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Optimization Method for Drive Train Topology Design and Control of Electric Vehicles

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Abstract

The present paper deals with an optimization problem of pure electric vehicles' power trains. The energy consumption is strongly influenced by the size of the components of the vehicle and is highly dependent on the chosen topology. Therefore a method defining possible topologies of the drive train in advance of the optimization is presented in this paper. The chosen reasonable topologies are optimized with respect to the energy efficiency and the additional needed copper for the electrical machines and lithium for the energy storages using a Genetic Algorithm. The method, the chosen optimization algorithm and the results are presented and discussed within this paper.

Keywords: multi-objective optimization, topology, drive train, electric vehicle

1 Introduction

Vehicle software components are most likely to be optimized since changing them is cheap. Therefore the most often component optimized in case of hybrid electric vehicles is the control strategy [1-3]. But also the size of the drive train's components and the topology strongly influence the energy consumption of the vehicle [4]. Due to the reduced space requirement of electrical machines compared to internal combustion engines further degrees of freedom exist while designing electric vehicles, since new drive train topologies are possible. The possibility of hybrid energy storage systems meaning, e.g. the usage of a Lithium battery and a double layer capacitor in one car, leads to additional degrees of freedom. Therefore a method of defining all, under the given demands possible, drive train configurations and selecting only the reasonable ones is presented. Afterwards these chosen topologies are optimized with respect to energy consumption, additional needed copper for the electrical machine and lithium for the energy storage taking into account the components' size and, if necessary, the parameters of the control strategies in case of hybrid energy storages or multiple electrical machines. In the present paper the method of defining and selecting the drive train topologies is presented and discussed. Furthermore the algorithm used for the optimization of the drive train's dependent components will be explained and the different results of the optimized topologies will be scrutinized.

2 Simulation Model

The simulation model used within this paper is a pure energetic backward model of an electric drive train. Thereby, the control strategy in case of more than one machine or a hybrid energy storage is adaptable on the topology. The vehicle data are those of a small city car and are given in Table I. The electrical machine might be either an induction machine or a permanent magnetic synchronous machine.

Table I: Parameters of the city vehicle.

Parameter	Value
Weight of the car	500 kg
Front face	1.8 m^2
Drag coefficent (c_w)	0.28
Radius of tyres	0.3 m
Rolling resistence coefficent	0.008
Power demand of auxiliary users	500 W
Power of IM (unscaled)	17.3 kW
Power of PMSM (unscaled)	17.3 kW

Both machine models are scalable to a certain extend and were described in [6]. The power of the unscaled machines is 17.3 kW. The energy storage might be either a double layer capacitor or a LiIon battery. Both might be scaled by the variation of the number of serial and parallel cells. The variation of the weight resulting from the scaling and number of the components is considered during the simulation. The simulation model is modular and highly flexible so that diverse drive train topologies might be considered and optimized.

In case of electrical vehicles the drive train might be either centre, wheel selective, front rear independent or a tandem drive. The energy storage might be either hybrid or not hybrid. Depending on the available components there are further topologies thinkable as e.g. a mixture of front rear independent and tandem drive. Beyond that, all topologies might be combined using diverse energy storage combinations. Figure 1 illustrates some of those thinkable drive train configurations. The main question within this paper is: How could an optimization routine be used to optimize not only a given topology but to expand it by a method defining all possible topologies and excluding senseless topologies before the optimization of the remaining topologies starts? Using this method the user has only to define the case of application and the maximum number of available components and will receive an optimal drive train design. In order to explain the idea of the preselection algorithm an illustrative example is given in the following section and the algorithm is explained.

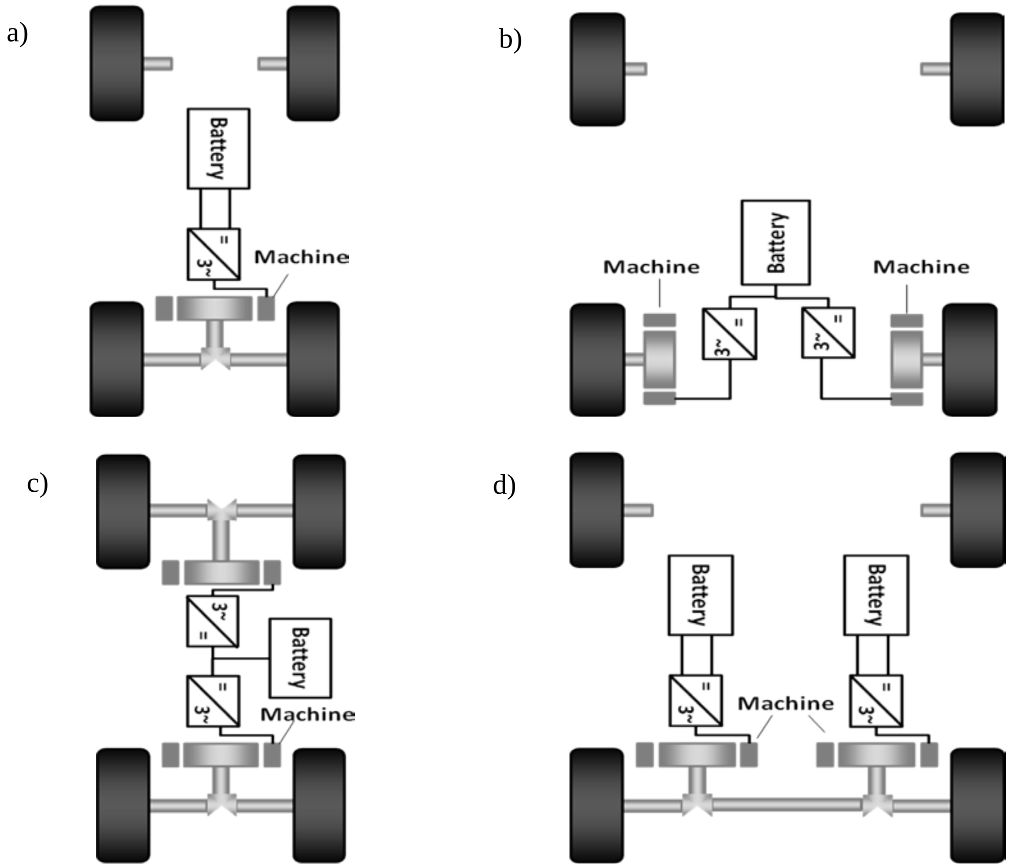

Figure 1: Possible drive train topologies for electrical vehicles. Center drive (a), wheel selective drive (b), front rear independent drive (c) and tandem drive (d) with respect to the components given in the example. The battery might be a hybrid energy storage, double layer capacitor or LiIon battery. The machine might be an induction machine or a permanent magnetic synchronous machine.

3 Preselection Algorithm

Assuming that a maximum number of possibly used components are given, e.g. one induction machine, one permanent magnetic synchronous machine, one double layer capacitor and one LiIon battery a certain number of topologies is conceivable. In case of this example and assuming a centre drive there are $2 \cdot 2$ possibilities for the energy storage system and 2 possibilities for the machine which means that we have $2 \cdot 2 \cdot 2 = 8$ possible configurations of the drive train. Further it can be decided whether it is a front, a rear or an all wheel drive which leads to $8 \cdot 3 = 24$ different versions for the configuration of a centre drive having only this small number of components. Additionally there are 18 variations for a tandem drive, 10 for a FRID and 20 variants of a wheel selective drive possible. The number of possible combination considering only pure centre, tandem, FRID and wheel selective drives might be calculated by equation 1-5, where n_{em} is the number of available electrical machines and n_{es} is the number of available electrical energy storages. Looking at this small example and the equations it becomes clear that a routine capable of higher numbers of components is needed.

The preselection algorithm starts by analysing the possible topologies with respect to asymmetries between the right and left side of one axis. Having for example a synchronous machine at the left back wheel of the car and an induction machine at the right back wheel of the car the disadvantages of both technologies come into effect at any moment of operation as e.g. the efficiency of the IM is higher in case of high speed while the efficiency of the PMSM is higher in case of a speed close to the nominal point.

Within this example the preselection algorithm would therefore exclude all wheel selective drives. Further the drive train model used within this paper is a backward and pure energetic simulation model not taking into account any dynamic behaviour of the vehicle and is therefore not able to display differences in front, rear or all wheel drives which reduces the number of analysed centre drive train variations to 8, the tandem drive variations to 6 and the number of FRID variants to 5. Thus the number of possible drive train topology variations is reduced from 72 to 19 by those two steps of the preselection algorithm. The rules of rejection might be divided into three types which are physical reasons, resulting from the objective functions or limitations of the simulation model. All rules of the preselection algorithm are explained in the following subsections.

3.1 Rejection due to Physical Reasons

The most relevant physical aspect of rejecting a drive train topology is the question, if an axis is symmetrically constructed. This means that in case of a wheel selective drive train the machine of the left rear or front wheel has to be on par with the right one. This includes type and size of the machine. Assuming an unsymmetrical axis where the machine type is the same but the machine on the right hand side has twice the power of the machine on the left side, despite in case of a left curve there will never be the possibility to use a higher power on the right then on the left side since this would always lead to a curve.

$$p_{cd} = 3 \cdot n_{em} \cdot \sum_{i=1}^{n_{es}} \frac{n_{es}!}{(n_{es}-i)!} \tag{1}$$

$$p_{td} = 3 \cdot (n_{em} - 1) \cdot n_{em} \cdot \sum_{i=1}^{n_{es}-1} \left(\sum_{i=1}^{n_{es1}} \frac{n_{es1}!}{(n_{es1}-i)!} \cdot \sum_{i=1}^{n_{es}-n_{es1}} \frac{(n_{es}-n_{es1})!}{(n_{es}-n_{es1}-i)!} \right) \tag{2}$$

$$p_{FRID} = (n_{em} - 1) \cdot n_{em} \cdot \sum_{i=1}^{n_{es}-1} \left(\sum_{i=1}^{n_{es1}} \frac{n_{es1}!}{(n_{es1}-i)!} \cdot \sum_{i=1}^{n_{es}-n_{es1}} \frac{(n_{es}-n_{es1})!}{(n_{es}-n_{es1}-i)!} \right) \tag{3}$$

$$p_{ws} = 2 \cdot \left(2 \cdot (n_{em} - 1) \cdot n_{em} \cdot \sum_{i=1}^{n_{es}-1} \left(\sum_{i=1}^{n_{es1}} \frac{n_{es1}!}{(n_{es1}-i)!} \cdot \sum_{i=1}^{n_{es}-n_{es1}} \frac{(n_{es}-n_{es1})!}{(n_{es}-n_{es1}-i)!} \right) + \frac{n_{em}!}{(n_{em}-4)!} \cdot \right.$$

$$\left. \sum_{i=1}^{n_{es}-1} \left(\sum_{i=1}^{n_{es1}} \frac{n_{es1}!}{(n_{es1}-i)!} \cdot \sum_{i=1}^{n_{es}-n_{es1}} \frac{(n_{es}-n_{es1})!}{(n_{es}-n_{es1}-i)!} \right) \right) \tag{4}$$

$$p_{topologies} = p_{cd} + p_{td} + p_{FRID} + p_{ws} \tag{5}$$

Since in case of a regular usage of the car there will always be as many left as right curves there is no advantage of a diverse power dimensioning. Assuming an asymmetric axis, where the machines' power is the same but the type of the machine is on the one side an induction machine and on the other side a permanent magnetic synchronous machine; the result is that in each driving situation the disadvantages of one machine type occur while the advantages of the other machine type might not become visible. In those cases it would be wise to use a tandem or FRID topology. The same goes for the energy storages.

3.2 Rejection due to the Objective Functions

In context with the physical reasons some of the topologies can be rejected when considering the objective functions. Assuming a vehicle configuration where the energy storage consists of a system illustrated in Figure 2; in this case the advantage of the energy storage system is a redundant energy storage system on the one hand and an independent placing of the energy storage on the other hand. Both advantages do not influence the objective functions of energy consumption and needed lithium and copper in a positive way. The energy consumption would be increased by the additional components. Therefore those cases are rejected within the preselection algorithm. Consequently the number of consider worth configuration can be further reduced since the considered number of energy storages n_{es} can be replaced by the number of divers energy storage technologies available, which is less or equal to the number of energy storages.

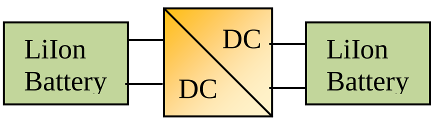

Figure 2: Redundant energy storage system consisting of two batteries of the same technology.

3.3 Rejection due to Limitations of the Model

The drive train simulation model used within this paper is a pure energetic modelling. Therefore all dynamic aspects as load distribution in case of acceleration and so on cannot be considered and are not of interest within here. Therefore the difference of front and rear drive cannot be analysed using those models. This leads to a huge reduction of the possible topologies. First thing is that it is not possible to differ between a FRID and a tandem topology since a FRID is nothing else than a tandem split up to the two axis. Therefore only tandem topologies are considered within here. Further the number of tandem drive configurations can be reduced to one third of the possible tandem configurations, the same goes for the centre drive.

The number of wheel selective configurations can be reduced to two third of the original possible number. Since the dynamic behaviour of the car is not described within the models the difference between machines positioned near to the wheel and wheel hub machines is not visible, which leads to a further reduction of the wheel selective topologies to one third of the original possibilities. Consequently the number of possible topologies can be reduced to the possibilities calculated by equation 1-5 after removing the red factors.

A further reduction of the configurations which have to be considered is not possible and therefore the optimization algorithm has to be drawn out on the remaining number of configurations. Figure 3 gives an overview over the whole optimization process. Starting with the initialization and the generation of all possible topologies the preselection algorithm, which had been described before, selects the sense full topologies and gives them to the optimization algorithm. When all relevant topologies are optimized the algorithm stops. To draw this out on a certain example, it is first of all necessary to introduce the optimization algorithm used within this paper.

4 Optimization Algorithm

Within multi-objective optimization genetic algorithms are often used. The main challenge of multi-objective optimization is that the results may not be sorted, since according to Pareto optimality two results might be equivalently good but different. In case of a Pareto optimal solution the improvement of one objective function leads automatically to the worsening of one or more other objective functions. The optimization algorithm used within this paper is a multi-objective Thermodynamic Genetic Algorithm and was described in detail and proven to be suitable to those problems in [4]. The main idea of the Genetic Algorithm is to mimic the biological evolution the thermodynamically part is introduced to prevent the premature convergence of the genetic algorithms and is used during the selection of individuals of the Genetic Algorithm.

This optimization algorithm is drawn out on the remaining reasonable topologies. Thereby the size of the machine and the energy storage might be influenced as well as the gear ratio and if necessary the parameters of the control strategies. The objective functions are the energy consumption and the additionally needed copper and lithium. The results of this optimization process are presented and discussed in the following section.

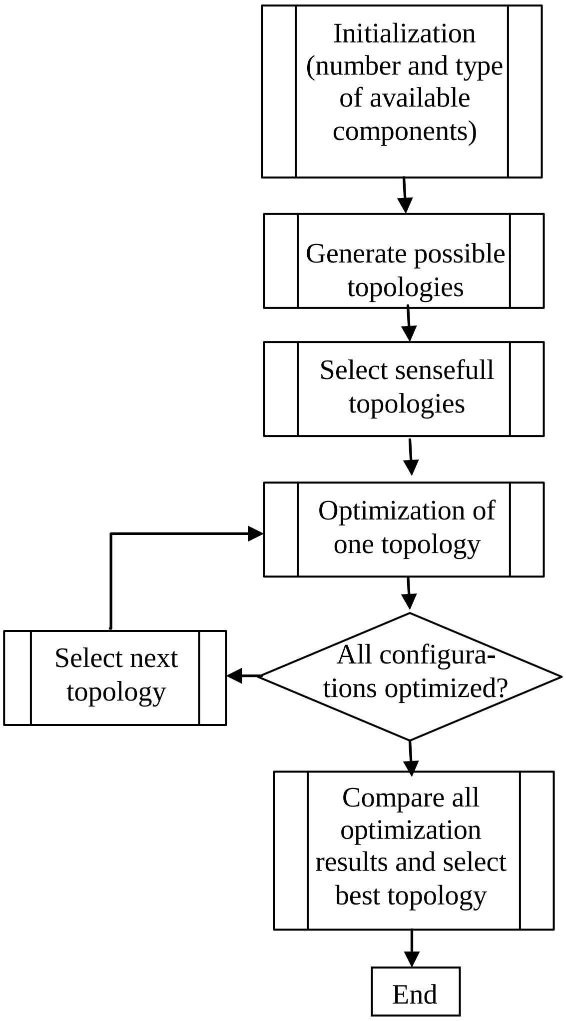

Figure 3: Simulation and Optimization process of the preselection algorithm.

5 Results

Within this section the preselection and optimization algorithm is drawn out on the example given in Table II. The drive train might consist of up to two induction machines and one permanent magnetic synchronous machine. The energy storage system might consist of up to two LiIon batteries. In this case hybrid energy storages are not considered.

Table II. Available Drive Train Components

Max. no.	Component
1	Permanent magnetic synchronous machine
2	Induction machine
0	Double layer Capacitor
2	LiIon Battery

5.1 Remaining Reasonable Topologies

In cases where the driving cycle is fixed to one without curves and the given objective functions wheel selective drives cannot be better than tandem drive or FRID therefore wheel selective drives are not considered in the following.

The remaining possible and reasonable topologies which have to be optimized are the following.

- Center Drive PMSM
- Center Drive IM
- Tandem Drive 2 IM
- Tandem Drive 1 IM and 1 PMSM
- Tandem Drive 2 IM and 1 PMSM

Since the redundant behaviour of the system is not part of the objective functions, the number of energy storages used can be reduced to one, as it had been explained in Section 3.2.

Consequently the number of topologies is reduced to 5 which will all be optimized in the following. The optimization is drawn out on the New European Driving Cycle. And the results will be discussed in the following.

5.2 Optimization Results of the Topologies

The optimization algorithm was drawn out on all five remaining topologies. The fifth topology consisting of 2 IMs and 1 PMSM was less good in all considered objective functions since the power demand of the car is too small to make three machines necessary and the size of the machines could not be further reduced since the scalability of the machine models is limited. Therefore the fifth topology is not considered in the following in order to increase transparency while discussing the results of the first four topologies.

Figure 4 shows the Pareto frontier with respect to energy consumption over the needed copper. Thereby the needed copper is expressed in form of an equivalence factor without unit. In case of topology 3 and 4 a clear Pareto Frontier can be recognized even though the third dimension is not displayed within this Figure. The energy consumption in case of topology 4 where one PMSM and IM is used is slightly lower than in case of topology 3 where two IMs are used for propulsion. This might be explained by the fact that the scaling of the machines and the power demand are limited in this special case. Therefore the diverse characteristic of the torque speed efficiency map of the IM and PMSM might be combined in an optimal way within here.

It can be further seen that in case of a centre drive (compare topology 1 and 2) no clear Pareto frontier becomes visible within those two dimensions. Further there is no advantage of either machine type recognizable. This leads to the suggestion that the optimization of a topology where two permanent magnetic synchronous machines are used, under the circumstance of the limited scalability of the machine models, would have similar results as topology 3.

In Figure 5 the Pareto frontier with respect to lithium needed over needed copper is illustrated. Thereby as before the needed copper is expressed in form of an equivalence factor without unit, the same goes for the needed lithium. Looking at these results the same suggestions as in case of Figure 4 might be drawn on the topologies 3 and 4. This is due to the fact that higher energy consumption leads in this case automatically to a higher number of cells needed for the Lithium battery, since there is no hybrid energy storage system which might compensate this effect.

While looking at topology 1 and 2 the lesser energy consumption does not automatically lead to a smaller value of needed lithium. This might be due to the fact that a certain voltage of the energy storage is needed, to guarantee minimal energy consumption.

While looking at the Pareto optimal sets which belong to the Pareto frontiers shown here it is conspicuous that except due to physical limitations as a minimal machine size or minimal energy storage to fulfil the power and energy demand no regularity in the values might be found. This emphasizes the theory that an optimized reconciliation of the components is absolutely necessary.

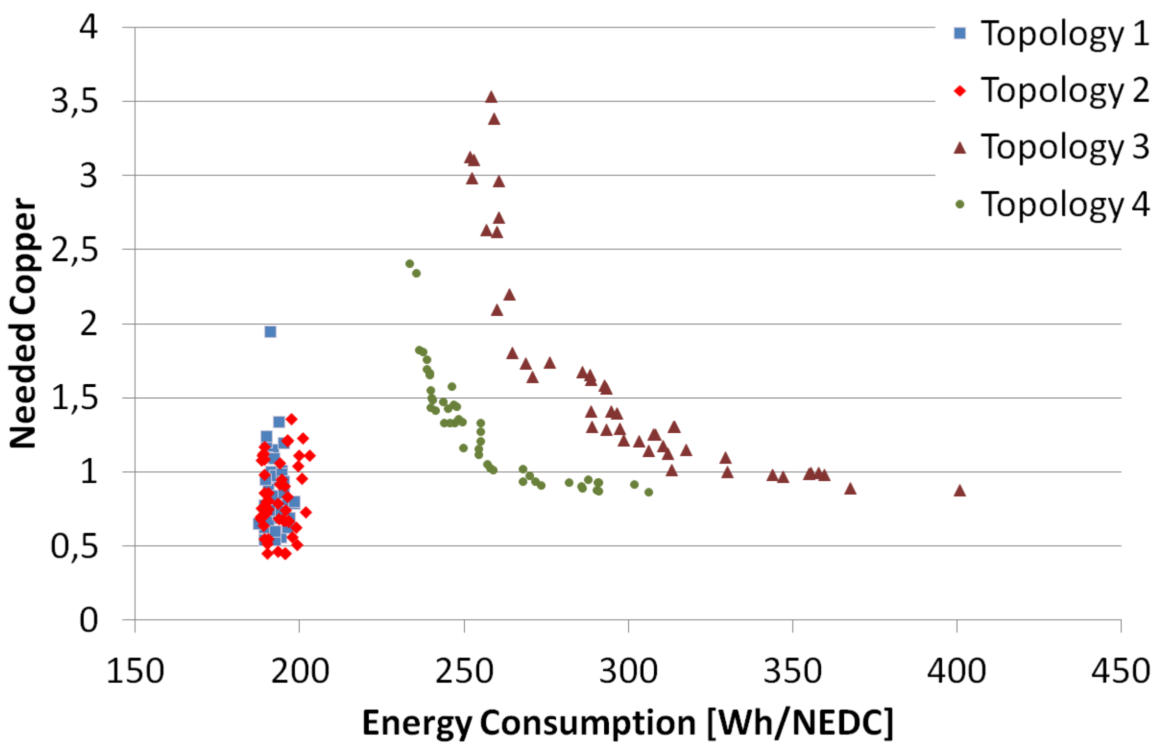

Figure 4: Pareto Frontier in the perspective of needed copper and energy consumption of the 4 topologies.

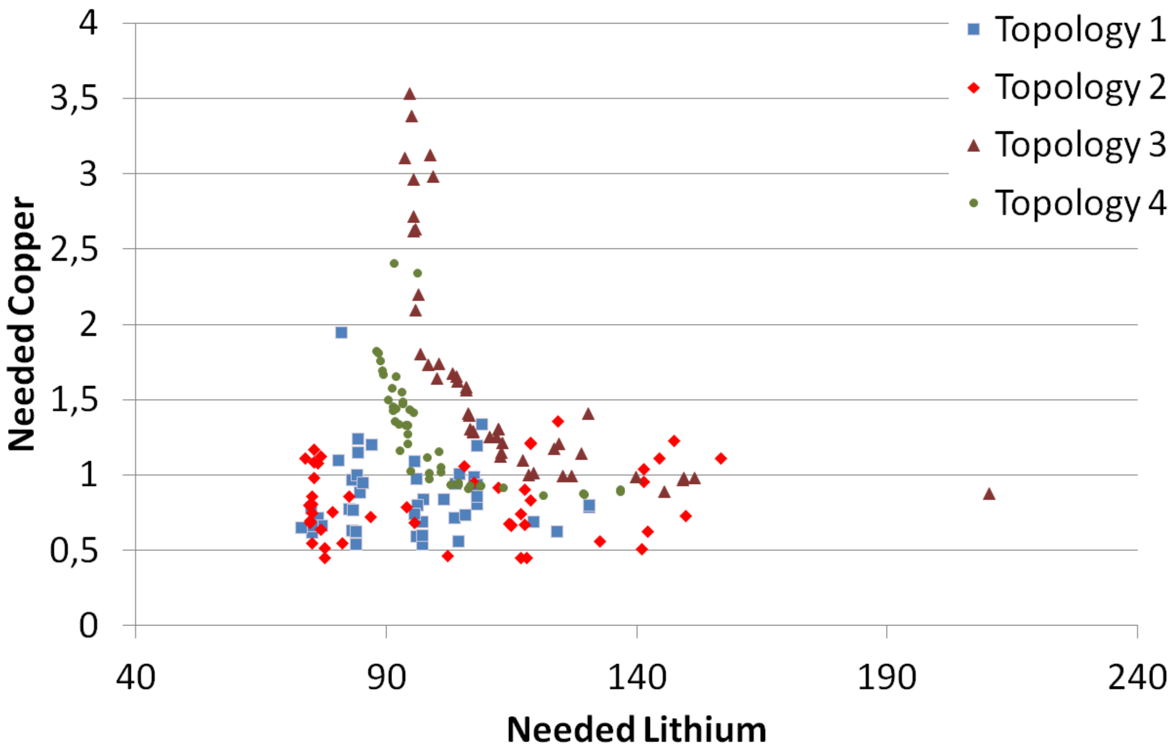

Figure 5: Pareto Frontier in the perspective of needed copper and needed lithium of the 4 topologies.

6 Conclusion

Within this paper it was shown that the combination of preselection algorithm and drive train optimization is capable of a certain number of components. As the number of components increases so will the number of reasonable topologies which should be optimized afterwards. In case of a certain number of components it will be faster to do the creation of the topologies on the flight during optimizing the vehicle as it was done in [5]. A further analysis has to be made where the limitation of the number of components lies and whether the two strategies can be combined reasonably.

Beyond that it was shown that the values of the Pareto optimal set differ significantly from each other. In future work the limits of this optimization routine have to be scrutinized and the influence of the given driving cycle on the optimization results has to be analysed in detail.

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