

Linear Flux-Switching Machine Design - A Multiobjective Optimization

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Abstract

In this paper, a linear electric machine is designed for the application of a free-piston engine to generate electrical energy. Due to the high thermal load on the mover, only machine topologies with a passive mover are considered. It is shown that flux-switching machines (FSM) are capable of fulfilling the requirements.

A preceding thermal analysis provides the temperature distribution within the machine. The selection of the magnetic materials is determined based on the results. Subsequently an electromagnetic model for a 12 slot/14 pole FSM is created and optimized. Due to the application, the use of three design targets is appropriate: The efficiency η , the mass of the mover m_M and the permanent magnet (PM) mass m_{PM} . To take all the objectives into account, a multicriterial optimization using the NSGA-II algorithm is performed.

I Introduction

Free-piston engines with a linear generator, as shown in fig. 1, are used to generate electric energy out of combustion. They consist of a combustion chamber (1), a linear generator (2) and a rebound device (3), all linked by a piston (4). The piston is moved periodically back and forth by the force of the combustion and the rebound device. The electric generator converts the mechanical energy into electrical energy. Free-piston engines can be used as a range extender for electric vehicles [1] or as combined heat and power plants for decentralized energy supply [2].

Due to the linear movement, a crankshaft is not needed. This has the advantage of a variable compression and thus a variable fuel like petrol, methane or hydrogen. Another benefit is the lower number of mechanical components, which decrease the mechanical losses.

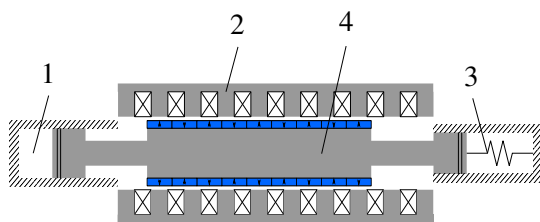


Fig. 1: Free-piston engine components:
1 - combustion chamber, 2 - linear electric generator,
3 - rebound device, 4 - moving piston

A major challenge in operating these engines is the thermal load due to the combustion process. Because of the low thermal resistance between the combustion chamber and the mover of the electrical machine the cooling requirements for the electric machine and in particular its mover are high.

The maximum temperatures are determined by the permissible temperature rise in the winding

and the permanent magnets. In addition, due to the higher temperature of the mover, PM with expensive and environmentally harmful additives, such as dysprosium, have to be used. Electric machines with passive movers on the other hand either have no PM or the magnets are located in the stator, which is thermally better connected to the cooling medium. The passive structure of the mover consequently increases its maximum permissible temperature.

Possible linear machine topologies with a passive mover structure that could be used for the free-piston machine are those without any magnets, such as switched or synchronous reluctance machines [3] and topologies with PM placed in the stator, like doubly-salient, flux-reversal or flux-switching machines [4, 5]. A literature study and an initial design study using finite-element analysis (FEA) show that a tubular flux-switching linear machine (FSM) with 12 stator teeth and 14 mover teeth (12/14-FSM) is the most suitable for the application, as it fulfills all force requirements with the lightest mover.

Mechanical requirements

Piston dynamic simulation dictates the mechanical requirements that the linear generator has to meet. A maximum stroke of $s_{\max} = 80$ mm is specified by the piston. Thereby, the generator must apply an effective value of the braking force of $F_{\text{rms}} = 1.2$ kN and a maximum braking force of $F_{\max} = 2$ kN, as shown in Tab. I. The machine is designed for the rms value of the force. The maximum value is obtained by a higher current density for a short time.

Table I: Requirements from piston dynamic simulation

Parameter	Value
Maximum stroke s_{\max}	80 mm
Force (rms) of electric generator F_{rms}	1.2 kN
Force (max) of electric generator F_{\max}	2 kN
Airgap width δ_g	1 mm

II Investigation of thermal effects

A thermal analysis is carried out for the 12/14-FSM by means of a 2d-FEA. For this purpose, a cooling concept is first developed and then the thermal parameters required for the simulation are determined. The thermal simulation is performed before the optimization to estimate whether the electric machine is sufficiently cooled and also to choose a material for the permanent magnets. Although the subsequent optimization changes the boundary conditions, it is expected to improve the efficiency and thus reduce the power dissipation and the temperature rise.

Water cooling with axial channels is chosen as the cooling concept. For the given geometry, laminar flow results in a heat transfer coefficient from the stator to the coolant of $h = 440 \text{ W m}^{-2} \text{ K}^{-1}$. The coolant inlet temperature is 60°C .

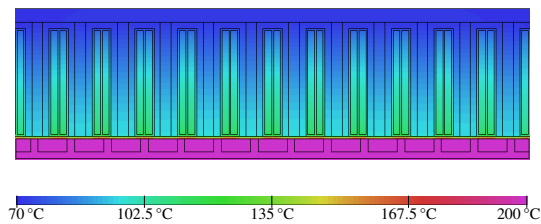


Fig. 2: Results of the thermal simulation

The temperature distribution of the electric machine is shown in fig. 2. The maximum temperature can be found in the mover as a heat input from the combustion process results in an assumed boundary condition of 200°C in the mover. The temperature of the stator decreases continuously in the radial direction. Here, the stator iron and the permanent magnets have approximately the same temperature axially. The slot shows a slightly higher temperature due to the ohmic losses.

The maximum temperature of the permanent magnets is 97°C . This relatively low temperature means that magnet materials can be used that have a minimum proportion of dysprosium and thus have a higher remanence flux density. VACODYM 247 [6] with coercive field strength of 730 kA m^{-1} at 100°C is

chosen as PM material. This material is free of dysprosium according to the datasheet. Due to the cylindrical geometry, a 3d magnetic flux is present. Therefore the Somaloy 700 3P 800 MPa from the Höganäs [7] is selected as soft magnetic material to reduce the eddy-current losses.

In summary, the thermal analysis shows that the cooling concept with a water cooling for the free-piston engine is sufficient. The low temperatures of the permanent magnets mean that the use of dysprosium can be avoided. It is expected that machines with modified geometry will be sufficiently cooled too, since there is a high difference between prevailing temperatures and permissible temperatures.

III Electromagnetic optimization of the FSM

The optimal design of an electric machine usually represents a compromise between multiple contradicting objectives. For the application illustrated in this paper, a high efficiency is crucial. Furthermore, the reciprocating mover mass must be kept as low as possible, since the power is inversely proportional to the square root of the moving mass. Moreover the mass of the permanent magnets should be considered, since it accounts for the majority of the material costs.

This chapter explains the applied optimization algorithm. Afterwards the design space of the optimization and the consideration of the iron saturation are discussed. Finally the results are presented.

Multiobjective optimization

The nature of multiobjective optimization is that there are several independent design targets. In most of the cases, there is no solution where all objective variables are at the optimum at the same time. In many applications, they even contradict each other [8].

A possible approach to this problem is defining the individual variables as partial objectives and converting them into a common objective function by means of weighting factors. The multicriterial optimization is then reduced to a single overall criterion [9]. However, a decisive disadvantage of this method is the necessary definition of the optimization premises prior to the optimization. The design space is only analyzed according to these assumptions. The position of the found solution relative to the unknown pareto front cannot be determined. Thus, no conclusion about the goodness of the found solution according to the pareto optimality is possible.

NSGA-II

A method more suitable is a multicriterial optimization, where different objective functions are minimized simultaneously. In the case with contradicting objectives, there is no unique optimal solution, but rather the goal is to identify the set of pareto optimal solutions.

A common optimization algorithm is the *Non-dominated Sorting Genetic Algorithm*, NSGA-II, which was described by *Deb et al.* in 2002 [10]. It is a variation of the Genetic Algorithm for multicriterial optimization in which individual designs are ranked using a non-dominated sorting process. The NSGA-II quickly became popular for multiobjective optimization problems as this algorithm is less subject to errors, fast and robust, and therefore superior to other optimization methods.

It has also frequently been used for optimizing electric machines, like a switched reluctance machine [11], a permanent magnet synchronous machine [13], induction machines [12], or a flux-switching machine [14].

The process of the algorithm is illustrated in fig. 3. After defining the number of decision variables x , the number of objective functions $f(x)$, the maximum number of generations i_{\max} and the population size n_{pop} , a random population of chromosomes (i.e. individual machine designs) is initialized. This population is evaluated by magnetostatic FEA simulation. All individuals are then sorted according to the non-dominated sorting principle, checking which one is superior to another with respect to the target variables (forming the pareto front). Chromosomes with the same rank are furthermore sorted by crowding distance. This ensures diversity among the individuals.

In order to produce a new generation that differs from the starting population, a parent population is defined. The choice of the parent generation is based on binary tournament selection: Two random pairs

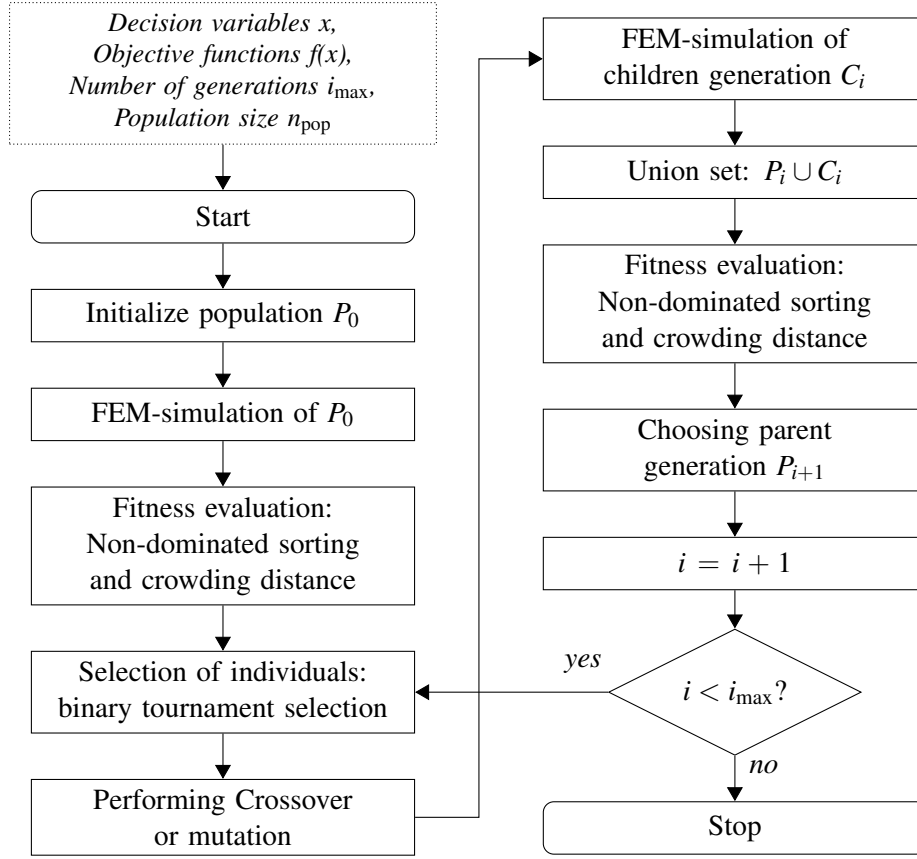


Fig. 3: NSGA-II optimization procedure

of individuals are compared and the superior ones (lower rank or higher crowding distance) are selected as parents. The following generation of individuals is generated by crossover (with a probability of 80 %) or by mutation of a certain gene (with a probability of 20 %).

After a subsequent FEM-simulation of this children generation, the parent and children generation are merged and the previously described sorting process is performed again. The n_{pop} fittest individuals are then selected as the parent generation for the next iteration.

Design space for the optimization

The parametrization of the FSM and the chosen design space is explained. Fig. 4 presents all the relevant geometric parameters for designing the electric machine.

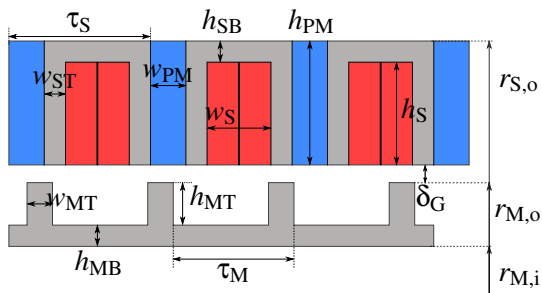


Fig. 4: Geometry parameters of the FSM

For the optimization of the FSM eight input parameters are considered. These are stator outer radius ($r_{S,o}$), the mover length, the mover outer radius ($r_{M,o}$), width of stator slots and teeth (w_S , w_{ST}), width and height of the mover teeth (w_{MT} , h_{MT}), inner radius of the mover ($r_{M,i}$) and thus the height of the mover back iron ($h_{M,b}$).

For the genetic optimization it is recommended to use relative parameters to describe the geometry. One advantage over absolute parameters is that unfeasible designs

like a negative width of the permanent magnets are avoided. Another benefit is that the combination of two machines in the process of genetic evolution is always a feasible solution. This is not guaranteed with absolute parameters. Therefore the following relative parameters are defined in Tab. II.

Table II: Relative design parameters

Parameter	Range	Parameter	Range
$k_1 = \frac{r_{S,o}}{r_{S,o,max}}$	$\in [0.3, 1.0]$	$k_5 = \frac{w_{ST}}{\tau_S - w_S}$	$\in [0.2, 0.4]$
$k_2 = \frac{r_{S,o}}{l_M}$	$\in [0.2, 0.5]$	$k_6 = \frac{w_{MT}}{\tau_M}$	$\in [0.1, 0.6]$
$k_3 = \frac{r_{M,o}}{r_{S,o}}$	$\in [0.3, 0.8]$	$k_7 = \frac{r_{M,i}}{r_{M,o}}$	$\in [0.4, 0.9]$
$k_4 = \frac{w_S}{\tau_S}$	$\in [0.2, 0.6]$	$k_8 = \frac{h_{MT}}{r_{M,o} - r_{M,i}}$	$\in [0.2, 0.8]$

The maximum radius of the stator is set to $r_{S,o,max} = 140$ mm by a preceding parameter study. In the same way the boundaries for the coefficients k_x are chosen. The correct choice of the boundaries is necessary for proper results. Too big intervals lead to a poorly filled design space and too small intervals result in suboptimal designs. The distribution of the final design parameters of all optimal machines shows that no boundary condition is set too narrow, as there is no accumulation near the boundaries.

The three objectives are the negative efficiency $f(1) = -\eta$, the mass of the mover $f(2) = m_M$ and the mass of the permanent magnets $f(3) = m_{PM}$. The used algorithm leads to a minimization of each objective. For maximization of the efficiency, a negative sign is used.

Saturation of the iron

Each design is initially simulated with a current density of 6 A mm^{-2} and the generated force is evaluated. Due to the requirement of a low mover mass, there can be designs with highly saturated iron in the mover. Therefore the dependency between current density and force is nonlinear. To calculate the correct current density the Newton-Raphson algorithm is used.

Based on the initial current density and a step width, the gradient of the force with the current density in this point is calculated. Then the new linear approximation for the current density is calculated. This process is repeated until the simulated force is equal to the required force.

This method considers the saturation of the iron precisely. However it increases the simulation time drastically. The average number of iterations per individual is 3. In each iteration the calculation of a gradient is done, which needs two simulations. Thus the total computation time increases by a factor of six.

Reference machine

The mechanical modeling is not part of this paper. Instead, the velocity distribution from [2] is assumed for a mover with a mass of $m_{M,ref} = 3$ kg. The mass consists of the mass of the mover of the electrical machine and a constant mass of 1.5 kg which considers the additional moving parts like the piston. Therefore a root mean square value of $v_{rms} = 4 \text{ m s}^{-1}$ is assumed. Together with the rms force the following mechanical power is calculated for the reference machine:

$$P_{mech,ref} = F_{rms} \cdot v_{rms,ref} = 4.8 \text{ kW} \quad (1)$$

It can be shown that for a constant force the mechanical power is reduced by the square root of the mover mass caused by the lower velocity. The dependency of the mechanical power of a design in relation to the power of the reference is:

$$P_{mech}(m_M) = P_{mech,ref} \cdot \sqrt{\frac{m_{M,ref}}{m_M}} \quad (2)$$

This equation is used for the calculation of the efficiency together with the ohmic losses. Iron losses are not calculated during the optimization, because this would need the calculation of the magnetic flux density for several time steps, which would increase the calculation time drastically.

One problem with a multiobjective optimization like NSGA-II is that even designs with low efficiency are possible optimal designs. Because the total number of designs is limited, a boundary for the lowest efficiency of $\eta_{min} = 60\%$ is used. Any individual with a lower value is ranked worse than one with a suitable value. In this way the result is a more dense filled parameter space. [10]

Optimization results

For the multiobjective optimization 50 generations with 1500 individuals each with a total number of designs of 75000 are calculated. Out of these designs, there are some points in which the improvement of one objective requires the decrease of another objective. All these points are optimal designs and form the pareto front which is shown in figure 5. The pareto front is a surface in the three-dimensional space due to the three objectives. Additionally the two-dimensional pareto fronts of two objectives each are shown. In the figures only the relevant designs are depicted. The one with a higher mass of the mover or the permanent magnets are neglected.

In the two-dimensional plots there are points which have a higher value of both objectives. For these points the third objective has to be taken into account which decreases. Therefore these are the optimal designs.

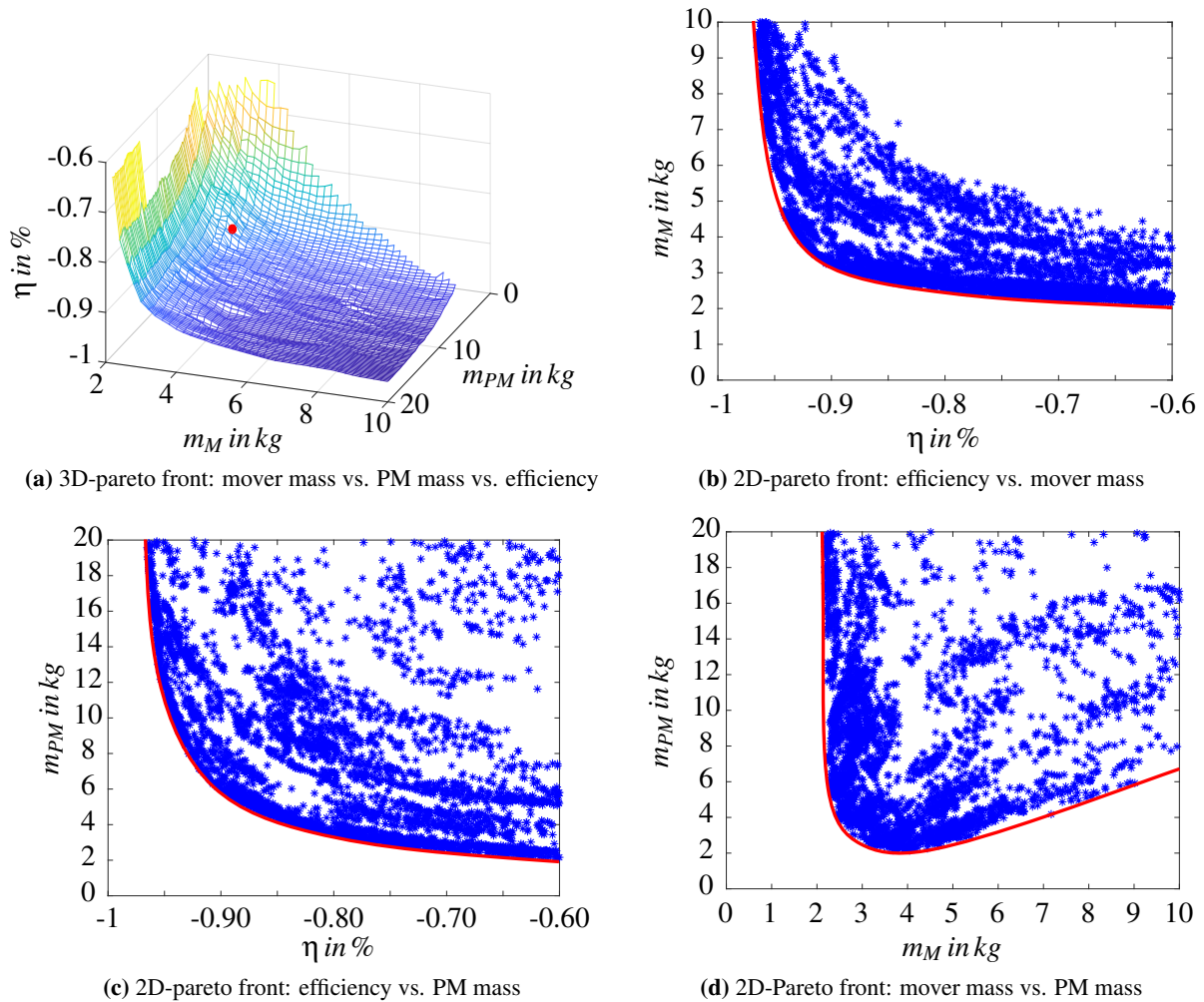


Fig. 5: Pareto front of the FSM

The next step is to choose one of the optimal designs which is suitable for this specific application. One approach is to specify a normal vector which determines exactly one point on the Pareto front. In this case the point on the surface with the highest curvature in figure 5a is chosen. This point is marked red. Other points on the surface are also suitable. But for example for points with a high mass of the permanent magnets like 15 kg a rise in mass of the permanent magnets leads to a small change in efficiency. It would be an unbalanced optimum.

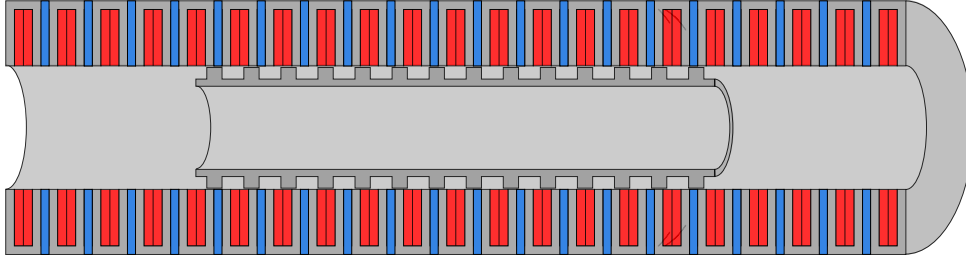


Fig. 6: Final flux-switching machine design

The chosen design has a mass of the mover of 3.77 kg, a mass of the permanent magnets of 7.33 kg and an efficiency of 85.88 %. The final machine design is shown in Fig. 6, table III presents the geometric parameters.

Due to the mover length of 280 mm, the stator length of 486 mm and the maximum stroke of 80 mm, it is possible to reduce the number of stator teeth to 16. This increases the efficiency to 89.63 % and reduce the mass of the permanent magnets to 5.5 kg. Thereby all three objectives are sufficient for the application in a free-piston machine.

The maximum braking force of 2 kN is obtained with a current density of 9.67 A mm^{-2} . This shows the non-linearity between current and force as the required current density is about 7 % higher than expected from a linear correlation.

Concerning demagnetization in the final design, it can be observed that even at maximum current, the field strength in the magnets does not exceed the coercivity H_C of 730 kA m^{-1} .

It can be seen that the three dimensional pareto front is convex. This is especially useful for the optimization. Deterministic algorithms converge without the trouble of being trapped into local optima. In this case the fully deterministic Hooke-Jeeves-algorithm is also used to find an optimum. The found optimum is a part of the pareto front. A drawback of the Hooke-Jeeves-algorithm is the strong dependency on the chosen parameter for the one dimensional objective function.

Table III: Final design parameters

Parameter	Value	Parameter	Value
Number of stator teeth (total) $N_{S,\text{total}}$	21	k_1	0.49
Number of stator teeth (active) N_S	12	k_2	0.25
Number of mover teeth N_M	14	k_3	0.47
Copper fill factor k_{Cu}	0.5	k_4	0.42
Air gap width δ_g	1 mm	k_5	0.34
Radius of the stator $r_{S,o}$	69 mm	k_6	0.41
Radius of the mover $r_{M,o}$	333 mm	k_7	0.69
Length of the mover l_M	280 mm	k_8	0.62

Calculation time

About 15 generations are needed until an approximation of the pareto front is recognizable. Nevertheless up to the 50th generation there are improvements in the pareto front. The front is more densely populated and there are some better designs due to crossover and mutation.

For the optimization 50 generations are calculated in total. The optimization is done in parallel, using 2d finite element simulation with the open-source software FEMM. Each model is composed of approximately 60000 mesh elements. Using 24 parallel calculations, one generation needs a computation time of about 2 h. So the total time is about 100 h. The processor used for the optimization is an Intel Xeon Platinum 8268 with 24 cores and a base clock speed of 2.90 GHz.

IV Conclusion

This paper deals with the design of a linear generator for use in a free-piston machine. It must meet the requirements in terms of braking force and have the highest possible force density and efficiency. Due to the thermal load on the mover, only machines with a passive mover were considered. The Flux-Switching Machine turned out to be most appropriate and was then further investigated. A cooling concept was analyzed to assess the thermal situation.

Afterwards the electromagnetic design was optimized via the optimization algorithm NSGA-II. The chosen design space and the consideration of the iron saturation were discussed. The result is a three-dimensional pareto front. The chosen design is a compromise with respect to the three objectives, which are the mover mass, the mass of the permanent magnets and the efficiency. Furthermore the machine meets the force requirements.

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