



University
of Glasgow

James Watt
School of
Engineering

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Artificial Neural Network For Preliminary Multiple NEA Rendezvous Mission Using Low Thrust

Giulia Viavattene

1. Introduction
2. Neural Network Design
3. Sequence Search
4. Sequence Optimisation
5. Optimised NEA Sequences
6. Conclusions



Artificial Neural Network For Multiple NEA Rendezvous Mission Using Low Thrust

Near-Earth asteroids

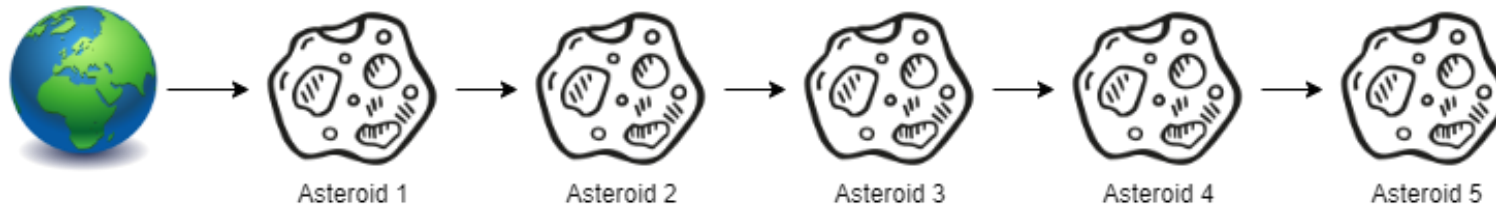
- Science
- Earth protection
- Resource exploitation

- Reduced cost per transfer
- Increased range of possibilities to visit NEAs of interest

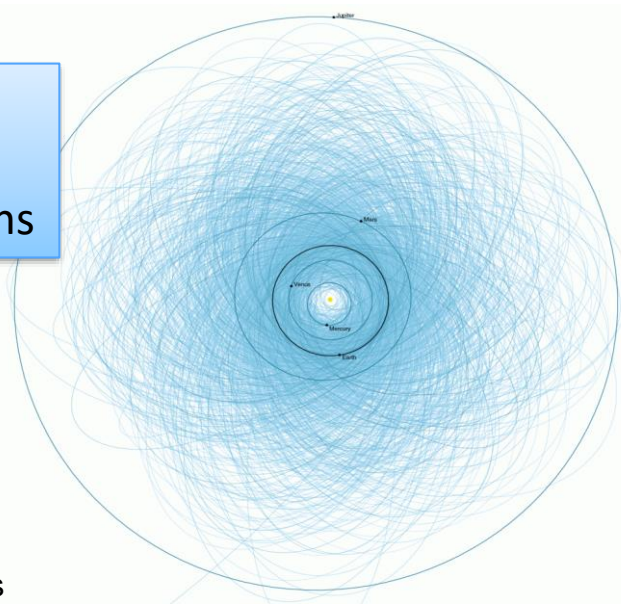
- High energy interplanetary missions
- Less propellant required



Artificial Neural Network For Multiple NEA Rendezvous Mission Using Low Thrust

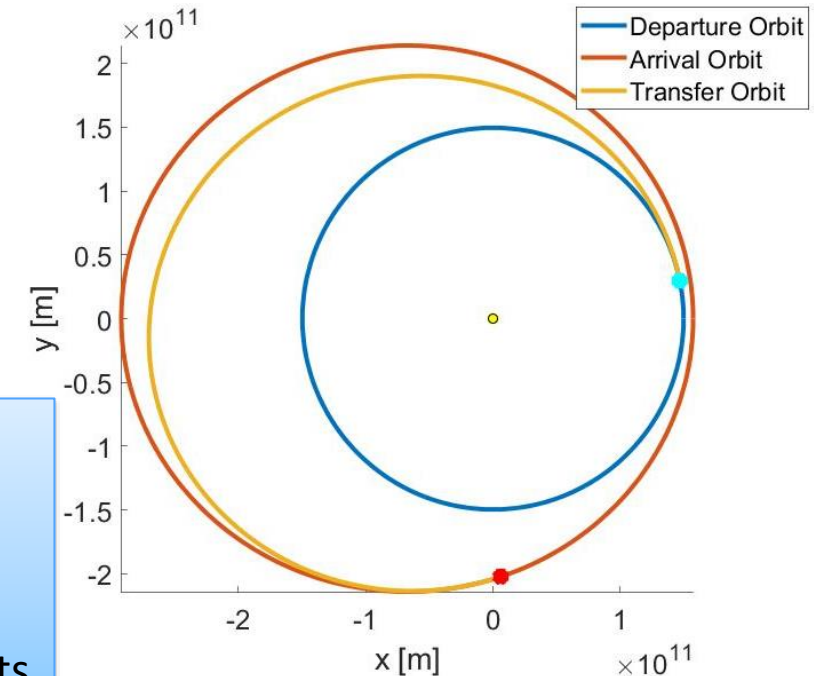


22,000 NEAs
↓
Trillions of permutations



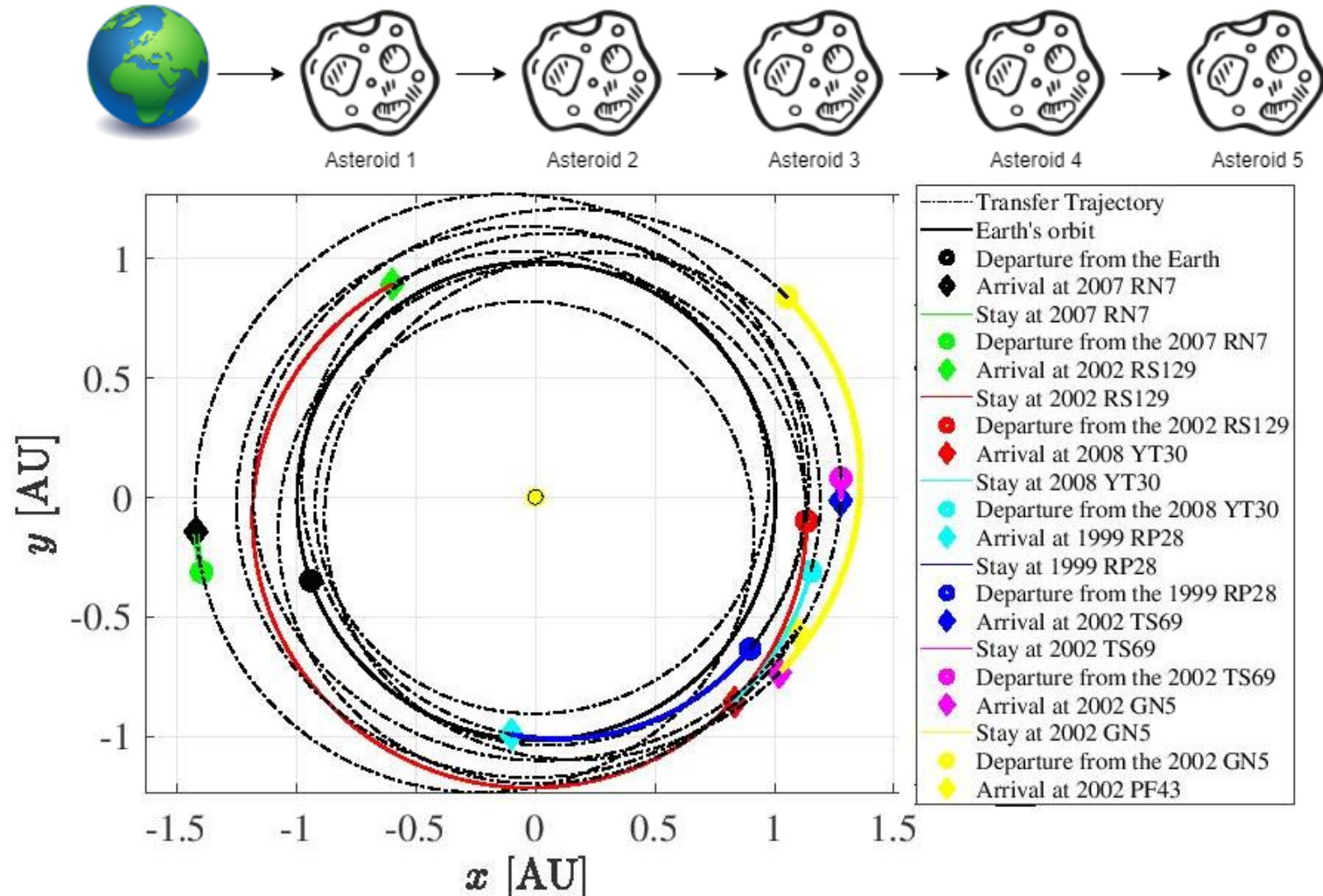
Optimisation problem

- ↓
1. Optimal trajectory
 2. Control history
 3. Mission requirements



NEA: Near-Earth asteroids

Introduction



Identify
the best sequences
of asteroids

Solution to the
optimisation problem

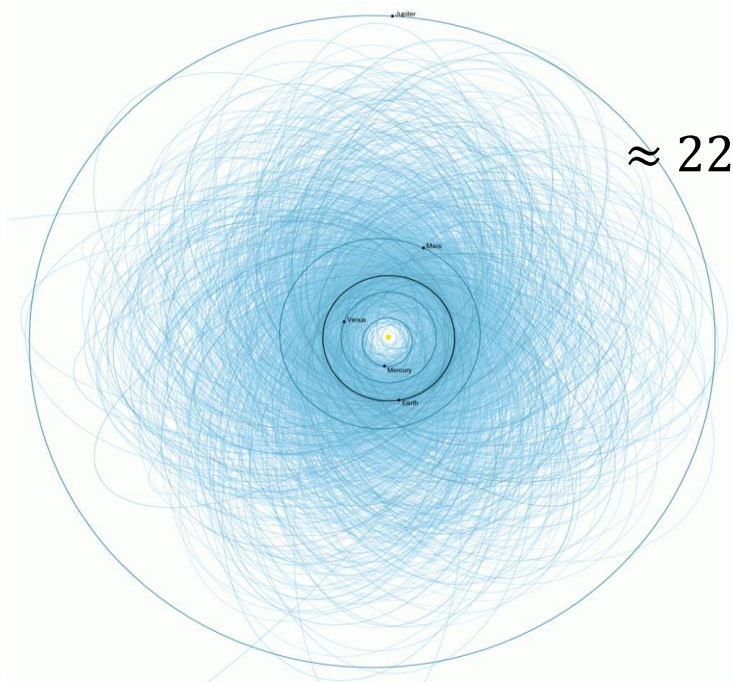
Multiple NEA rendezvous mission

Large combinatorial part

Selection of the asteroid sequences

Continuous part

Solution of optimal control problem (OCP)

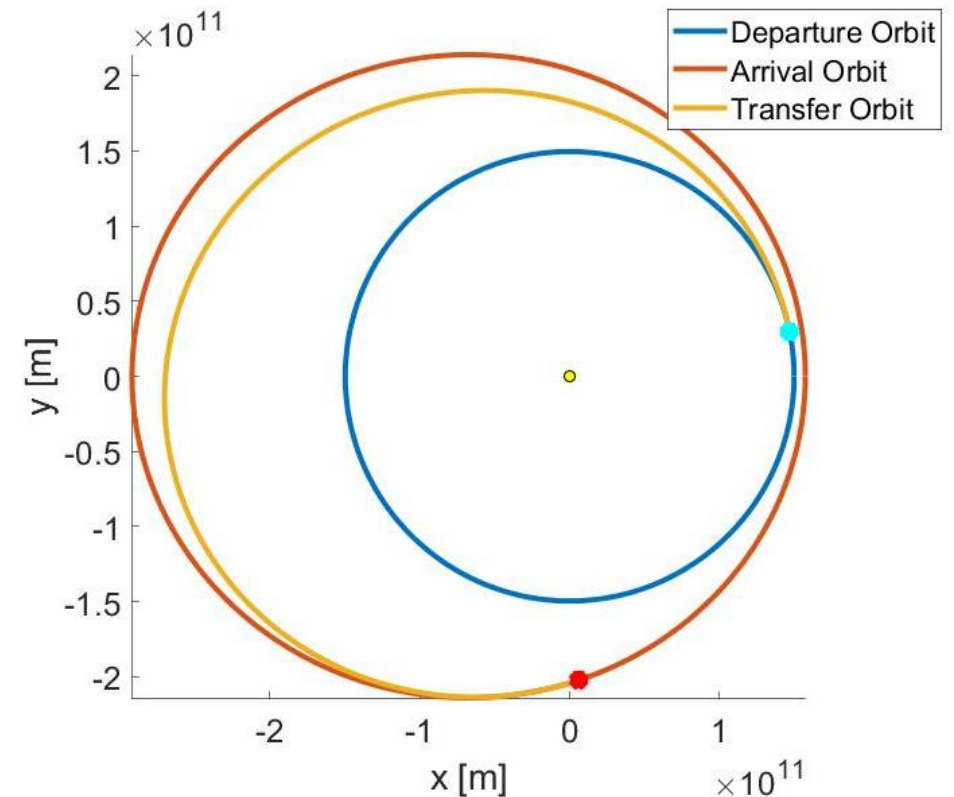
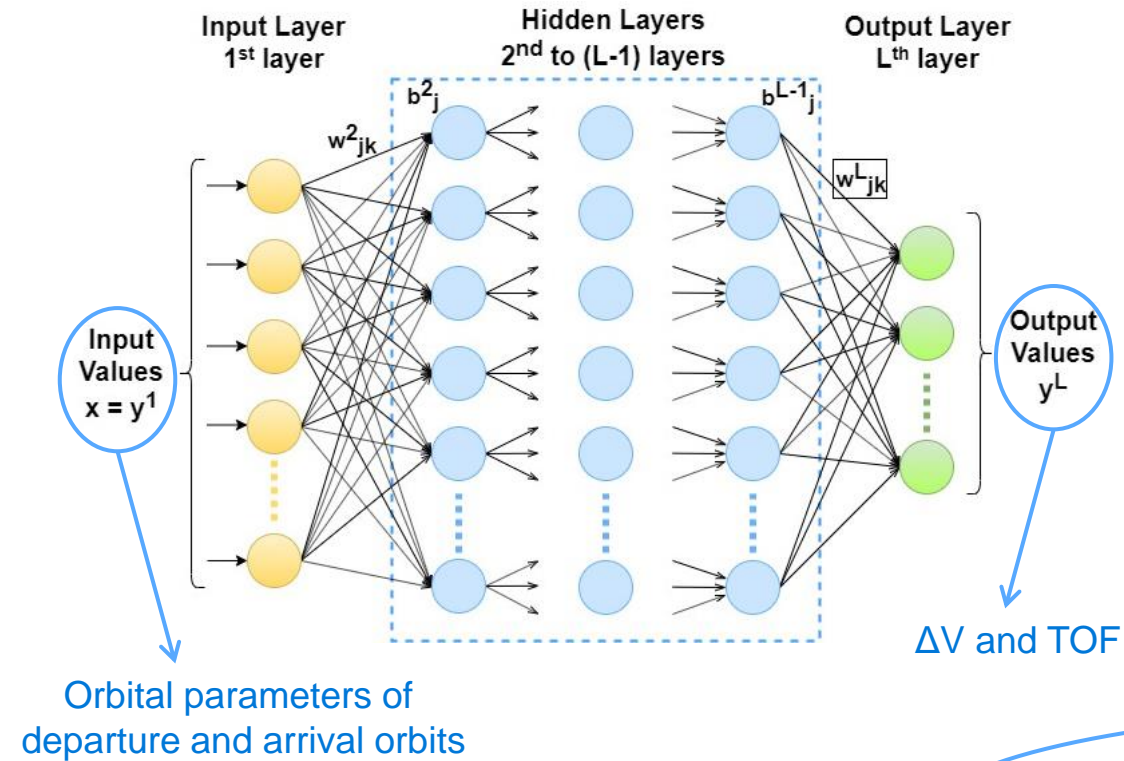


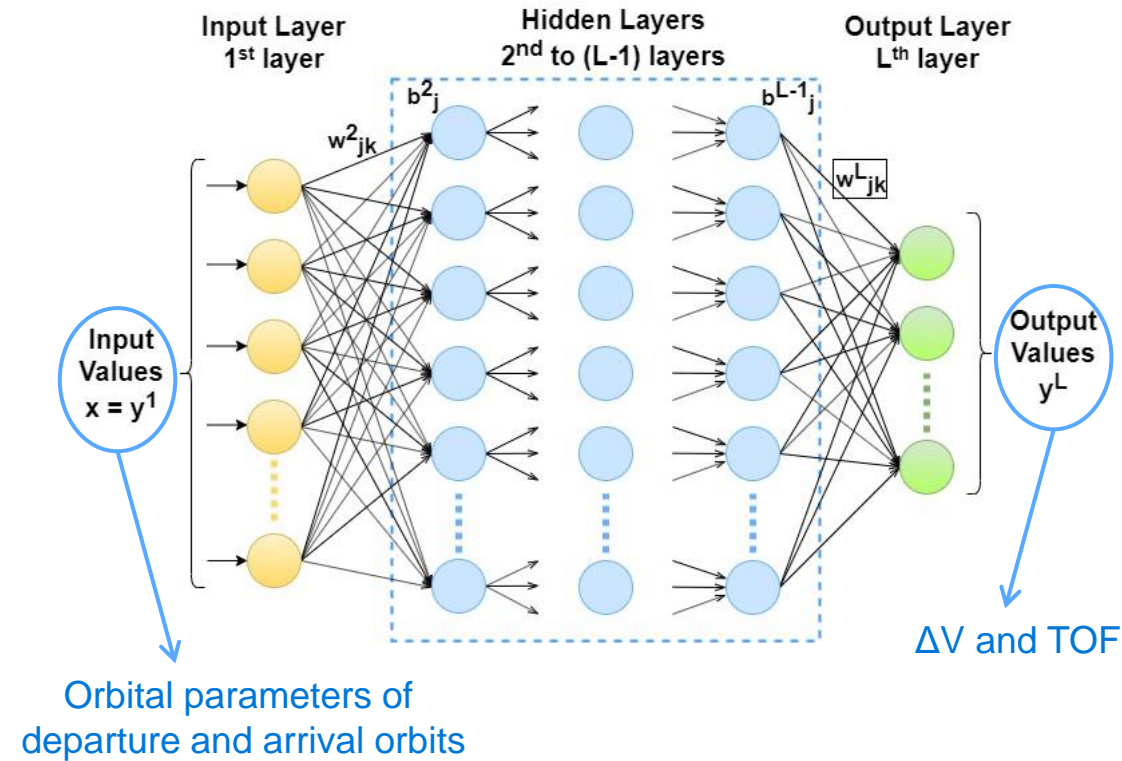
Need

Quick estimation of the cost ΔV and time of flight (TOF) of a transfer between NEAs

Artificial Neural Network

Neural Network Design





TRAINING DATABASE

→ Collection of $(\mathbf{x}, \mathbf{t})_i$ with $i \in [1, N]$

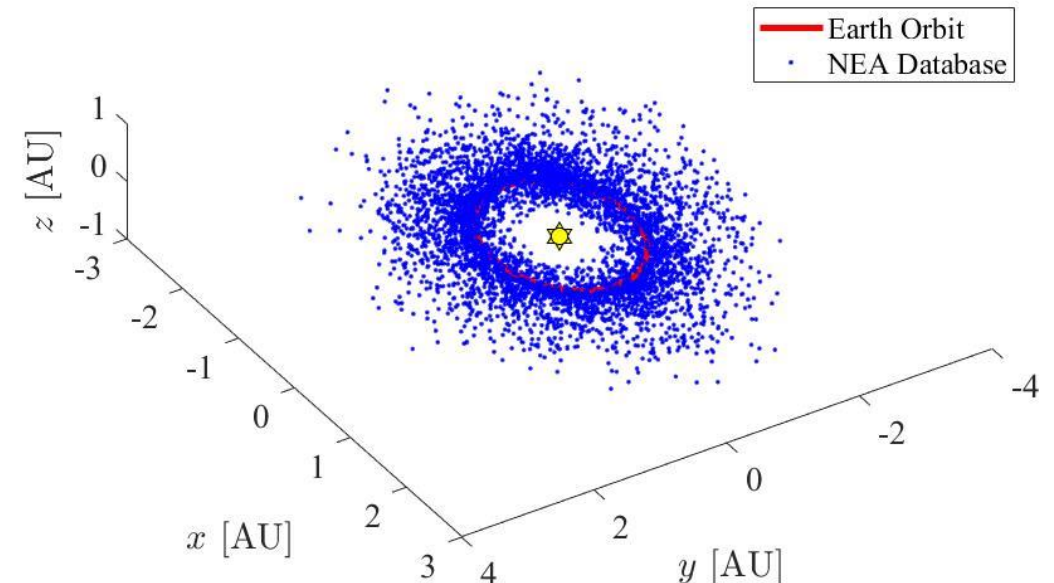
→ Shape-based method

MSE: Mean-Squared Error
SEP: Solar Electric Propulsion

TRAINING

→ Define w_{jk}^l and b_j^l so that MSE is minimised

$$MSE = \frac{1}{N} \sum_{i=1}^N \|\mathbf{y}_i - \mathbf{t}_i\|$$



Architecture & Parameter Tuning

1) NETWORK INPUT:

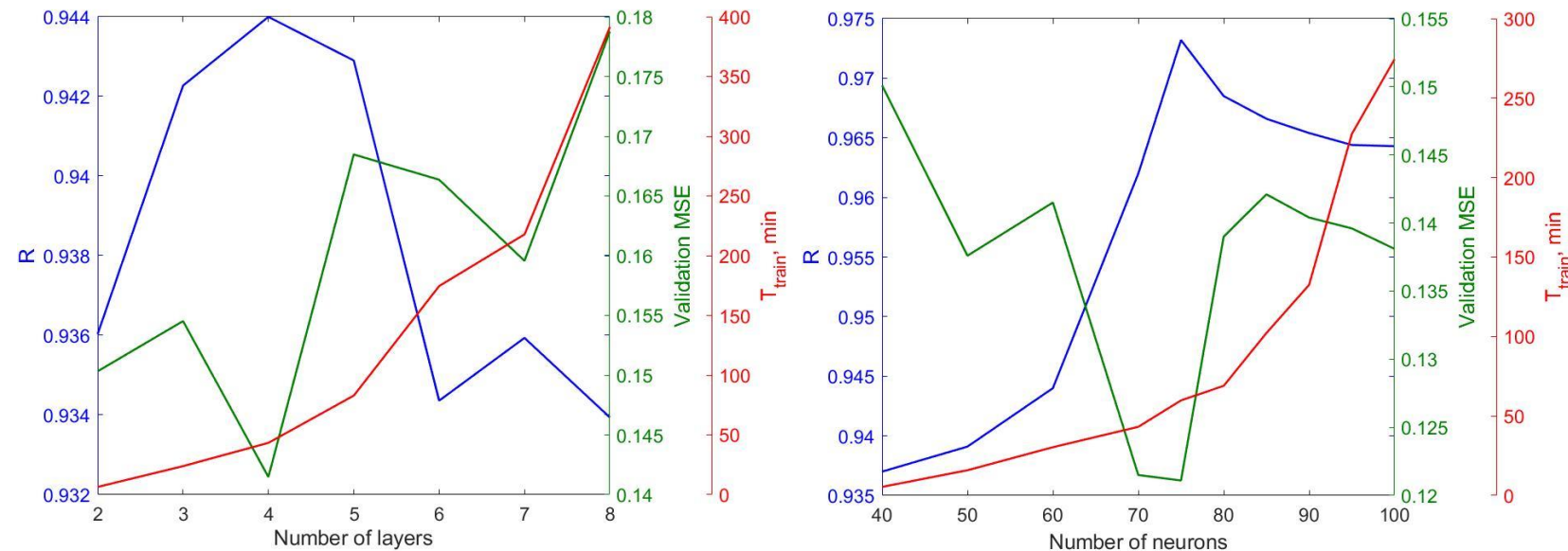
Classical Orbital Elements
Equinoctial Elements
Modified Equinoctial Elements
Cartesian Coordinates
Delaunay Elements
Eccentricity and angular momentum vector

	Correlation	Validation-Set Error
COE	0.855	0.530
EE	0.856	0.487
MEE	0.925	0.236
Cartesian	0.551	0.761
Delaunay	0.694	0.862
eH	0.908	0.221

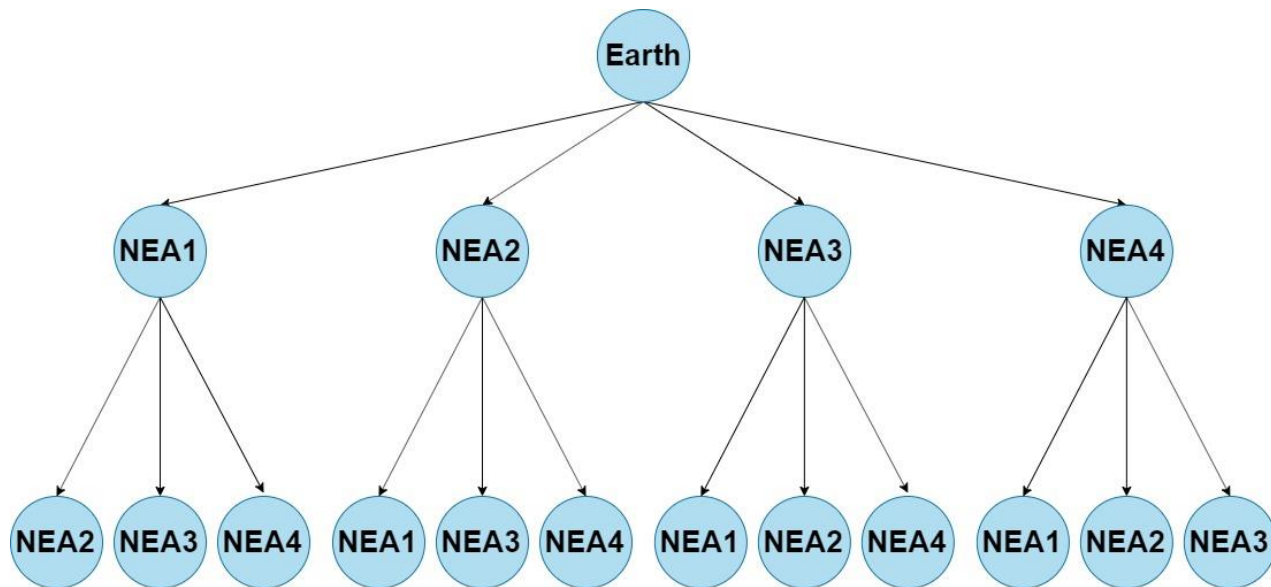
**Best
Performance:**
R = 0.9732
MSE = 0.1211

2) STRUCTURE:

- Learning algorithm
- Activation function
- Gradient constant
- Decrease factor
- Dataset division



Tree-search method

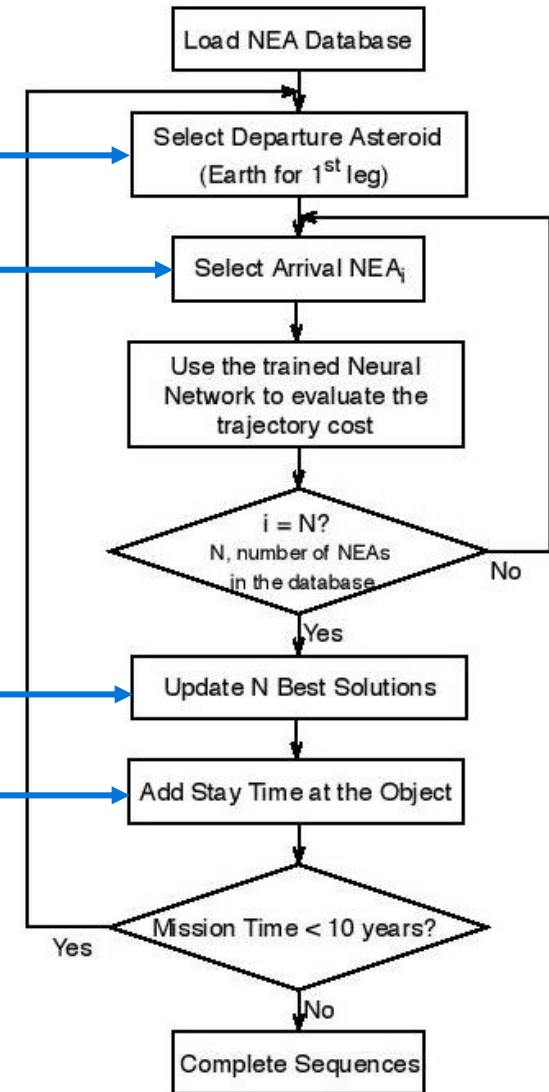


Update position of the object

Update position of the object

$N = 200$

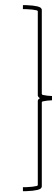
Stay time = 100 days



Sequence Optimisation

→ Obtain the optimal flight trajectory and control history

- State vector: $\mathbf{x} = (p, f, g, h, k, L, m)$
- Control vector: $\mathbf{u} = \mathbf{N} = (N_r, N_\theta, N_h)$

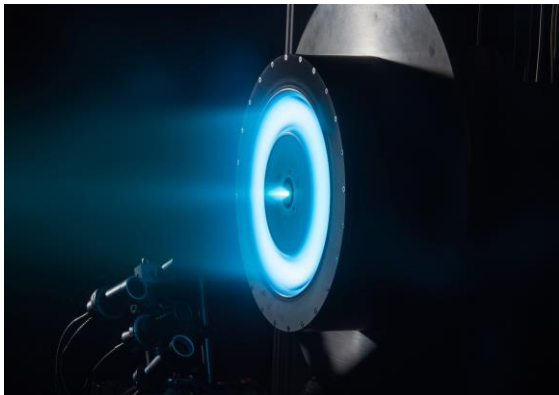


Dynamics:

$$\dot{\mathbf{x}}(t) = \mathbf{A}(\mathbf{x})\mathbf{a} + \mathbf{b}(\mathbf{x})$$

➤ Solar Electric Propulsion (SEP)

$$\mathbf{a} = \frac{T_{max}}{m} \mathbf{N}$$



- Electric power by onboard solar arrays
- Use 10 times less propellant

➤ Solar Sailing (SS)

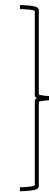
$$\mathbf{a} = a_c \left(\frac{r_\oplus}{r} \right)^2 \cos^2 \alpha \hat{\mathbf{N}}$$



- Radiation pressure
- No propellant

→ Obtain the optimal flight trajectory and control history

- State vector: $\mathbf{x} = (p, f, g, h, k, L, m)$
- Control vector: $\mathbf{u} = \mathbf{N} = (N_r, N_\theta, N_h)$



Dynamics:

$$\dot{\mathbf{x}}(t) = \mathbf{A}(\mathbf{x})\mathbf{a} + \mathbf{b}(\mathbf{x})$$

➤ Solar Electric Propulsion (SEP)

$$\mathbf{a} = \frac{T_{max}}{m} \mathbf{N}$$

➤ Solar Sailing (SS)

$$\mathbf{a} = a_c \left(\frac{r_\oplus}{r} \right)^2 \cos^2 \alpha \hat{\mathbf{N}}$$

→ Optimal Control Problem:

determine \mathbf{u} so that propellant mass expenditure (or TOF for SS) is minimized.

1. Dynamic constraint
2. Path constraint: $0 \leq \|\mathbf{N}\| \leq 1$ for SEP

$$\|\hat{\mathbf{N}}\| = 1 \text{ for SS}$$

Optimised NEA Sequences



SEP: $I_{sp} = 3000 \text{ s}$, $a_{max} = 0.2 \text{ mm/s}^2$

Total TOF = 4292 days (11.7 years)

Total $\Delta V = 51.95 \text{ km/s}$

SS: $a_c = 0.3 \text{ mm/s}^2$

Total TOF = 4406 days (12.1 years)



142 days more than SEP, but zero propellant

Transfer	Stay Time [days]	Departure	Arrival	TOF [days]	ΔV [km/s]
Earth	—				
↓		2035/01/01	2036/11/15	684	7.8
		• 2035/01/01	• 2037/03/12	(553) • 801	(7.04) • -
2011 AM24*	196 • 158				
↓		2037/05/30	2039/07/30	791	8.05
		• 2037/08/17	• 2039/11/10	(675) • 815	(6.9) • -
2003 MM	83 • 114				
↓		2039/10/21	2040/12/25	431	6.11
		• 2040/03/03	• 2041/04/27	(414) • 420	(6.25) • -
2006 SF6	134 • 184				
↓		2041/05/08	2043/04/15	707	9.04
		• 2041/10/28	• 2044/04/28	(524) • 913	(8.28) • -
2008 YT30	271 • 110				
↓		2044/01/11	2045/05/11	486	6.92
		• 2044/08/16	• 2045/11/21	(503) • 462	(5.24) • -
1999 FA	68 • 45				
↓		2045/07/18	2046/10/02	441	6.21
		• 2046/01/05	• 2047/01/24	(502) • 384	(4.67) • -
2019 FU2**	—				

* PHA

** NHATS

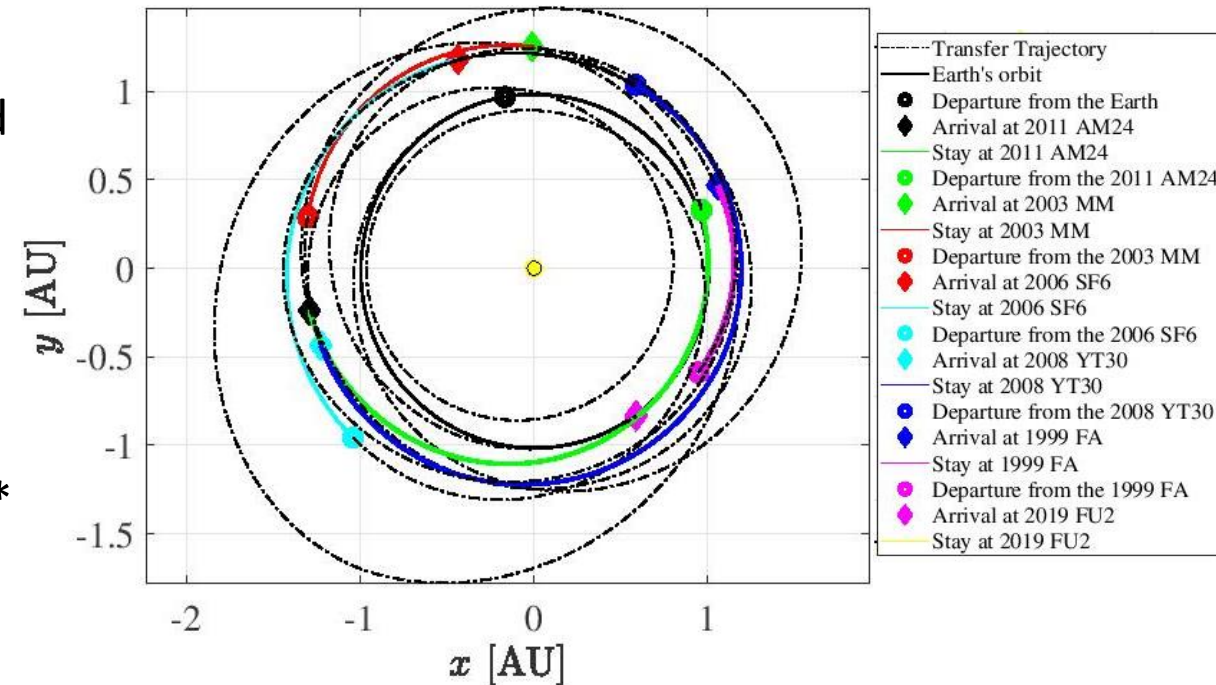
• Results using solar sailing.

(.) ANN results

- ✓ ANN can provide a quick estimation of the cost of a transfer
- ✓ ANN architecture and parameters can be optimised for this application

ANN vs. Optimisation

- Sequence search algorithm using ANN results to be 25 times faster compared to others methods*
- Difference in TOF and ΔV generally limited
- Average percentage error for ΔV and TOF < 10 %



*A. Piloni, M. Ceriotti, and B. Dachwald. Solar-Sail Trajectory Design for a Multiple Near-Earth-Asteroid Rendezvous Mission. Journal of Guidance, Control, and Dynamics, 39(12):2712–2724, Sep 2016

Any questions?



University
of Glasgow

James Watt
School of
Engineering

SET Presentation, 13th May 2020

Thank you!

Giulia Viavattene

g.viavattene.1@research.gla.ac.uk