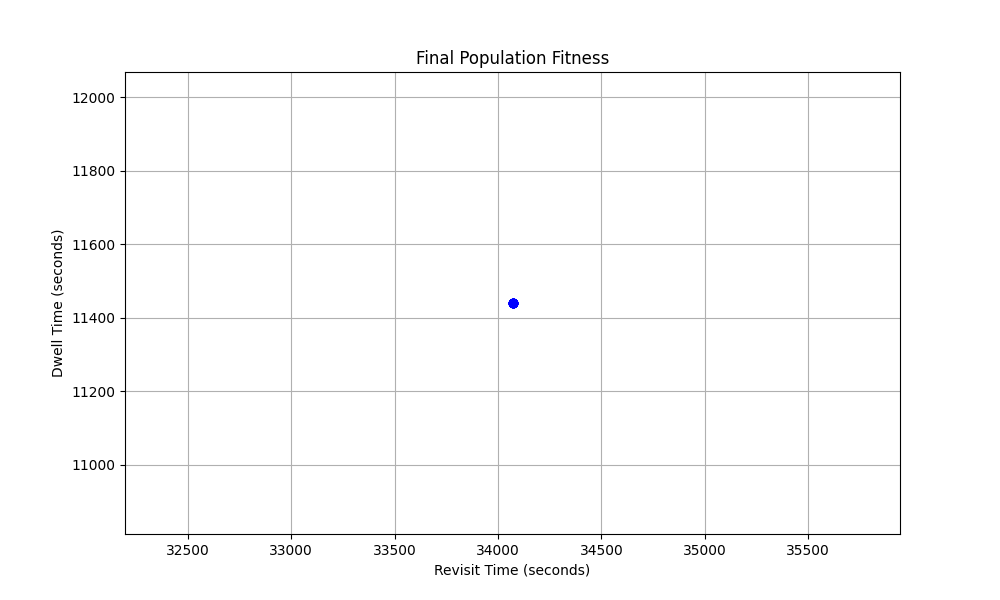
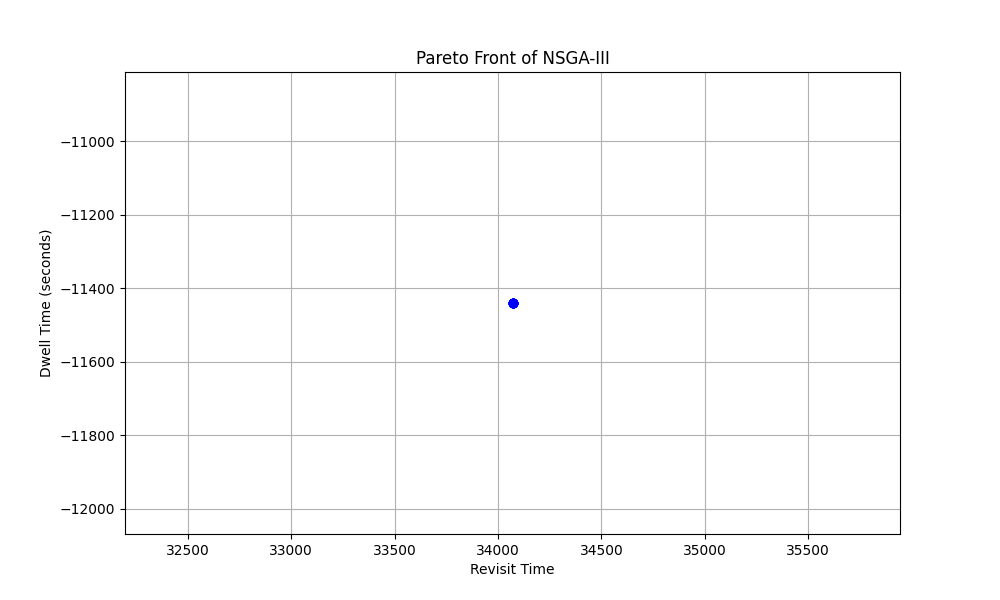


Fig. cumulative dwell time per individual in generation





**Test3: NSGA3 optimizer, for best fit inclination angle and raan angle for the constellation of 3 plane and 4 satellite in each plane, where mutation and crossover probability keep changing as per dynamically for population of 50 with 40 generation**

**In this test We applied the eamucommalambda (concept, where next generation is totally dependent on offspring generated, and population sizes (mu) is also decrease by 5% with generation to reduce computing cost.**

**Parameter edit and update on algorithm:**

We applied mu plus lambda algorithm to run the algorithm, to gradually decrease the population size (i.e.. the number of individual) in each generation with best fitted values.

Here we have the parameters that influences the update in population sizes, and number of offsprings each generation.

 initial\_mu: The initial population size.

 min\_mu: The minimum population size.

 decrease\_rate: The number of individuals to decrease per generation.

 lambda\_: The number of offspring generated each generation. Lamda >= mu

Parameters:

Initial crossover probability = 0.7 dynamicly decreasing with genereation, allow exploration

Initial mutation probability = 0.2. dynamically increasing with generation, allow diversity

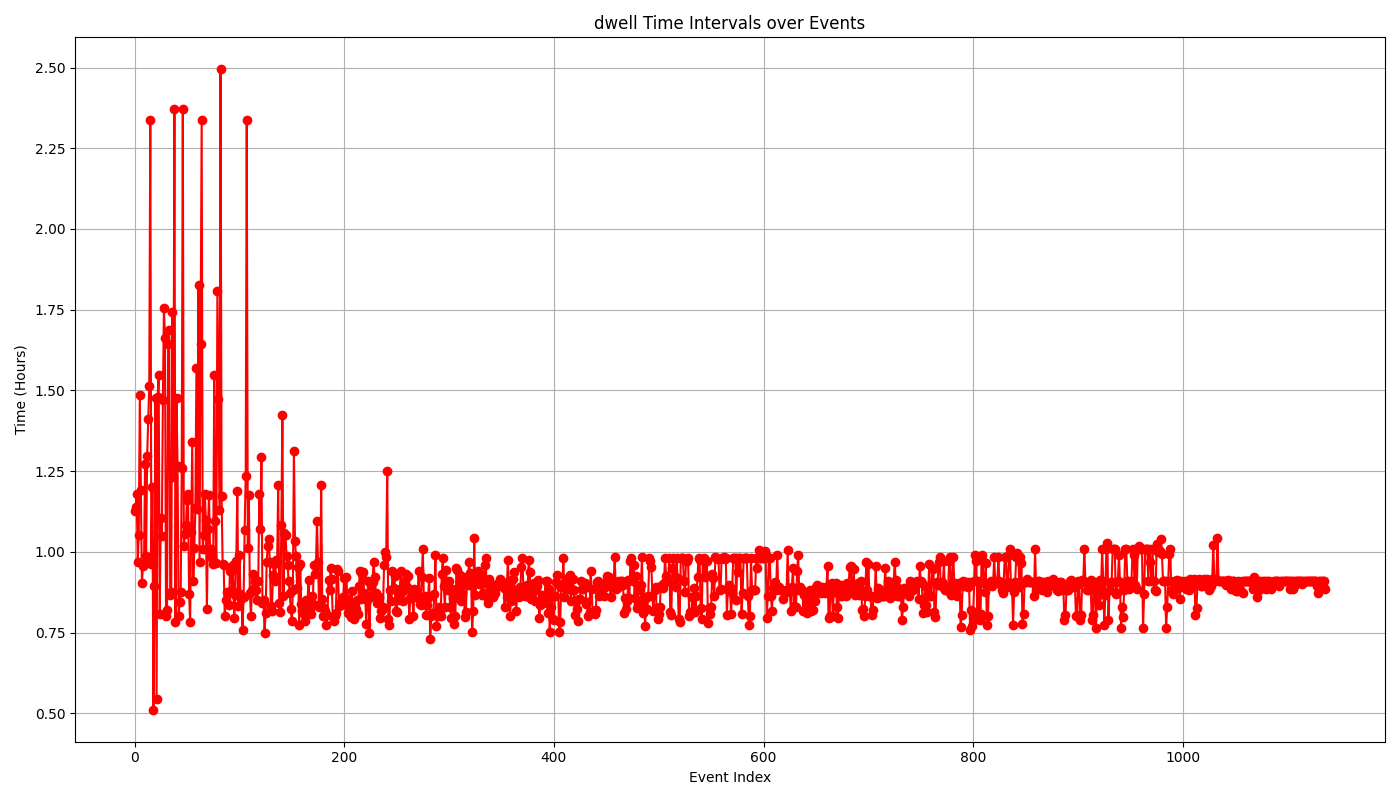
Outcome:

Best inclination and RAAN angle for 3 planes

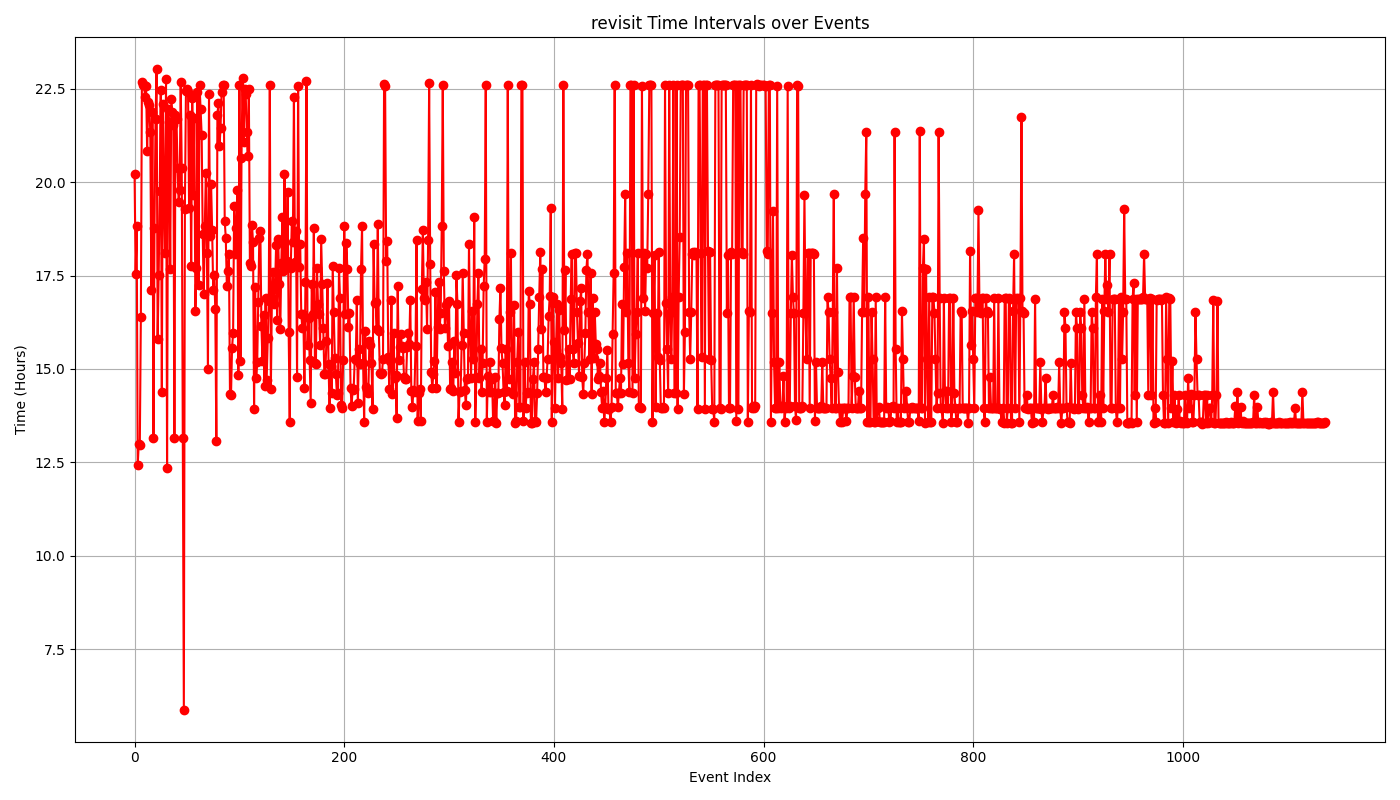
Inclination: [99.34108805931591, 121.76238824637625, 110.12169502075129]

RAAN = [189.10910461827805, 185.22904706307273, 193.28992953380373]

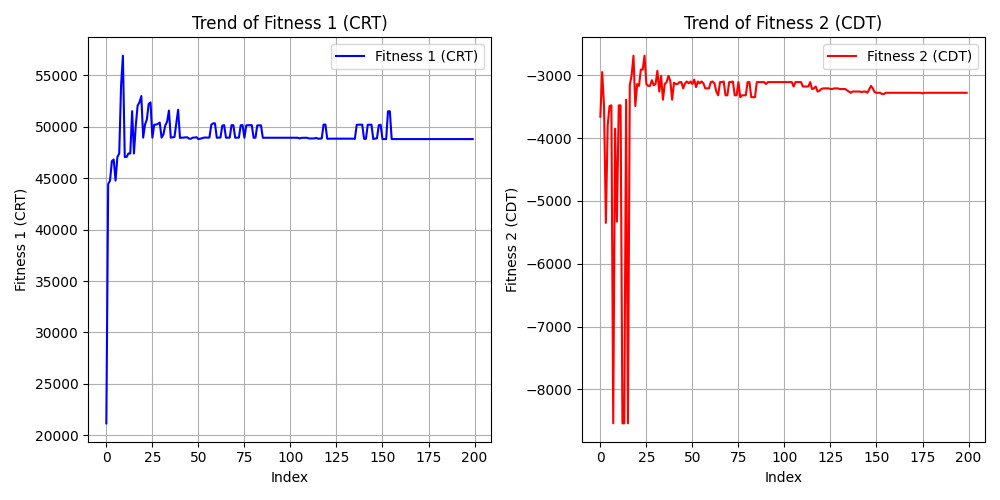
Final Best fitness cumulative revisit time of 48790.0 seconds and cumulative dwell time of 3280.0 seconds when simulating for approximately 1 day.

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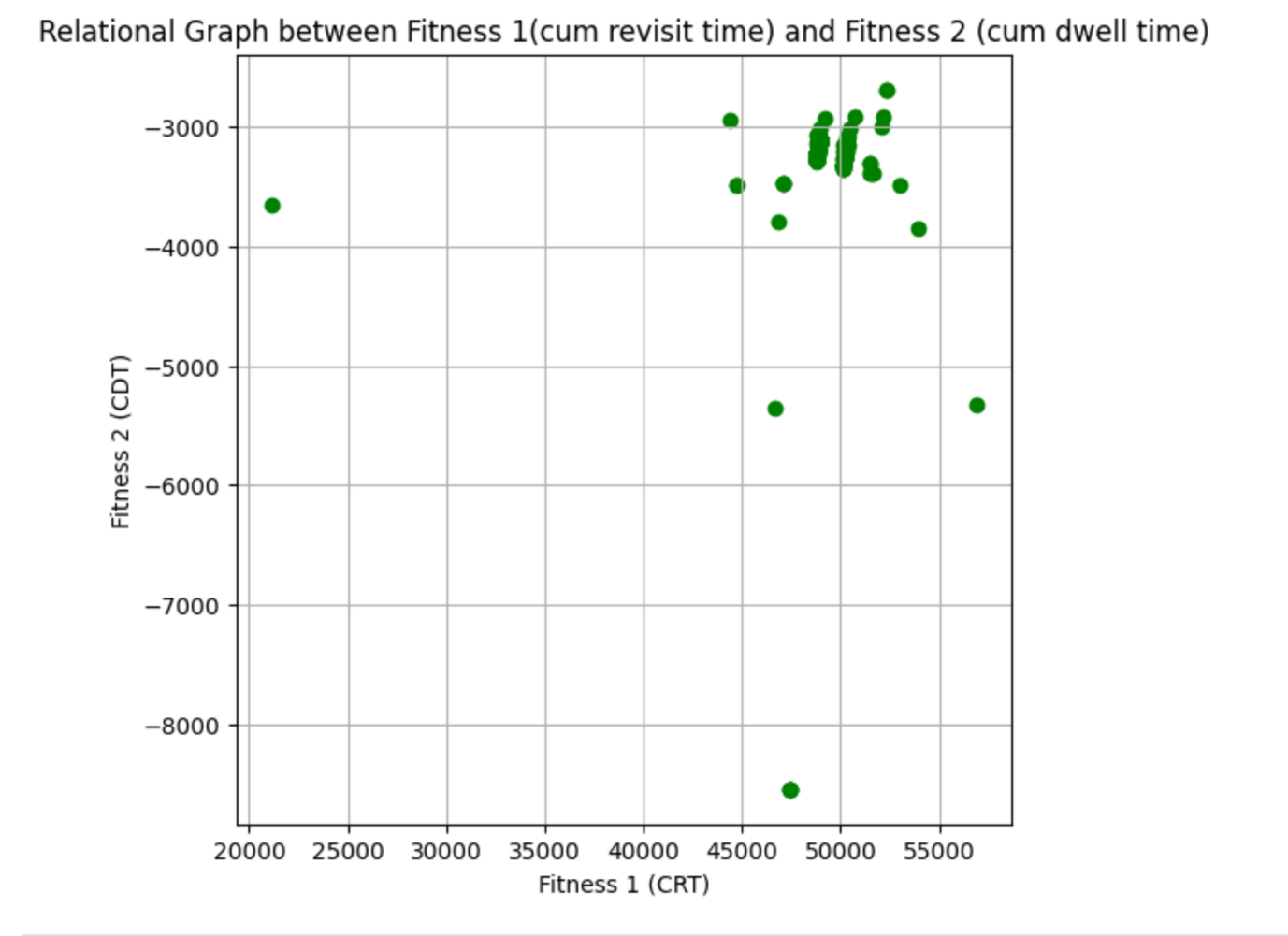
**Fig. cumulative dwell time of individual over generations**

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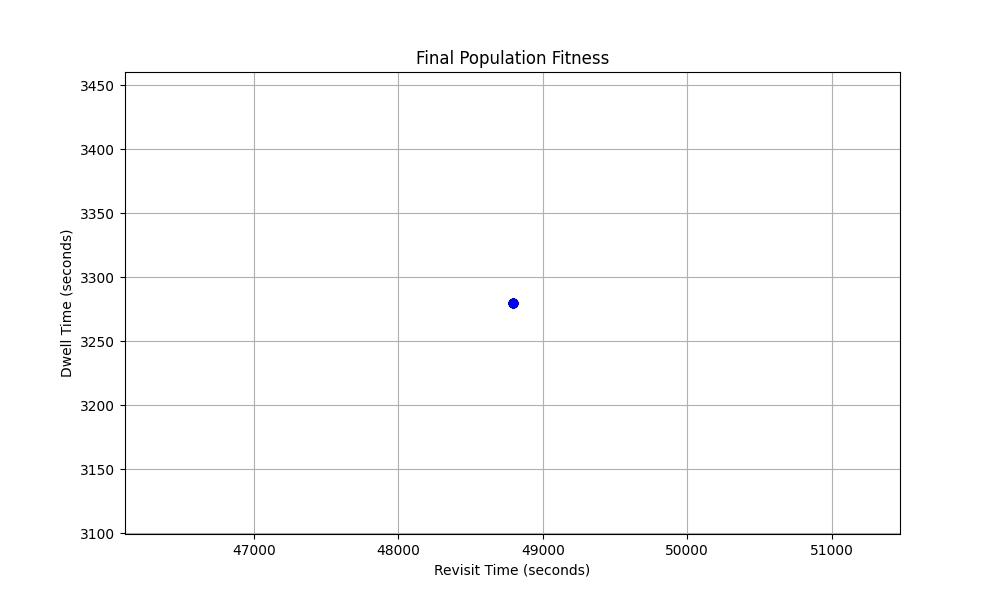
**Fig. cumulative revisit time of individual over generation**

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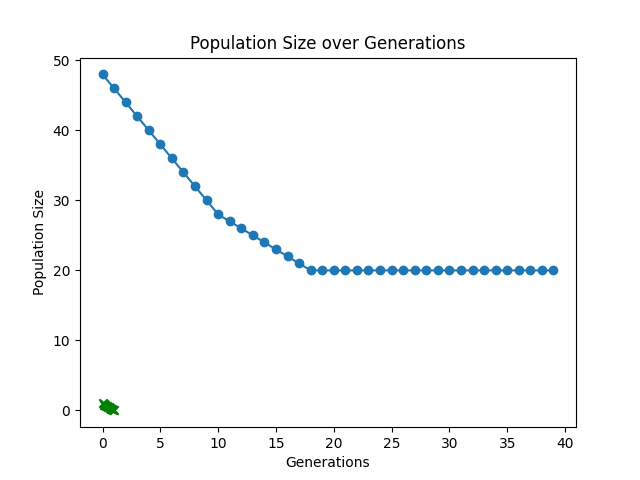
**Fig. Analysing top 5 fitness values (cum. Dwell time and revisit time) in each generation**

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**Fig. Relational graph between top 5 best fit cum dwell time and revisit time per generation**

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**Fig. final population fitness**

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**Fig. number of population individuals per generation**

**Test4: NSGA3 Optimizer, for best fit inclination angle and rran angle for the constellation of 3 plane and 4 satellite in each plane. The test applies with eaMuPlusLambda concept, where new generation is updated from the combination of best population and offspring, while keep reducing the population size (mu) by 5% per generation, till the minimum of individual size 30. Starting the crossover probability high with 0.9 and keep downgrading with generation, so the algorithm explore in earlier phase. And the mutation probability initialize with 0.05 and keep increasing with generation, so the algorithm diversify later.**

**Dynamic change in crossover and mutation probability mathematical explaination,**

**Pc = initial\_Pc \* (1 – gen/nGen)**

**Pm = initial\_Pm + (Pm\_end – initial\_Pm) \* (gen / nGen)**

**Where,**

**Pc = crossover probability for current generation**

**Pm = mutation probability for current generation**

**Pc + Pm <=1.0**

**initial\_Pc = start value for Pc ( in this case 0.9)**

**gen = current generation number**

**nGen = total generation**

**Pm\_end = maximum value for Pm ( in this case 0.4)**

**initial\_Pm = minimum start value for Pm (in this case 0.05)**

**Test5: NSGA3 optimizer, for best fit inclination angle and raan angle for the constellation of 3 plane and 4 satellite in each plane, where mutation and crossover probability keep changing as per dynamicly. For Population of 200 with 100 generation**

**Test6: Performance analysis when gradually decrease the population sizes NSGA3 optimizer, for best fit inclination angle and raan angle for the constellation of 3 plane and 4 satellite in each plane with initial population size 200 for 100 generation**

**Future studies:**

Further studies includes the research and experiment over Earth's gravity field, measurements such as the geoid, gravity anomalies, deflections, and dynamic Doppler effect.

AGENCY, U. S. D. M. 1987. *Department of Defense World Geodetic System 1984: its definition and relationships with local geodetic systems*, Defense Mapping Agency.

HASSANAT, A., ALMOHAMMADI, K., ALKAFAWEEN, E. A., ABUNAWAS, E., HAMMOURI, A. & PRASATH, V. S. 2019. Choosing mutation and crossover ratios for genetic algorithms—a review with a new dynamic approach. *Information,* 10**,** 390.