Optimization of Low-Thrust Earth-Moon Transfers Using Evolutionary Neurocontrol

A. Ohndorf, B. Dachwald, and E. Gill

***Abstract*—Although low-thrust propulsion is an interesting option for scientific and reconnaissance missions to targets in planetary space, like the Moon, associated transfer strategies pose challenging requirements in terms of optimal control. The method of Evolutionary Neurocontrol (ENC), which has been applied very successfully to interplanetary low-thrust transfer problems, is now used for solving this type of steering problem. For exemplary validation, two low-thrust transfers from an Earth-bound geostationary transfer orbit into a Moon-bound orbit are optimized with respect to minimum flight time.**

I. INTRODUCTION

In the last years, several nations announced or have already started initiatives towards the Moon, some of them involving big-scale human spaceflight missions, e.g. the U.S.-program, while smaller scientific missions involve probes and/or orbiter spacecrafts. For example, India currently conducts the Chandrayaan 1 mission and plans to launch Chandrayaan 2 in 2011. Besides scientific instruments, the first one also carries an impact probe for surface examination and the second one is intended to bring even a rover for in-situ analysis to the Moon surface. These and other missions in the past rely on proven chemical propulsion systems although Electrical Propulsion (EP) systems, whose foundations are basically known for decades, already demonstrated its capabilities with successful missions like Deep Space 1 or Hayabusa. The ESA mission SMART-1 also showed how to fly to the Moon electrically.

The main advantage of EP over chemical propulsion, the superior propellant efficiency, becomes obvious by looking at the respective specific impulse values (I_{sp}). The specific impulse, as a universal measure of propulsion system performance, is calculated from the thrust force F_{t}, the propellant mass flow $\dot{m}$, and the Earth's standard gravitational acceleration at sea level g_0 with

$$I_{\mathrm{sp}} = \frac{F_{\mathrm{t}}}{\dot{m} \cdot g_0} . \qquad (1)$$

Due to the chemical properties of available propellant/oxidizer combinations, the I_{sp} of chemical propulsion systems is inherently limited to values of less than 500 s. In the contrary, the practical limit of EP is currently set by the amount of electrical power onboard the spacecraft.

Space-tested electrical thrust units already reach an I_{sp} of about 3000 s and thrust levels of approximately 100 mN. Next generation thrusters being qualified today are about to attain even twice that I_{sp}-level with also higher thrust values. Although, theoretically, by usage of several thrust units in parallel, thrust regimes of a few Newtons seem possible, EP is not suited for high-thrust applications. However, its superior fuel efficiency and large ΔV-capability makes EP suitable for challenging mission scenarios. Until now, not only practical problems in implementing high performance EP-system hardware have prevented further success, but also the necessary but not easily found optimal control strategies. Having thrust durations in terms of months rather than minutes the demands on optimization methods for finding these strategies are different than for chemical propulsion trajectories.

A very successful mission involving EP was SMART-1. Equipped with only a single ion engine with a maximum thrust of 70 mN, it reached a Selenocentric orbit by following a preset thrust profile. This steering command history was developed with significant effort by a team of flight dynamics experts. For future application and greater onboard autonomy it is thus desired to find reliable, easy-to-use, and robust techniques to find optimal steering strategies for low-thrust trajectories. This problem is addressed by numerous researchers and engineers with different approaches and remarkable results have already been found. Betts and Erb [1] showed that direct transcription or collocation methods can be successfully applied to this problem but they constrained the solution space by dividing the trajectory into distinct phases. Herman and Conway [2] combined the method of collocation with nonlinear programming (NLP) to solve the transfer problem in the

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context of two coupled two-body problems taking into account the respective third-body disturbance accelerations of Earth and Moon. Constraints are used to enforce the necessary state-variable continuity across the arbitrarily chosen point of switching from the Earth-centered two-body problem to the Moon-centered two-body problem. Additionally, the method needs the partial derivatives of certain system constraints with respect to the free parameters. Finally, as with many local optimization methods, an initial guess trajectory to start the optimization from is needed (although, for this method, even a discontinuous non-valid trajectory works).

A promising method to overcome the described constraints is called Evolutionary Neurocontrol (ENC). Developed by Dachwald [3] it has been used very successfully for finding and optimizing steering strategies of several *interplanetary* trajectory types (rendezvous, fly-by, escape). The method is implemented in an optimization program named InTrance, which stands for "INtelligent spacecraft TRAjectory optimization using NeuroController Evolution". The intention of the program is to enable also non-experts in astrodynamics and optimal control to conduct preliminary mission analysis involving EP.

By extension of ENC to the planetary case of an Earth-Moon transfer, this work shows that automatic optimization of low-thrust trajectories crossing the boundary of the spheres of influence between the involved celestial bodies is feasible with ENC. Thereby no subdivision into distinct phases, no initial solution and no state derivatives have to be provided. Due to the limitation on a single sphere of influence (SOI) crossing only, the method is currently not developed to its full extent, but already shows promising results. The SOI is the almost sphere-shaped zone around a celestial body, where the motion of a small body is determined primarily by the body's gravitational force. The gravitation of distant other bodies, even if they are heavier, acts only as disturbing force.

The underlying concepts are explained briefly in the following section and details of the application to the problem of optimizing low-thrust trajectories are described. Section III shows the results of calculated Earth-Moon transfers. The transfer type chosen for validation poses remarkable challenges on finding steering strategies that lead to valid trajectories, let alone an optimal one. It is a realistic three-dimensional trajectory problem in a three-body environment and, due to the very low thrust acceleration, involves many revolutions about the respective bodies (Earth, Moon). The spacecraft used within this work achieves an initial thrust acceleration of less than $5 \cdot 10^{-5}\, g_0$, which makes it only half as powerful as the one used in [1] for trajectory optimization.

II. METHOD

A. Evolutionary Neurocontrol (ENC)

In simple terms, ENC is the application of artificial neural networks (ANN), trained by Evolutionary Algorithms (EA), to optimal spacecraft steering. Explained in [3] and more detailed in [4], only the basic principles are briefly outlined in the following sections.

1) Evolutionary Algorithm (EA)

Inspired by nature's evolution in its principles, a lot of the vocabulary used in the context of Evolutionary Computing is lent from biology. One of the core elements of an EA is a number of potential solutions gathered in the so-called population. Every single solution, also called individual (or string ξ or chromosome), completely describes exactly *one* possible strategy to tackle the posed optimization problem but, obviously, not the optimum one a priori. The individual's ability to solve the problem is measured with a scalar value called objective function value or fitness value or just the fitness. The better the solution, incorporated by an individual, is suited solve the problem, the higher is its fitness value. In the context of trajectory optimization, the calculation of the fitness value usually follows a trajectory integration and subsequent evaluation of boundary constraints fulfillment, as well as achieving the respective optimization objectives.

As the chromosome data is randomly initialized at the beginning of the optimization process, the fitness values of the population individuals spread over a wide spectrum. The EA then tries to breed better individuals until convergence is achieved. This happens if no individual with a higher fitness than that of any other population member can be generated for a pre-set number of reproductions. The evolutionary principle of 'survival of the fittest' is used to find a global-optimal solution because at the end of optimization the population is crowded with members having fitness values differing only slightly from each other. Former population members, identified as being inferior to competing individuals during the selection process, have been replaced by offspring individuals and thus not "survived" the process of evolution. Appropriate selection schemes assure that individuals considered appropriate to contribute positively to the population's genome pool have higher chances for reproduction as inferior ones. The selection scheme used in this work is called tournament selection, in which four individuals are randomly selected for two tournament rounds with two competitors each. The tournament results are determined by fitness value comparison which leaves two "winners" and two "losers". The latter ones are to be replaced by the generated offspring individuals. These children individuals are generated by recombination of the two winner's genome information and subsequent mutation on both children. Mutation is an important element of EAs as it introduces new information to the individual's genome code and thus to the problem's solution space. Therefore, it helps to reduce the probability of premature convergence to a local optimum.

2) *Artificial Neural Networks (ANN)*

In their underlying principles ANNs are inspired by information processing in nervous systems of animals. Thus they have remarkable features like massive parallelism, analog signal transfer, fault tolerance and adaptiveness. Also their robustness and insensitivity to noisy input data, and especially their capability of generalization make them interesting for spacecraft steering. For example, if it would be possible to find an ANN and the corresponding optimal input data set for solving the general low-thrust rendezvous problem of two bodies, this ANN could steer any low-thrust spacecraft between any two bodies on an optimal rendezvous trajectory.

Basically, ANNs map an input data set onto an output data set by applying its built-in transfer function $\mathsf{N}_{\boldsymbol{\pi}}$. This transfer function may be of arbitrary complexity but is composed of connected primitive processing units, called neurons. Every single neuron has a transfer functions (also activation function) by itself, and the one used within this work, the sigmoid, is defined by

$$y_{\mathrm{i}} = \frac{1}{1 + \exp\left(- \frac{\sum_{\mathrm{j}} w_{\mathrm{ij}} y_{\mathrm{j}} - \theta_{\mathrm{i}}}{\gamma_{\mathrm{i}}} \right)} \tag{2}$$

where y_{i} is the output of neuron i, θ_{i} the neuron input bias, w_{ij} the weight factors that determine to what extend the output y_{j} of neuron j contributes to the input of neuron i, and the slope defining constant temperature parameter γ_{i}. Assuming a known ANN topology, the parameter set $\boldsymbol{\pi}$, which comprises of all neuron bias values, neuron transfer function parameters and neuron connection weights, completely defines the ANN transfer function. Crucial for an effective utilization of ANNs is to find appropriate network parameter sets. This general learning problem has been addressed by a number of learning algorithms, one of the most widely known for reinforcement learning problems is the gradient-based backpropagation algorithm. Learning algorithms strive to train ANNs to achieve the desired generalization, that is to understand the nature of the problem instead of memorizing correct output values of formerly given training data sets. For example, if the ANN "understands" the deeper nature of how a rendezvous trajectory must be flown optimally, it should be capable of generating optimal steering commands also for changed initial conditions like different launch dates, different target bodies or changed propulsion system capabilities. Unfortunately, learning algorithms like backpropagation fail for delayed reinforcement learning problems, where no training data sets of input and output values exist.

The ANN transfer function not only depends on its neuron transfer functions but also on the interneuron connections, the connection weight factors w_{ij}. For example, the connection weight parameter of the connection between two neurons A and B determines to what extent the output of neuron A contributes to the input of neuron B. As a simplification, in our context the neurons are organized in a layered structure and there exist only forward connections from neurons of the predecessor layer to the subsequent layer. This type of feed-forward ANNs with a user-provided configuration for the number of hidden layers and neurons per layer is implemented in InTrance and therefore used for calculations within this work.

3) *Low-Thrust Spacecraft Steering using ENC*

In contrast to chemical propulsion, where the direction and magnitude of single velocity increment vectors is subject to optimization, low-thrust trajectories require steering profiles covering time spans being much longer (in the range of days or months instead of minutes). Such a profile may be seen as a series of thrust commands, i.e. thrust direction and magnitude, which is to be followed in order to fly the trajectory defined by that profile. Each such profile is a steering strategy and, consequently, the global-optimal trajectory is achieved by executing the commands of the global-optimal steering strategy.

The method of ENC uses ANNs for spacecraft steering to determine the current optimal steering command by application of the ANN's transfer function on a set of input values, e.g. spacecraft and target coordinates. The problem of finding an optimal strategy that leads to an optimal trajectory is thus transformed into the determination of the optimal network transfer function $\mathsf{N}_{\boldsymbol{\pi}*}$. The optimal network transfer function itself is completely defined by the optimal ANN parameter set $\boldsymbol{\pi}^*$. Optimality in this context of course depends on the optimization criteria. This may be for example a minimum transfer time or a minimum propellant mass consumption. As in general the optimal trajectory is unknown, the optimal steering command history is unknown either, which makes training of an ANN an example of a *delayed reinforcement learning problem*. Because the concept of EAs has already been applied successfully to this type of learning problem it is used within ENC to find transfer trajectories by optimizing the steering controllers transfer function $\mathsf{N}_{\boldsymbol{\pi}}$. The algorithm takes advantage of the fact that the corresponding parameter sets $\boldsymbol{\pi}_{\mathbf{i}}$ may be coded onto strings ξ_{i} which are then exposed to the EA. Further details of the implementation, especially how neuron parameters are mapped onto a string, can be found in [4].

B. Extending ENC to Planetary Mission Analysis

As shown by Dachwald [3], ENC is a robust method for finding global-optimal steering strategies for a variety of low-thrust transfer problems, i.e. rendezvous and fly-by transfers to celestial bodies and also escape missions. The scope was thereby limited on *interplanetary* trajectories only. As will be shown, ENC may also be applied to the optimization of *planetary* low-thrust missions. In this environment the non-negligible disturbance acceleration of third bodies and, depending on the distance, non-homogeneous gravity fields may have significant influence on the spacecraft's trajectory. Furthermore, possible shadow

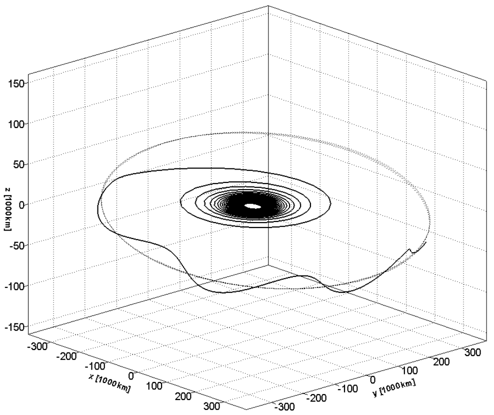

Fig. 2. Transfer A from a GTO-type orbit into circular Moon orbit

It took about 36 hours of computation time on a custom 2.66GHz processor and 114,000 EA reproductions to find the transfer B that is still considered to be suboptimal. As the goal is to develop a method that automatically finds and optimizes challenging low-thrust trajectory types, e.g. like the one of the SMART-1mission, it is open whether other ANN topologies in combination with different input data sets lead to better results.

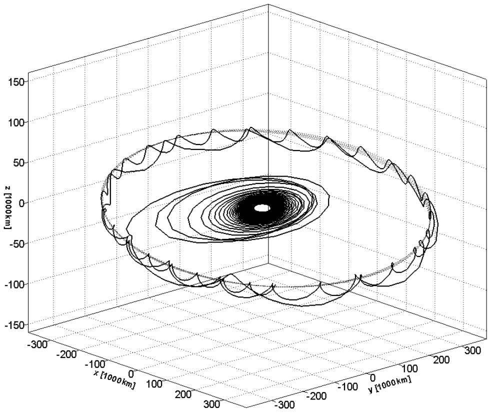

Fig. 3. Transfer B from a GTO-type orbit into a SMART-1-type orbit

IV. SUMMARY AND CONCLUSION

It was shown that ENC is not only applicable to interplanetary low-thrust trajectory optimization but also to planetary low-thrust transfers involving a single SOI crossing. Although not yet being fully developed, the method already shows promising results using a single NC for the complete transfer. This is demonstrated by calculation of a low-thrust transfer starting from a GTO-type orbit into a circular Moon-bound orbit well within the SOI radius. Additionally, the challenging SMART-1-type transfer into a highly-elliptic Selenocentric polar orbit was computed. It is to explore, whether optimized transfers to such target types may be achieved with NCs having more complex network topologies and/or different input data sets. Further on, only a single NC was used so far to steer the spacecraft along its flight path. Additional investigations have to show, whether the use of a NC for *each* phase, one for the transfer to the Moon's SOI and a second one for the orbit-to-orbit transfer inside the SOI, results in better trajectories. This approach would involve the optimization of the switch point from one NC to the other. Furthermore, additional validation of ENC with other objective functions is needed, e.g. minimum propellant mass consumption.

Having answered these questions, a logical next step would be the application of ENC to the problem of optimizing transfers with more than one SOI boundary crossing. An example for such a transfer would be the low-thrust trajectory from Earth to an orbit around a Jovian moon.

Another more general improvement of ENC for the use within detailed mission analysis would be the combination with a local optimization method to find near global-optimal high-accuracy trajectories.

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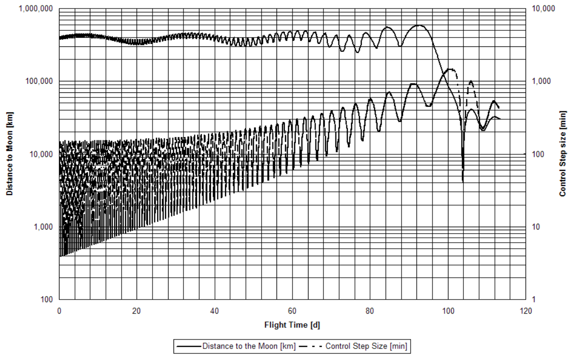


Fig. 1. Control step size and distance between the Moon and the spacecraft

The drop in control step size at approx. 100 days of flight marks the point where the Moon becomes the dominating body. Adapting the steering step size this way not only improves runtime behavior of the EA, but also supports convergence to valid solutions.

2) *Setup of Neurocontroller and EA*

To steer the spacecraft into the desired lunar orbit the NC needs input data to derive steering commands by application of the strategy determined by its ANN topology and the associated parameter set. There are many possible input data sets and combinations of them. Finding the optimal input data set as well as the optimum ANN topology is a field of research of its own. However, investigations showed that the type of coordinates in which the information is expressed in is less important than the amount of used problem-specific data. For example, if the disturbing influence of third bodies should be considered, the NC should be given information about it. In the case of the considered Earth-Moon transfer the primarily acting bodies are the Earth and the Moon and therefore the NC needs know about them.

But which data is to be provided to the NC? Transferred to the transfer problem you may think of the position and velocity of the spacecraft and the involved celestial bodies. This information may be relative or absolute and expressed in Cartesian or polar frame coordinates. You could also use completely different state descriptions like the classic orbital elements and the equinoctial orbital elements. Combining them even increases the number of possible input data sets. For the calculations within this work an ANN with 37 input neurons and 5 output neurons is used. The first 14 input neurons hold the spacecraft's position and velocity expressed in Cartesian and polar frame ECI coordinates. To prevent discontinuities in the polar angles input, instead of the plain azimuth and elevation angles the respective sinus and cosines values are used. Therefore the number of needed input neurons is increased from 12 to 14. The next 14 input neurons hold the same type of data for the Moon.

As the target state is an orbit around about the Moon, also the spacecraft's current orbit elements (semi-major axis a, eccentricity e, inclination i, right ascension of ascending node Ω with 2 neurons) and the desired elements of the moon-centered target orbit (a, e, i) are provided with the next 8 input neurons.

Propelled by an ion engine thruster the mass of the spacecraft changes during flight and therefore the last input neuron holds the relative propellant mass (as fraction of the initial propellant mass).

The first three output neurons hold the components of the commanded thrust direction vector in orbit frame coordinates. From this the two steering angles are computed. The first one, the cone angle, is defined between the thrust direction vector and the radial unit vector. The so-called clock angle is defined between the projection of the thrust vector onto the plane perpendicular to the radial unit vector and the tangential unit vector.

The output of the fourth neuron is mapped onto the continues interval (0,1) representing the throttle setting of the engine, where 1 means maximum thrust level and 0 represents a shut-off engine.

All optimizations of this work have been done with an EA having a population size of 35 and a mutation probability of 0.93. That means after every reproduction the freshly generated offspring individuals experience a mutation at one randomly selected position of their chromosome data with a probability of 93 percent.

3) *Objective Function*

The fitness function *f* drives the EA towards the optimal solution. Its proper formulation is therefore crucial for the optimization process and often an art in itself. It has not only to consider the posed constraints but also the optimization criteria. Here, the total time of flight is subject to minimization which makes it the one and only criterion to optimize after fulfilling the constraints. Constraints are the allowed maximum distance to the target orbit ΔR and a maximum allowed relative velocity ΔV. Together with the maximum integration time ΔT, the fitness function value *f* is calculated as follows:

$$f = \begin{cases} 1 - \dfrac{\Delta t}{\Delta T} & \text{if } \Delta r \le \Delta R \wedge \Delta v \le \Delta V \\ -\sqrt{\left(\dfrac{\Delta R - \Delta r}{\Delta R}\right)^2 + \left(\dfrac{\Delta V - \Delta v}{\Delta V}\right)^2} & \text{if } \Delta r > \Delta R \vee \Delta v > \Delta V \end{cases} \quad (8)$$

Equation (8) assures that every solution satisfying the constraints (positive values of *f*) and having a shorter flight time Δt than a competing solution receives a higher fitness value. As long as the required conditions are not matched it also assures that solutions being closer to the target orbit receive higher, but still negative, fitness values than solutions with higher deviations. Fitness function values are calculated at the end of every solution evaluation, i.e. after trajectory integration. As can be seen in (8), the flight time Δt, the lowest distance to the target orbit around the Moon Δr, and the lowest relative velocity Δv, is needed for the calculation of *f*. As long as the Moon's SOI is not reached Δr

and Δv are almost equal to the distance and velocity relative to the Moon and that's why they are used up to this point. As optimization continues and yields better solutions, a few of them result in trajectories entering the Moon's SOI. In this case Δr and Δv are set with the spacecraft's distance and relative velocity w.r.t. a *virtual orbit* around the Moon. As the orbit is not completely specified (only a, e and i), the missing orbital elements are taken from the spacecraft's current Moon-centered orbit elements.

III. CALCULATIONS AND RESULTS

A. Spacecraft configuration and simulation setup

To validate the described method, two low-thrust transfers from an Earth-bound orbit into a Selenocentric orbit are calculated. TABLE 1 contains the spacecraft data and TABLE 2 the specification of the respective orbits.

TABLE 1
SPACECRAFT DATA

Dry Mass [kg]	283
Fuel Mass (Xenon) [kg]	84
Total Mass [kg]	367
Specific Impulse Isp [s]	3,714
Maximum Thrust [mN]	135

A Runge-Kutta 8(7) DP (Dormand & Prince) integrator is used for integration of the equations of motion (4)-(6) in ECI frame coordinates with maximum allowed relative and absolute accuracy limits of 10^{-6}. The DE405 ephemerides catalogue of JPL is used for position and velocity of the Earth and the Moon.

TABLE 2
INITIAL AND TARGET ORBIT SPECIFICATION

Orbit Element	Orbits		
	Launch	A	B
Central Body	Earth	Moon	Moon
Semi-major Axis [km]	24,505	20,000	7,238
Eccentricity	0.725	0	0.62
Inclination [deg]	0	40	90
Node [deg]	0	n/d	n/d
Argument of Pericenter [deg]	0	n/d	n/d
Mean Anomaly [deg]	0	n/d	n/d

In order to reduce numerical problems it might be advantageous to conduct the computation of the Selenocentric trajectory leg in Moon-centered coordinates instead of Earth-centered ones. As the automatic determination of an optimum switch point is not straightforward and the focus of this work lies in developing a robust method for finding near-global optimal solutions the authors decided against it. Furthermore, with long double precision, the floating point accuracy of current computers is sufficient for the purpose of this work.

The circular target orbit A with a semi-major axis of about a third of the Moon's SOI radius is chosen to demonstrate an assured lunar capture. Furthermore, it is an appropriate initial point for subsequent orbit lowering maneuvers to conduct science and reconnaissance operations. The allowed final deviations in position and velocity are set to 670 km and 33 m/s. That means, the distant constraint is matched if the spacecraft's closest distance to the target orbit is ≤ 670 km. Consequently, the velocity constraint is matched if the spacecraft's velocity relative to a virtual point on the target orbit at that closest distance is ≤ 33 m/s.

In validation case B the spacecraft starts from a GTO-like orbit and ends in a highly-elliptic Selenocentric polar orbit with a semi-major axis of 7,238 km. The allowed final distance and relative velocity w.r.t. the virtual target orbit are set to 500 km and 25 m/s, as can be seen in TABLE 3.

Clearly, in both cases these deviations are not sufficient for detailed mission analysis. The reason for this is the bad local search behavior of the EA-based method of ENC. Unlike local optimization methods, often starting from a given initial trajectory that matches the target orbit exactly, ENC first needs to find valid solutions before it can optimize with regard to the respective criterion. Solutions are valid if they satisfy the user-provided accuracy limits. Valid solutions, and the hopefully also valid offspring solutions created by the EA from their genome code, are then evaluated w.r.t. the respective optimization criterion. So, if too challenging accuracy requirements are chosen at the beginning of optimization, ENC tends to "stick" to the first valid solution found. The unintended consequence would be a significant degradation of the EA's global search behavior.

B. Results

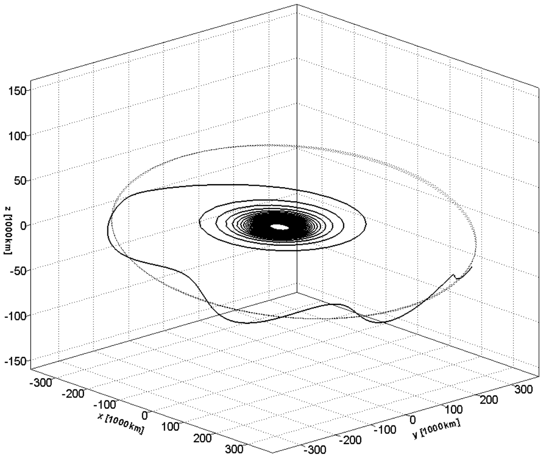
Transfer A into a circular orbit, as seen in ECI frame, is visualized in Fig 2.

TABLE 3
RESULTS

	Transfer to Orbit	
	A	B
Flight Time [d]	119.8	193.4
Propellant Mass [kg]	34.5	56.0
Distance [km]	670	500
Rel. Velocity [m/s]	33	25
Computation Time [h]	31.4	35.7

The transfer takes about 120 days and needs 35 kg of propellant. As expected, most of the transfer time is spend with spiraling out from the GTO-type orbit to the Moon's SOI. The subsequent phase from the SOI boundary into the final orbit around the Moon takes only a few days. Of course, attaining lower target orbits requires additional revolutions around the Moon and thus longer transfer durations.

Transfer B, shown in Fig. 3, lasts 193 days with a propellant mass consumption of 56 kg. The spacecraft now spends more time in the lunar system to reach the desired target orbit, as is expected because of the lower target orbit altitude.



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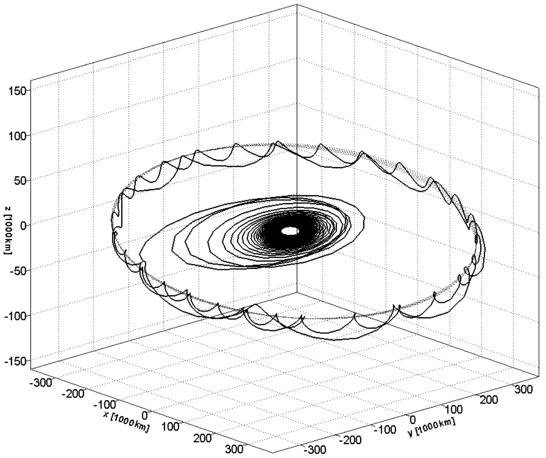

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