Optimization of particle trajectories inside an ion-thruster

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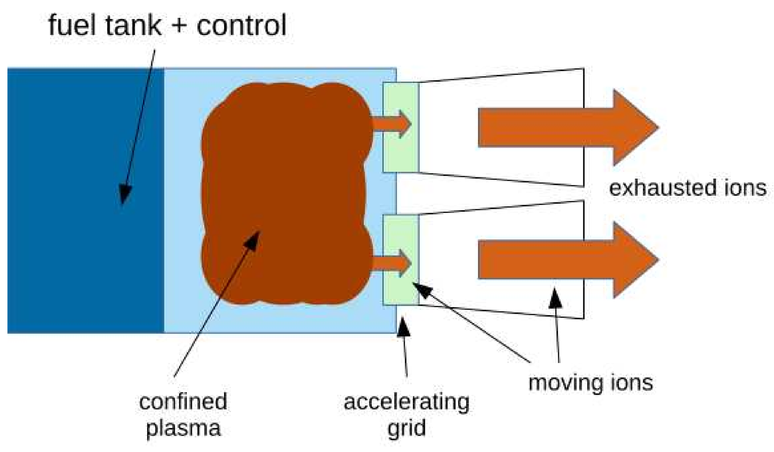
Abstract

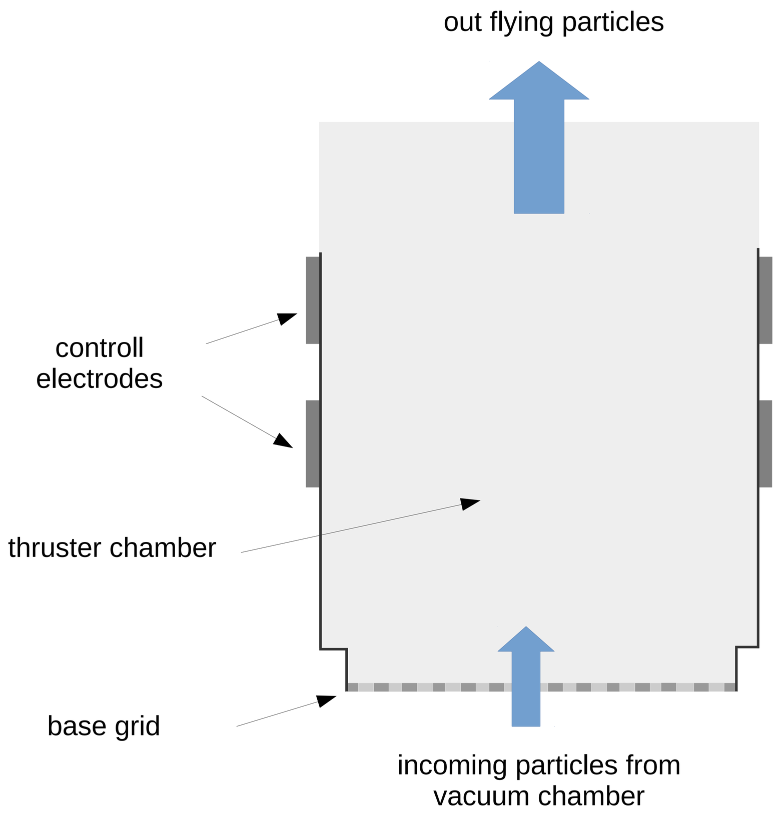
We present optimization of trajectories of particles that fly from vacuum chamber to the outer world. Expected trajectories are defined by control point regions that must be entered. We present a simple quasi electrostatic model for the system of electrodes. Potentials are calculated using a supervised machine learning (SML) algorithm.

Motivation

- small satellites can be steered using ion thruster (shown on upper figure)
- confined plasma creates positively charged ions, these are accelerated by an accelerating grid
- on the other side of accelerating grid is nozzle that directs ions, metallic parts of the nozzle are used as guiding electrodes
- trajectory of ion beams guided by electrostatical forces caused by potential differences of the guiding electrodes and accelerator grid
- geometry of nozzles (and electrodes) are fixed parameteres, controlling potential of guiding (control) electrodes means controlling of trajectories



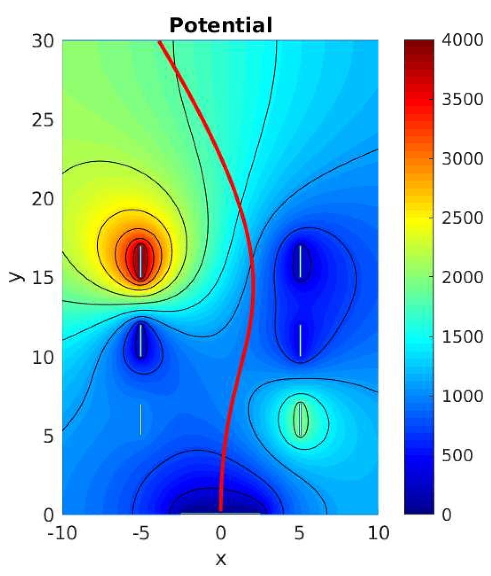
schematic of an ion thruster chamber



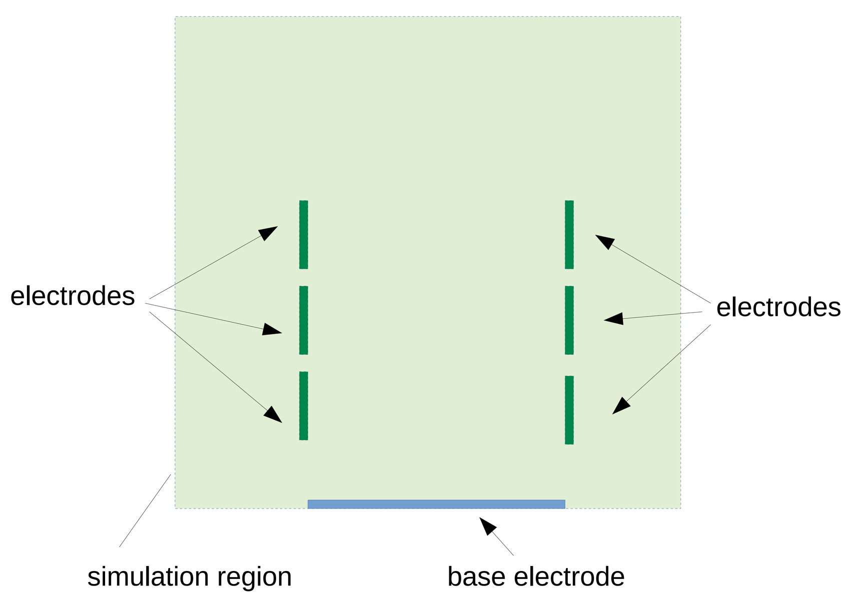
model of the thruster nozzle

Electromagnetic model of the nozzles

- no change or slow change in potentials
- magnetic field effects are neglected
- electrostatic problem
- geometry does not change



potential (colored contour) and a trajectory of an ion (red line)



- electrodes :

$$\varphi_i = U_i$$

- base electrode : $\varphi = 0$
- inside simulation area :

$$\nabla \varepsilon_0 \nabla \varphi = 0$$

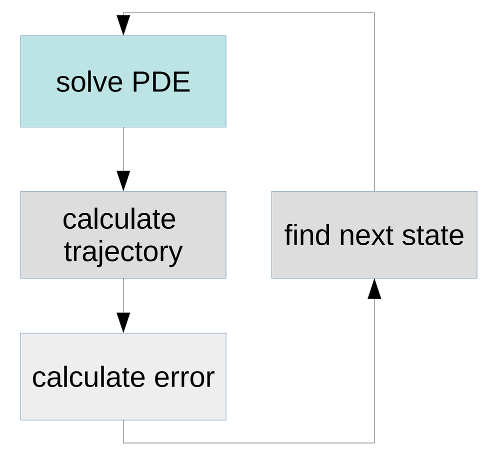
- border of simulation area :

$$\frac{\partial \varphi}{\partial n} = 0$$

- Trajectory is calculated using electric field $\mathbf{E} = -\nabla \varphi$ and solving

$$m \cdot \frac{\mathrm{d}^2 \mathbf{r}}{\mathrm{d}t^2} = \mathbf{E}$$

Optimization



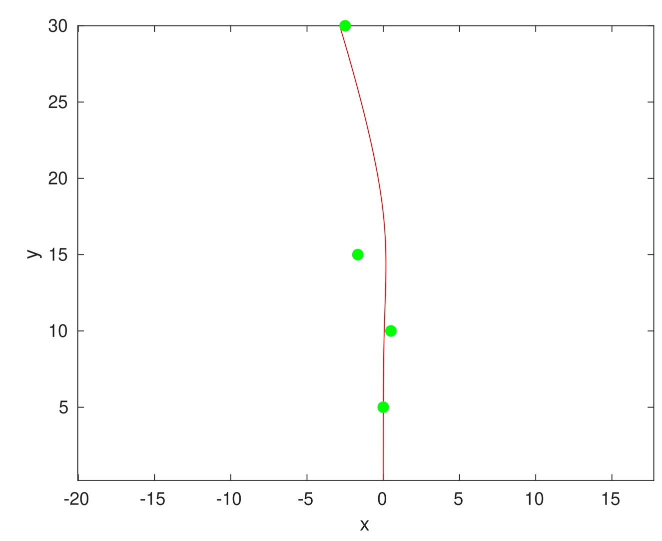
- Supervised Machine Learning - potentials are changed to best fit a trajectory to prescribed one
- target of optimization is defined (e.g. we want to get set of electrode-potentials for a given set of control-points)
- error is minimized using Least-Mean-Square error-function on horizontal distance of trajectory and control points
- update of next state-vector :

$$\mathbf{W}_{\mathbf{next}} = \mathbf{W}_{\mathbf{prev}} + 2 \cdot \mu \cdot \text{error} \cdot p$$

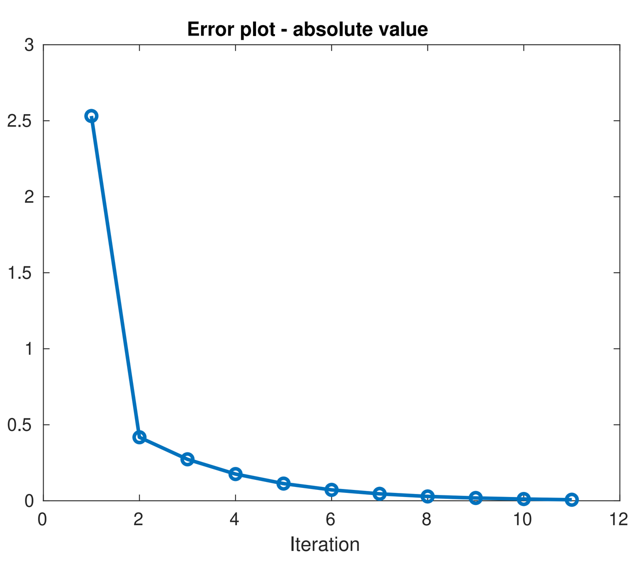
where $\mathbf{W}$ is parameter-vector, μ learning-factor, error is sum of errors at all control points, p is scaling factor

- iteration stops if error is less than a prescribed limit

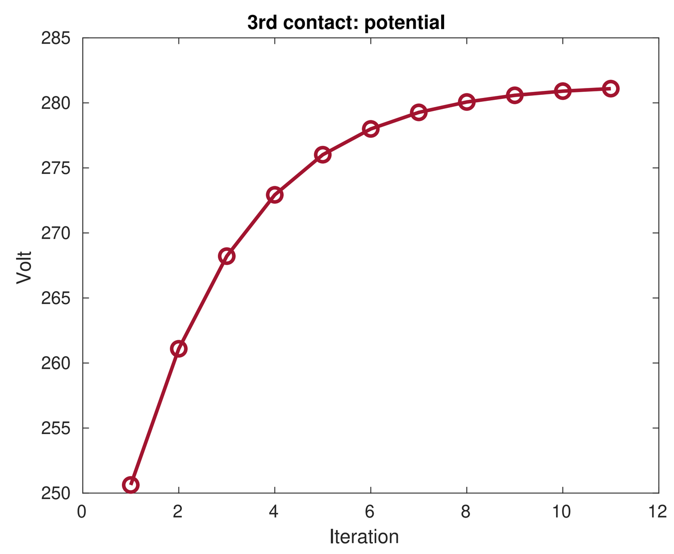
Results of an optimization



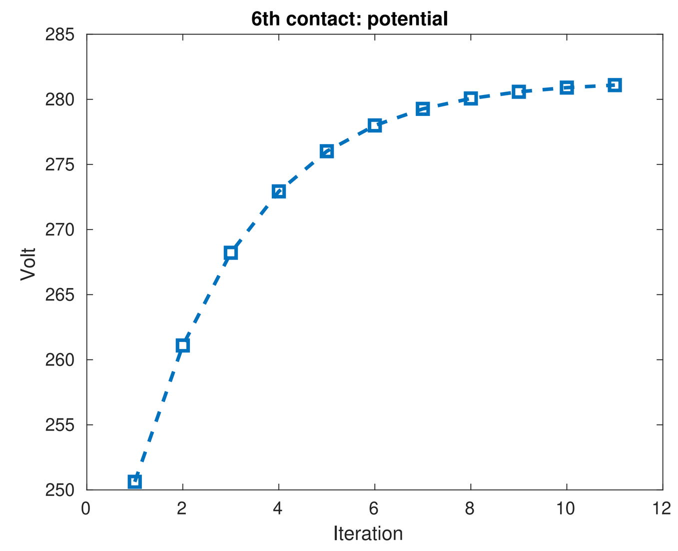
calculated (optimized) trajectory (red line) and control points (green points)



error as a function of iteration number



potential of 3rd contact as a function of iteration



potential of the 6^{th} contact

Conclusions

- trajectory of ions can be predesign to save fuel in space
- Supervised Machine Learning needs supervision of human
- LMS finds local minima and can't get out of it
- method is sensible to start position
- there is a lot of space for intuitional parameter tuning in this type of optimization

Bibliography

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