How Can Artificial Intelligence Help With Space Missions - A Case Study: Computational Intelligence-Assisted Design of Space Tether for Payload Orbital Transfer Under Uncertainties*

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***Abstract*—In the era of artificial intelligence (AI), many industry sectors, including space exploration, have experienced a shift in the way business is conducted due to the widespread use of AI technologies. In the past few years, AI has become a key tool used to explore the universe in space missions. In this paper, a multi-objective optimal design for payload orbital transfer involving space tethers is proposed based on a computational intelligence-assisted design framework with the artificial wolf pack algorithm (AWPA). Enlightened by the social behaviors of a wolf pack and its swarm intelligence, the AWPA is utilized for optimization problems in which a logsig function randomly obtains assignments for parents and offspring. Swarmwolf , a simulation toolbox with given initial conditions. The proposed method effectively performs optimization tasks based on index of evolutionary pathway trends, has been defined to demonstrate the optimizing process. The results show that the proposed approach works expeditiously for the optimization of space tether model and its application.**

***Index Terms*—Artificial intelligence, artificial wolf-pack algorithm, computational intelligence assisted design, evolutionary pathway, multi-objective optimization, payload orbital transfer, space tether.**

I. Introduction

Reflecting one of the most innovative activities, artificial intelligence (AI) has become essential to the global economy, and its positive effects on society in the context of efficiency are immeasurable and emerging in our daily lives. According to an analysis by PwC, by 2030, AI could add £232BN to the Gross Domestic Product of the United Kingdom, which is approximately 10past few years, AI has become a key tool in space activities and the exploration of the universe, and it can be utilized for space communications, navigation, big data analysis, autonomy evaluation, decision support for spacecraft system design [3], space mission operations [4], [5], planetary defense, mapping the moon [6], space exploration [7] and The associate editor coordinating the review of this manuscript and approving it for publication was Zhonglai Wang . universe exploration [8], among other tasks. Most previous works focused on space structure design, communications or flight simulations, and few have addressed the 'space tether'. The original space tether concept came from the 'space elevator', which was proposed by a Russian scientist in 1895. A space tether is a type of lengthy cable ranging from a few hundred meters to many kilometers. The cable makes use of a few bundles of thin strands of high-strength fiber to couple spacecraft to every different or other masses, and it provides a mechanical connection that allows the transfer of energy and momentum from one object to the other. Space tethers can be utilised in many applications, collectively with studies of plasma physics and electrical science in the Earth's upper atmosphere, the orbiting or deorbiting of space vehicles, payload transfer, inter-planetary propulsion, and specialised missions, such as asteroid engagement or, in severe form, as a well-publicized space elevator development of space technology, space tethers are broadly used in the exploration of Mars, or even deep space missions [2]. Recently, a few companies, e.g., Google and SpaceX, have been working on space projects related to space elevators, and these projects are mainly supported by developed AI tools. To fill the current research gap, this paper utilizes an AI-driven design tool for payload orbital transfer via a space tether using a computational intelligence-assisted design (CIAD) framework [9], [10], [22], [28]. An intelligent design system is created with the artificial wolf pack algorithm (AWPA) [24], and this gadget presents three practical advantages: (1)the mobilisation and flexibility of computing resources; (2) the embedment of a set of AI algorithms, and (3) the reducing computational cost as a design objective. In this research, a symmetrical motorized momentum space tether (MMET) with a payload at each end experiences centripetal acceleration when rotating about a facility [1], [11], [12]. In the last a few decades, the studies on the nature-inspired AI algorithms have been widely performed, such as the family of genetic algorithms (GAs) [25], which were inspired by the Darwinian theory and the concept of survival of the fittest; swarm intelligence and algorithms, including the ant colony optimization in 1992, the particle swarm optimization (PSO) in 1995, the Artificial bee colony in 1996, and the firefly swarm algorithm (Firefly) in 2013 [27], and others, based on the principles of natural phenomena, which reproduce the social intelligence of the behaviour of an animal or insect swarm. As one of the most broadly used evolutionary algorithms, the GAs provide a near-optimal solution for practical problems with massive numbers of variables and constraints, in which, the best possible control parameters, including the size of population, the crossover operation rate and the mutation operation rate, are difficult to determine. The typical motivation behind developing nature-based algorithms is to effectively and efficiently solve different optimization problems. During Earth's natural development, it is assumed that the behavior of nature is usually optimal. In this research, the AWPA, a newly proposed nature-inspired algorithm, is utilised to achieve global solutions for space tether's continuous nonlinear functions in a space mission, with low computational effort and excessive consistency. The remaining sections of this work are organized as follows. Section II introduces the social dynamic behaviors of a WP in the natural world, then it gives the AWPA algorithm with logsig randomness, which was stimulated by using the WP's swarm intelligence of its social behaviors, as added in Section II. To investigate the optimization performance, Section III defines the fashion indices for evolutionary optimization, which includes three pairs of trend indices. Section V offers the modeling of payload transfer the use of a house tether. Section VI discusses multi-objective optimization and fitness functions based on the relevant criteria. Section VII presents the empirical outcomes and a discussion

II. WOLF PACK'S SOCIAL MECHANISM AND ARTIFICIAL WOLF PACK ALGORITHM

Wolves are gregarious animals who mostly live in packs. A wolf pack (WP) is formed when a male (α) and a female wolf (β) meet and continue to be together as a mated pair. The pair establishes a territory to settle and increase cubs in most years. The cubs stay within the WP until they are old enough to leave home, generally when they are 3 years old, and they can then start a WP of their own. Thus, the social structure of a WP consists of a permanent core of a $\alpha + \beta$ pair plus their continuously dispersing offspring. A WP has a very strict stage of hierarchy that need to be adhered to by all the members of the pack, and it supports the WP to survive. For their social intelligence, wolves are considered one of the smartest animals in nature, and they have developed the potential to live on in a vast vary of surroundings, which varies from the wilderness to humid swamps to the Arctic region with temperatures of -40 and bitter winds. Basically, a WP has 3 types of behaviors in their social activities, namely, 'scouting', 'calling' and 'besieging', as shown in Figure 1, usually in a WP, an α male wolf is the leader wolf who is in the decision-making position

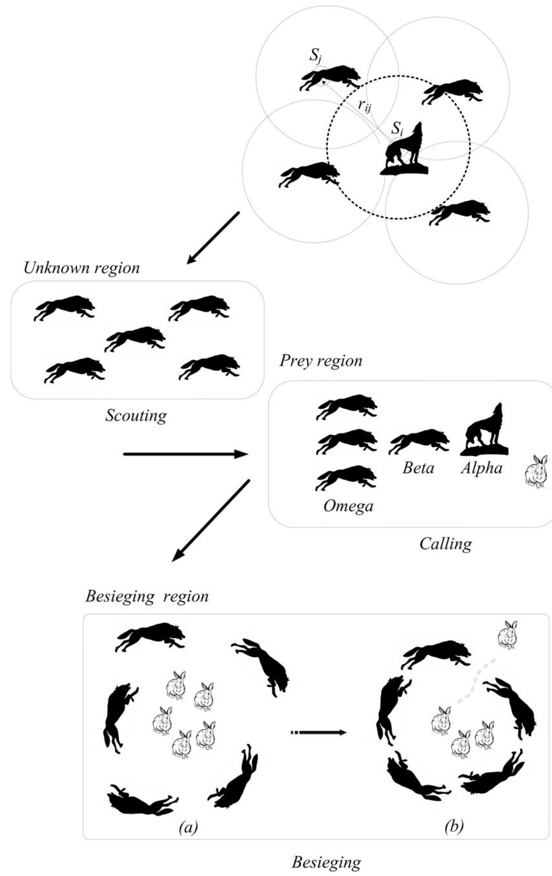

Fig. 1. A WP's social behaviors

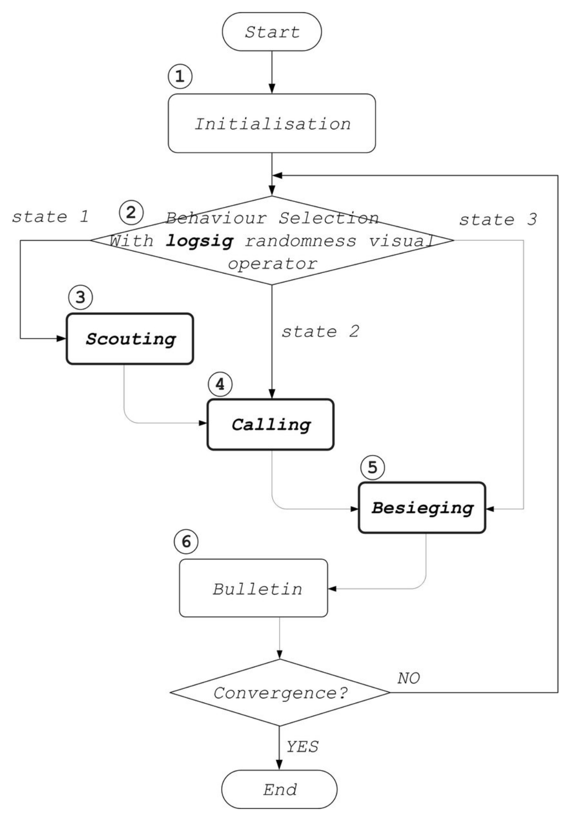

Fig. 2. The workflow of ar tificial wolf pack algorithm.

and is able to command all the other wolves to carry out suitable actions. Specifically, scouting: the scout group of wolves are deployed to explore unknown areas; calling: when the scout wolves have spotted and positioned the prey in an area, they will report this information to the α wolf and also communicate with other wolves by their howling; besieging: after the α wolf confirms the prey information and will be leading the WP toward the scout wolves, starting the grey hunting and capturing actions in the so-called the besieging area. Inspired by the swarm intelligence of a WP's social behaviors, an artificial intelligent algorithm, the Artificial Wolf Pack Algorithm (AWPA) is proposed by implementing three social behaviors of a WP, in which, there are six steps include: (1) initialization of all the variables; (2) the behavior selection from three social behaviors with the logsig() randomness; (3) the operation of scouting behavior; (4) the operation of calling behavior; (5) the operation of besieging behavior and (6) the bulletin step to summarise the results. Without loss of generality, in this section, Sj is considered the status of any artificial wolf with status j. The AWPA workflow is given in Figure 2. As shown in Equation (1), when performing the AWPA with a pre-defined function WPM×N , it first simulates the behavior of an individual artificial wolf (AW, as Sij), where M is the population and N is the number of individuals in a WP. Each AW searches for the local optimal solution and passes its result to the self-organized WP and so as to obtain the optimal global solution. As also shown in Figure 3, it gives the pseudocode implementation of the AWPA algorithm, in which, the 'maxgeneration' parameter is set as the terminal condition of the AWPA optimisation.

```
Initialise all parameters:
    x_i with variable population P,  fitness(x_0),
visual, try_number etc.

    While ( Not termination-condition) do
      Begin (2)

        t    =  t + 1;

        FOR i = 1: Population

            state = Behaviour Selection()
                IF( state ==1)
                   Scouting();

                Elseif (state ==2)
                   Calling();

                Elseif (state ==3)
                   Besieging();

                Else

                End

        ENDi

        evaluation fitness(x) and best solutions
```

Fig. 3. AWPA Pseudo Code

(1) Initialization: in this step, all the variables and parameters are set to the pre-defined values, in a case, population = 50, max generation = 200, etc., and the simulation program prepare for the subsequent steps

$$WP_{MXN} = \begin{bmatrix} S_{11} & S_{12} & S_{13}\dots & S_{1N} \\ S_{21} & S_{22} & S_{23}\dots & S_{2N} \\ S_{31} & S_{32} & S_{33}\dots & S_{3N} \\ S_{M1} & S_{M2} & S_{M3}\dots & S_{MN} \end{bmatrix} \tag{1}$$

(2) Behavior Selection: In the 'behavior selection', there are three types of 'states' to indicate three different types of behaviors of a WP, that is, 'scouting', 'calling' and 'besieging', in which, the 'scouting' state is set as the default state or initial behavior of each WP. Depending on the companion's number and the visual conditions, the prey density in the hunting region can be defined in Equation (2).

$$visual(t) = logsig\left(\frac{\frac{T}{2} - t}{k}\right) xrandom(t) \tag{2}$$

in which,

- logsig() is a logarithmic sigmoid transfer function;
- T is the maximum number of iterations;
- t is the current iteration number;
- k changes the slope of the logsig() function;
- random() is a random value within the range of (0,1).

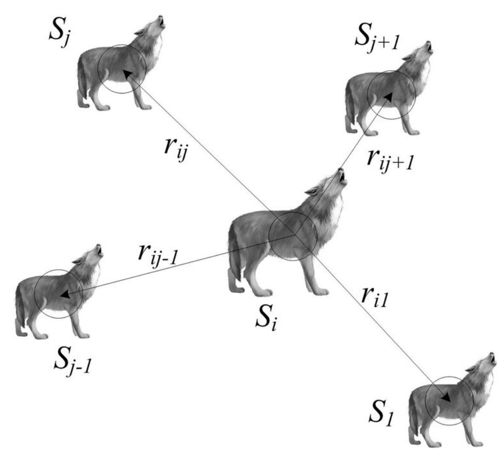

Fig. 4. The Euclidean distance between the AWi^{th} and AWj^{th} and states updating

(3) Scouting: For an AW individual k in a WP, let's define S as the finite state set, and there are states 1 to M that an AW can perform, as given in Equation (3). Within the AW's visual field, let's define $S_{(*)i}$ as the cur-rent state of an AW and $S_{(*)i}$ as the next state. Specifically, an AW moves from its current state $S_{(*)i}$ to the next state $S_{(*)i}$ randomly, and keep checking the state updating conditions, as stated in Equations (5) and (4), where ϵ is a random movement factor, δ is the iteration step, and ν is the visual constant of the AW. For a given AW, the prey density is defined as z D f (S), in which, z is the fitness function, z i and z j are the prey density in the state $S_{(*)i}$ and $S_{(*)i}$, respectively.

III. THREE PAIRS OF TREND INDICES

To evaluate the performance of the optimization process, and benchmarks for the AWPA algorithm, three pairs of trend indices are introduced in this section: 1) the trend index of moving mean of the average pre-cision (mmAP) and the index of moving mean of the standard deviation (mmSTD), as given in equations (13) and (14), respectively; The trend index of mmAP is dened as a moving aver-age score of the MEAN value of a vector fj, as given in equation (13), in which $i = 1, 2, \ldots j, \ldots p$, p is the size of the dataset's population, MEAN is the average function. The trend index of mmSTD is a moving average score of the STD value of vector fj, as given in equation (14), in which STD is the standard deviation function. Both indices of mmAP and mmSTD are employed to assess the short-term fluctuations by recording the long-term trend throughout their evolutionary process. 2) the trend index of 'moving max of the average pre-cision' (mmaxAP) and the index of 'moving max of the standard deviation' (mmaxSTD), as given in equa-tions (15) and (16), respectively.

IV. EVOLUTIONARY PATHWAY

As shown in Figure 5, from top to bottom, the solid lines are the trend indices of mmaxAP, mmAP and mminAP of a fitness function in a vector fj, as given in equations (15), (13) and (17), respectively. The dashed lines are the boundaries of $mmaxAP + mmaxSTD$, $mmAP + mmSTD$ and $mminAP + mminSTD$ values for each vector fj, as defined in Equations (16), (14) and (18), which illustrate the tracking shape of the evolution-ary pathway for the optimiza-tion process, generation versus fitness f in this case, as the upper and lower boundaries.

V. PAYLOAD TRANSFER USING SPACE TETHER UNDER UNCERTAINTIES

As illustrated in Figure 6, there are two sub-figures labelled as (a) and (b), which describes the orbital elements of payload release and transfer using space tether.

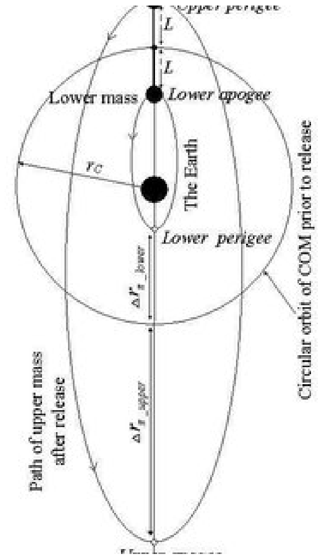

Fig. 5. Orbital elements of payload release and transfer

- Figure 6 (a), it demonstrates the payload transfer from a 3D perspective.
- Figure 6 (b), it describes the parameters for modeling of the payload transfer from a 2D perspective.

Generally, the space tether's payload transfer is in a low Earth orbit, where the space tether obtains rising angular velocity than it requires to remain in the orbit, however, it does not comprise sufficient energy to escape from the Earth's gravity field. During payload transferring, a robotic space tether, con-sists of a few modules including: the upper payload, the lower payload and a center of mass (COM), is in a low Earth orbit, where the upper payload can be released from the spinning space tether with enough angular momentum, which is aligned along the local gravity vector. After the release operation, the upper payload will enter an elliptical orbit (named as 'OU'), as shown in both sub-figures (a) and (b), in which the point A (the upper perigee of 'OU') is the release point. Then, half of moving on the elliptical orbit later, the upper payload reaches the point B (the upper apogee of 'OU'), where is further from the Earth than it was at release point. On the contrary, the lower payload will not have enough energy to maintain in its circular orbit after the release oper-ation, and it will enter into another elliptical orbit (named as 'LU'). Upon reaching the point D (the perigee of 'LU'), the lower payload is closer to the Earth than it was at the release point C (the apogee of 'LU'). Finishing above actions, the upper and lower masses of payloads are released from the spinning space tether, entering a raised orbit and lowered orbit, respectively. All the environmental effects that can influence the space tether modelling are assumed to be negligible in the space tether's modelling context, including solar radiation, aerodynamic drag, electrodynamic forces and no frictional losses. To build a model for the payload transfer, a set of parame-ters are defined here,

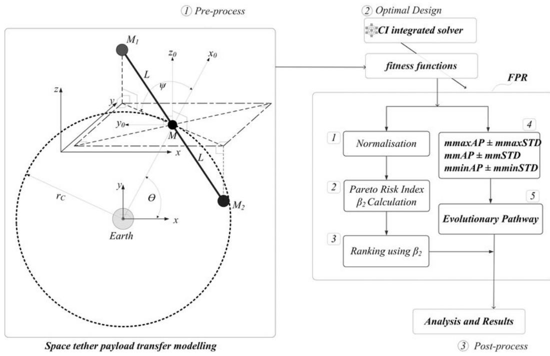

Fig. 6. Optimisation of Space Tether for Payload Orbital Transfer via CIAD Framework

VI. FITNESS FUNCTIONS AND OPTIMAL DESIGN CRITERIA

As shown in Figure 7, the multi-objective optimization process of the space tether for payload orbital transfer includes four steps, as listed below.

1) Pre-processing: This step includes the dynamic modeling of the space tether for payload orbital transfer as given in Section V;
2) The optimal design given by the computational intelligence approaches via the integrated solver;
3) Three design objectives. The MMET payload transfer and design strength problems are defined as three conflicting objectives that need to be balanced in the optimization study, in which the practical multi-objective problem of tether payload transfer can be expressed as follows [20]

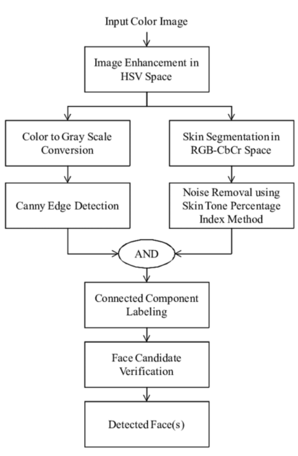

Fig. 7. FPR Flowchart

VII. OPTIMAL DESIGN FOR ORBITAL PAYLOAD TRANSFER

The computers used for the simulations have Intel Core i7-5500U 2.4 GHz dual-core processors with the Win-dows 7 flagship x64 service pack 1, 8.0-GB 1600-MHz dual-channel DDR3L SDRAM, and MATLAB R2010a. Table 1 lists the parameters for the optimization process, in which, the termination condition is set to‘ max-generation D100’ for each loop of evolutionary opti-misation; the try variable is 5; the population is 50; the total number of tests is 100; the iteration step is 0.001; the initial visual value is 2.5; the crowd value is 0.618. Table 2 gives the optimal combinations (MEAN STD) of z and the design variables (x1;x2;x3), and the results indicate that the overall performance of the AWPA in the optimal design of a space tether for orbital payload transfer is better than that of the algorithm and GA. Figures 9 to 12 give the max, mean and min fitness curves, which show that the AWPA converge near generation 30. Figure 9, Figure 10 and Figure 11 show the mmaxAP + mmaxSTD, mmAP + mmSTD and mminAP + mminSTD fitness curves over the full simulation period, respectively. Figure 12 illustrates the evolutionary pathway of the opti-mization process of the optimal design for space tether pay-load transfer using the mmaxAP + mmaxSTD, mmAP + mmSTD and mminAP + mminSTD fitness curves with their upper and lower boundaries. Obviously, the fitness values increases very quickly, and it reaches a plateau from generations 1 to 250. All curves converge from generation 280 to 300, which reflects the high efficiency of the proposed AWPA for this space tether payload transfer application.

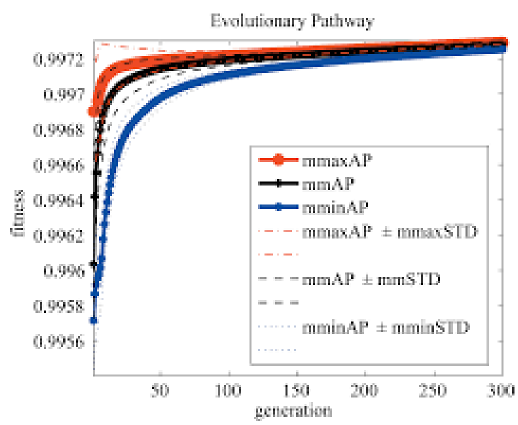

Fig. 8. Evolutionary pathway of space tether payload transfer

VIII. CONCLUSIONS AND FUTURE WORKS

In this study, the efficiency of payload transfer considering the perigee altitude loss and tether stress are defined for space tether payload orbital transfer, and three fitness func-tions are obtained using the newly devised trend indices for the multi-objective problem. Then, optimization is performed with the newly developed multi-objective AWPA. The following conclusions can be drawn with the results and discussions above

- The optimal design using the multi-objective AWPA exhibits good agreement with previous results.
- The evolutionary trends are accurately rejected by the three defined pairs of trend indices with variable uncertainty and tolerance levels
- the dynamic evolutionary behaviors of three pairs of trend indices are obtained and considered in optimiza-tion.

- the fast Pareto-optimal solution recommendation method is introduced, and a clear recommendation list is established for decision making.
- further studies on the implementation of experimental verification and validation for the space tether and space robotic and autonomous system;
- the development of the operational strategy of high efficient payload transfer using space tether systems;
- the studies on the high efficiency and reliability design for the key components of the space tethers;
- to develop a computational intelligence assisted design software package for industrial design and manufacture, as one of the components of cyber-physical system (CPS) for industry 4.0 applications in future space projects, using cutting-edge technologies, such as: 'digital twin' and internet of things;