Multi-Objective Design Space Exploration of Road Trains with Evolutionary Algorithms

Nando Laumanns[1], Marco Laumanns[2], and Dirk Neunzig[1]

[1] RWTH Aachen, Institut für Kraftfahrwesen (ika)
D-52074 Aachen, Germany
{laumanns,neunzig}@ika.rwth-aachen.de
[2] ETH Zürich, Institut für Technische Informatik und Kommunikationsnetze (TIK)
CH-8092 Zürich, Switzerland
laumanns@tik.ee.ethz.ch

Abstract. This paper examines the road train concept as a new alternative in long-distance freight traffic. The design of such a system is a difficult task since many different and conflicting criteria arise depending on the application spectrum, the legal conditions and the preferences of the carrier. Furthermore the evaluation of each decision alternative relies on a time consuming and sophisticated simulation. Evolutionary algorithms (EAs) have shown to be a useful tool for multi-objective optimization in engineering design. Based on a unified model, we develop a problem-specific evolutionary algorithm which features strong elitism, an unlimited archive of non-dominated solutions and density dependent selection. This EA is able to create alternatives which dominate previous manually engineered solutions as well as those derived from exhaustive search.

1 Introduction

In freight traffic the importance of trucks grows constantly. Based on a forecast by the Prognos-Institute experts expect an increase of transportation performance on German roads by 55 % until the year 2015 [7]. This would cause a proportional rise of the mileage with a higher traffic load unless transportation regulations are changed. One possibility to avoid this effect is to extend the vehicle load in freight transportation.

In Germany the vehicle load is limited to a maximum weight of 40 t with a maximum vehicle length of 18.75 m. This makes it possible to carry for example two C 782 containers with a load capacity of max. 25 t. In order to avoid road damages, the maximum load per axle of today has to be kept constant.

Based on concepts currently used in other countries, the ika (Institut für Kraftfahrwesen, RWTH Aachen) developed a road train concept, consisting of a semi-trailer truck and two semi-trailers, connected by a dolly (see Figure 1).

Fig. 1. Example of a road train with two semi-trailers.

First simulations of the longitudinal dynamics of those road trains showed a considerable decrease of fuel consumption in connection with an increase of traffic flow on German highways, although their power trains were not adapted to the new demands. Furthermore a rise in maximum speed by 25% from 80 km/h to 100 km/h resulted in a significantly lower increase of the fuel consumption of 5%. Therefore two versions of the road train are to be developed [6]. Maneauverability and transversal dynamical behaviour of road trains were investigated in [9].

This paper now focuses on the design space exploration of road trains concerning many different optimization criteria. The next section discusses the issues raised in road train design, states the resulting optimization problem in terms of decision variables and objectives and explains how each decision alternative is evaluated by extensive numerical simulation of different driving conditions. In section 3 we motivate the use of evolutionary algorithms for this design space exploration task and describe which algorithmic modifications were necessary to deal with the large number of objectives. The results are presented in section 4 and compared to previously known solutions. In section 5 we conclude with the implications of our results from the engineering as well as from the algorithmic point of view.

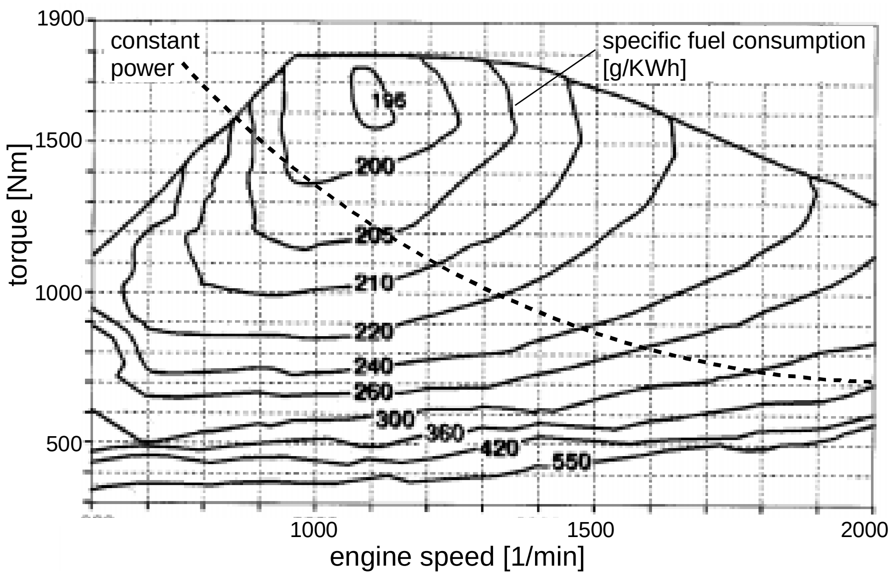

Fig. 2. Engine characteristic graph

2 Optimization of a Road Train

The optimization of a whole new vehicle concept with respect to fuel consumption and driving dynamics is a very complex subject, because the lack of existing data and knowledge leaves a wide open space for experiments concerning the power train and the overall weight of the road train.

An increase of weight leads to an increase of road and climbing resistance. That changes the engine operating point and therefore its efficiency and fuel consumption.

Every single driving condition defines a point in the engine characteristic graph. The number of revolutions is determined by the velocity of the vehicle and the total gear ratio, consisting of rear-axle ratio and transmission ratio. The necessary torque is a result of necessary power output (influenced by velocity, efficiency of the gear box, acceleration, and road gradient) and revolutions. A lower total gear ratio reduces the engine speed. Under the presumption of constant running resistance due to constant velocity and road gradient the required power remains unchanged. The line of constant power indicates this relationship in Figure 2.

Long-distance transport vehicles usually drive rather statically, operating at maximum authorized speed. This leads to the assumption that the gear ratio should be low enough to cause an engine operating point in the area of lowest specific fuel consumption. However, this area is close to the line of maximum torque. Small increases of the running resistance, resulting from headwind or road gradient, cannot be compensated by requesting more torque from the engine, but force the driver to shift gears or to go at a lower speed.

Since the drivability of the vehicle requires a big distance between the most frequent engine operating point and the line of maximum torque, resulting in powerful engines and high gear ratios, it opposes the attempt to reduce the fuel consumption.

The goal of the optimization is to find a combination of overall weight, gear box, engine and driving strategy minimizing fuel consumption, optimizing the driving performance and increasing driving convenience.

Another difficulty in the design process of a long-distance freight vehicle is the large application spectrum. Some carriers operate only in a rather even area, like the Netherlands for example. It is obvious that they would prefer a road train version different from one a carrier would choose whose standard route crosses the Alps. The latter puts much more emphasis on the climbing capacity than the other.

2.1 Overall weight

Based on current semi-trailer trucks the overall weight of an average prime mover with a nominal power of more than 310 kW can be set to about 8 tons. An ordinary semi-trailer weighs about 7 tons, leaving a load capacity of 25 tons. Therefore an upper limit for the overall weight of the road train can be set at 72 tons, representing a prime mover with two full-size semi-trailers.

Assuming a constant ratio of load capacity and overall trailer weight of 0.78125, the load capacity can be varied from 25 tons to 50 tons.

2.2 Power Train

The simulated road train has a power train consisting mainly of a combustion engine (diesel), a clutch, a manually shifted transmission and a rear-axle differential. The engine used as basis for the simulation is the Mercedes-Benz OM 442 LA. It was slightly modified to represent an average modern truck engine. It has a nominal power of 314 kW at 2000 rpm and an optimal specific fuel consumption of 193 g/kWh.

Two standard gear-boxes were chosen for the simulation. Both of them provide 16 gears, with the direct gear being 15^{th} and 16^{th} respectively. The efficiency of the gear box in the direct gear is assumed to be 2% higher than in the other gears, because the flow of power avoids the toothed wheels, which cause the loss of efficiency.

2.3 Resulting Design Variables

One part of the optimization process is the choice of a suitable engine. The engine characteristic graph of the modified OM 442 LA mentioned above is the basis for the engines used in the simulations. The creation of more powerful engines is achieved by

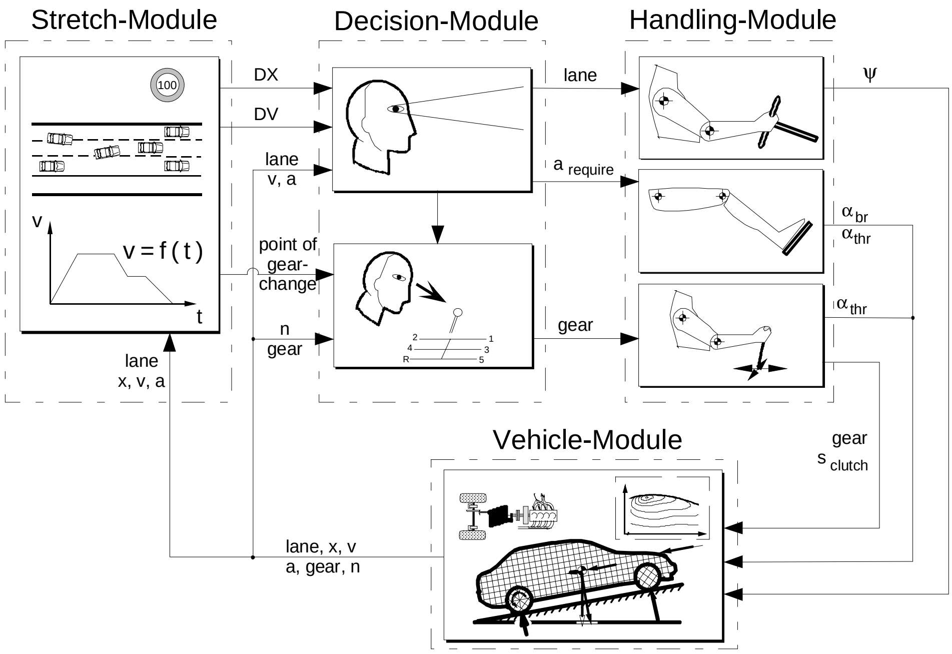

Fig. 3. Elements of PELOPS.

multiplying the engine torque with $1+x_0$, $x_0 \in [0,1]$, in every point of the engine characteristic graph. The relating efficiencies remain unchanged.

The second design variable x_1, $x_1 \in [0,1]$, defines the overall weight and therefore the load capacity as well.

The ratios of the manual gear-box remain unchanged, the total gear ratio is varied through x_2, $x_2 \in [0,1]$, responsible for the rear-axle ratio.

The driver can influence the vehicle performance by choosing the engine speed to shift gears. x_3, $x_3 \in [0,1]$, defines certain engine speeds and accelerations for initiating gear shifts.

Furthermore two manual gear boxes can be chosen. $x_4 \in \{0,1\}$ distinguishes between a gear box with direct 15th gear and one with direct 16th gear.

2.4 Simulation

Each setting of the design variables represents a decision alternative, and the resulting vehicle performance is determined through simulation. For this we apply the simulation tool PELOPS [5], which has been developed by the ika in cooperation with BMW. It analyses interchanges between vehicle, driver and environment. Its three main elements (see Figure 3) are the stretch-module, the decision-module and the handling-module. The cause-effect-principal is used to realize the relation between vehicle performance, environmental impacts and the driver's decisions.

Ten objective functions are defined to give a complete characterization of the vehicle performance considering fuel consumption and driveability. All these objective values are computed within the simulation. Thus, the resulting multi-objective optimization problem can be stated as follows (where the function *f* is implicitly given by the simulator):

min y_0 = time for acceleration 0-40 km/h
min y_1 = time for acceleration 40-90 km/h
max y_2 = maximal velocity
max y_3 = maximal velocity, 1,5% gradient, 14th gear
max y_4 = maximal velocity, 1,0% gradient, 16th gear
min y_5 = average fuel consumption per ton load and 100 km, 100 km/h
min y_6 = average fuel consumption per ton load and 100 km, 80 km/h
max y_7 = average speed on a highway (including road gradient)
min y_8 = average fuel consumption per ton load and 100 km on a highway
min y_9 = number of gear shifts on a highway

where $\mathbf{y} = (y_0, \ldots, y_9) = f(x_0, \ldots, x_4)$,
$x_0, x_1, x_2, x_3 \in [0,1]$,
$x_4 \in \{0,1\}$.

Six simulation scenarios are used to calculate the objective function values. A full-load acceleration, two constant-velocity scenarios (80 km/h and 100 km/h), two scenarios with constant gradient and the engine operating at full load and a highway scenario. The highway scenario consists of an 18 km drive over an empty highway, with road gradient varying from –4.5 % to +3.9%.

3 Multi-objective Design Space Exploration

Since the road train is a relatively new concept, only little is known about how its performance depends on the design variables and about the trade-offs between the objectives. Therefore the aim is to first explore the design space by approximating the set of non-dominated solutions as good as possible. No prior knowledge nor any preference information [3] is given beforehand in order not to preclude any efficient solutions from this high-dimensional objective space.

3.1 Evolutionary Algorithms for Multi-objective Optimization

In engineering design, the design space may be very heterogenous and the objective function is often given by a simulator and thus not in an analytical form. Evolutionary algorithms [1] can deal well with these kinds of optimization problems since they do not pose any preconditions to the objective function or the type of decision variables. Their population concept makes them especially suited to multi-objective problems, where they can approximate a set of efficient solutions in parallel [10].

Evolutionary algorithms work on sets of individuals which represent different decision alternatives. The individuals undergo a cycle of iterative variation and selection until some termination criterion is fulfilled. The variation operator usually consists of recombination (to exchange information between individuals) and mutation (to alter individuals randomly). In the selection part, the better individuals (in respect to the objective function) are kept for the production of offspring, while the worse alternatives are deleted.

In multi-dimensional objective spaces the partial order makes the selection decision more complicated. Modern multi-objective evolutionary algorithms use selection rules which avoid to aggregate the multiple objectives into a surrogate scalar function and thus retain the true multi-objective nature of the problem [2].

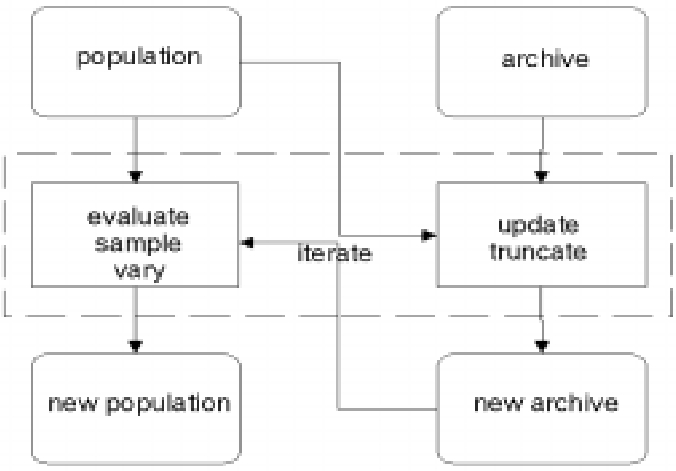

Fig. 4. Flow chart of a universal multi-objective evolutionary algorithm (UMMEA).

3.2 Choice of the Algorithm

Though a great variety of (multi-objective) evolutionary algorithms has emerged so far, many engineering design problems still require to define or to customize an application-specific implementation. Here, the Unified Model for Multi-objective Evolutionary Algorithms (UMMEA [4]) is used. This model allows to systematically combine the different operators that have been proposed and discussed in the literature and to include own problem-specific instances, a schematic view is given in Figure 4.

Like in many other algorithms, an archive is used besides the normal population to store all non-dominated solutions offline during the run. In our case the archive must be very large because the possible size of the trade-off surface increases with the objective space dimension. Practically we even do not have to bound its size at all because the long duration of the simulation (about 30 seconds) already limits the total number of alternatives that can be generated in a reasonable amount of computing time.

The parents for the next generation are selected exclusively from the archive. In order to avoid genetic drift and an oversampling of easily accessible objective space regions, it is necessary to employ density dependent selection: In each iteration the density is estimated for every point represented by the individuals, and the individuals are selected with a probability reciprocal to this density. This leads to a more uniform distribution of alternatives in the approximated trade-off surface.

Each individual represents a vector of design variables. The variation operator for this study only applies mutation, which is carried out by adding a normal distributed random variable

$$x_i^{(t+1)} = x_i^{(t)} + x_i', \quad x_i' \sim N(0,\sigma)$$

to each decision variable x_i, while a constant σ=0.02 was used. Recombination turned out not to be of use here since the interdependence of the design variables in every part of the objective space seems to be very high.

4 Results

In order to analyze the quality of the vehicles developed by the evolutionary algorithm a road train version is designed in a traditional way, based on simple rules for optimizing a power train of a truck [8,11].

In addition, two grid searches over the whole area of possible combinations are performed, each with a total number of 2160 elements. One of them was restricted to a maximum authorized speed of 80 km/h, the other to 100 km/h.

For the design space exploration with the evolutionary algorithm a hierarchical approach was used. The first run of the evolutionary algorithm is performed to narrow the design variable intervals. An analysis of the trade-offs between the different objectives leads to the conclusion that a focus on reducing the fuel consumption would not necessarily worsen the other objective values to an unacceptable amount. Furthermore, this goal is the main factor for the profitability of a vehicle concept and deserves special attention. Therefore we chose the average fuel consumption on the highway (y_7) as the objective value that defines a ranking of the solutions; y_3 and y_4 can be used to represent the second main part of the driving performance, the required climbing ability. In this case the reduction of the maximum velocity must not exceed 5 km/h. The solutions that did not meet this criterion were removed from the ranking.

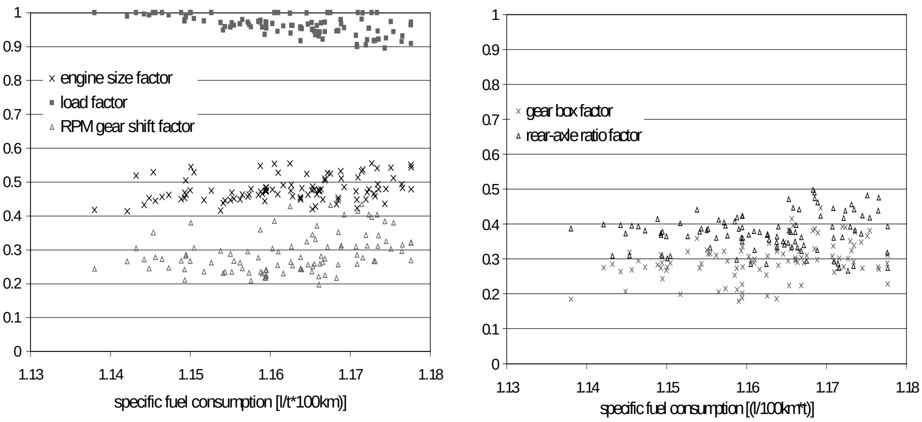

Fig. 5. Design variables and specific fuel consumption for the 100 km/h road train.

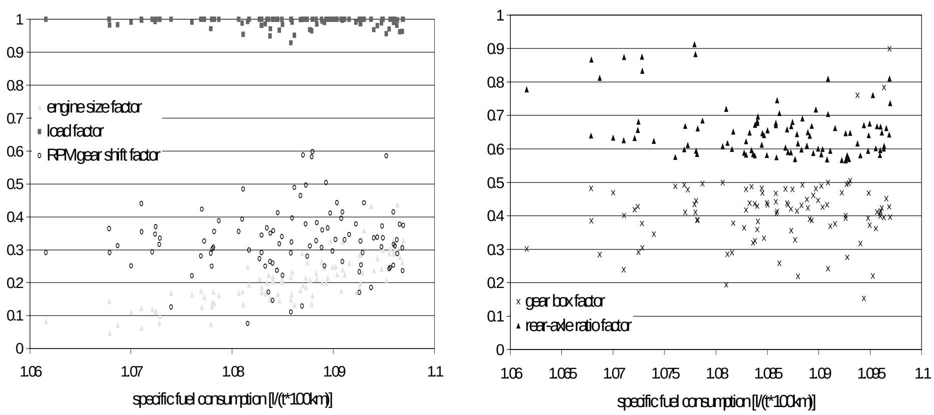

Fig. 6. Design variables and specific fuel consumption for the 80 km/h road train.

The remaining individuals were ranked according to the fuel consumption on highways. The top solution was considered as the best version.

According to Figures 5 and 6 the modified design variable intervals are defined as follows: $x_0 \in [0.4,0,6]$; $x_1=1$; $x_2 \in [0.3,0.4]$; $x_3 \in [0,0.5]$; $x_4=0$ for the 100 km/h road train and $x_0 \in [0.0,0,4]$; $x_1=1$; $x_2 \in [0.55,0.85]$; $x_3 \in [0,0.5]$; $x_4=0$ for the 80 km/h road train.

Limited to those intervals a second run of the same evolutionary algorithm then fulfilled a more exact approximation of the Pareto set in the region of interest. Of course, there are other ways to cope with the large number of incomparable alternatives in the presence of many objectives. These typically rely on preference information, for instance aggregating (or dropping) objectives, lexicographic ordering or the transformation of objectives into constraints. In many cases, however, it is very diffi-

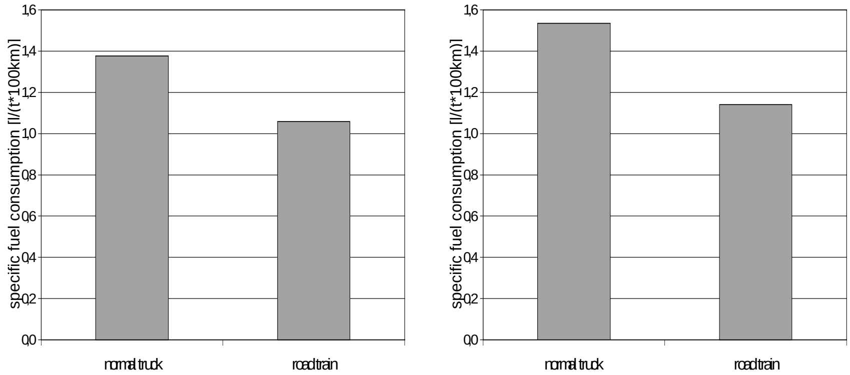

Fig. 7. Comparison between a normal truck and a road train concerning fuel consumption on a highway, maximum authorized speed of 100 km/h (left) and 80 km/h (right).

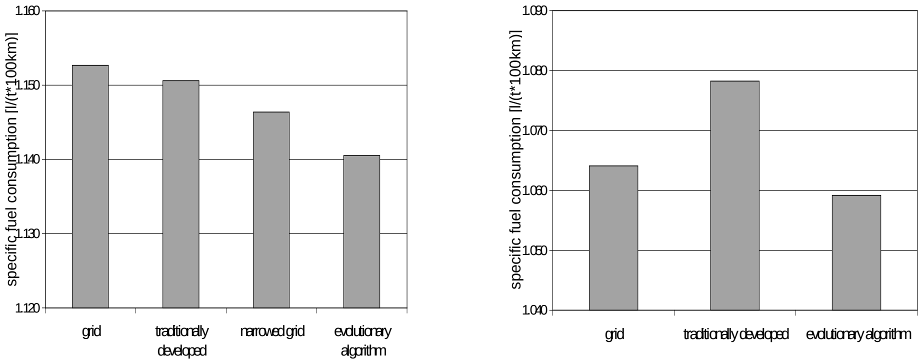

Fig. 8. Specific fuel consumption on a highway for the 100 km/h road train (left) and the 80 km/h road train (right).

cult to derive an exact numerical representation of the preferences, even if the designer certainly has some fuzzy preferences in mind. Moreover, since we had different decision makers with different preferences in mind, the aim is first to explore the Pareto set as broad as possible with a minimum number of simulations before exploiting interesting regions through restriction of the decision variable space as described above. Finally it should be mentioned that even dropping highly correlated objectives does not help since these correlations are usually not known in advance, can differ much in different regions of the search space, and they do not contribute to the dimensionality of the Pareto set.

Final results show a huge advantage of road trains with respect to fuel consumption. A decrease of 23% (80 km/h-version) respectively 26% (100 km/h-version) is achieved on highways in spite of the rather tough gradients. In steady-state operation fuel consumption advantages of up to 35% are accomplished. With acceleration being at a sensible level the road trains have no disadvantages in climbing ability and required gear shifts.

The comparison of the different road train versions indicates that the evolutionary algorithm is able to generate solutions which dominate all other results. Showing the same climbing ability and acceleration as the traditionally developed versions and the ones gained by a grid-scan over the whole parameter area, the EA-solution needs about 1% less fuel on the highway. The 100 km/h version is even better than the best version found out by a grid-scan of 1000 elements distributed over the narrowed intervals.

Fig. 9 shows the relation between the objective function y_3 (maximal velocity in 14^{th} gear with 1.5% road gradient) and y_8 (specific fuel consumption on highway). This relation provides information about the trade-off between drivability and fuel economy.

The creation of 1300 individuals already produces a rather large number of solutions, which have to be considered better than any solution found out without the evolutionary algorithm. This advantage in efficiency will become even more important when more sophisticated driving scenarios – and thus more time consuming simulations – will be used, which is subject to further research.

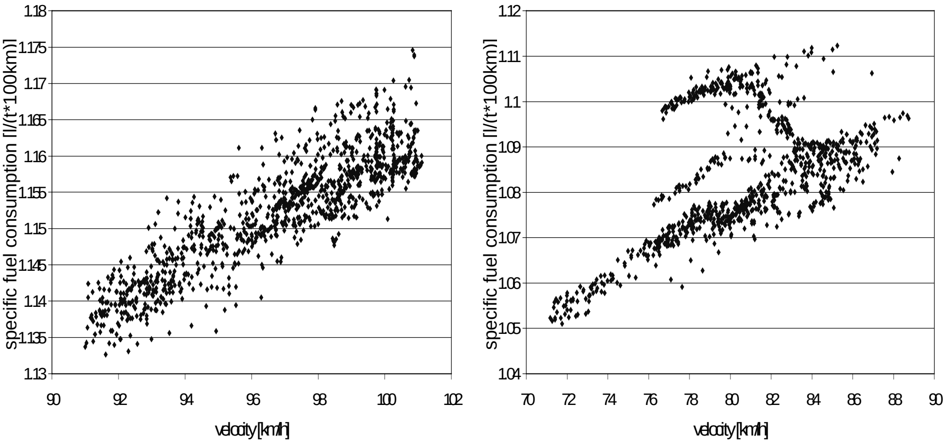

Fig. 9. velocity (1,5% road gradient) and specific fuel consumption on a highway for the 100 km/h road train (left) and the 80 km/h road train (right).

5 Conclusion and Outlook

The results of the design space exploration showed a number of interesting new aspects concerning the optimization of the road train concept. First of all road trains have huge advantages compared to standard trucks concerning fuel consumption per load. This efficiency is certainly the most dominating aspect when developing vehicles for long-distance transport. Furthermore the use of rather powerful engines considerably increases the climbing ability of the road trains without worsening the fuel consumption massively.

The approximation of the Pareto set enables engineers and carriers to choose the right configuration for a special application. A hand-made customization for every application spectrum would require a huge amount of time and work. Thus the design space exploration performed in this paper is a powerful tool in vehicle development. Other possible future fields of operation are the analysis and optimization of vehicles equipped with driver assistance systems or collision avoidance, which need extensive human-machine-interaction.

From the algorithmic point of view the optimization problem turned out to be a challenging task for the evolutionary algorithm because of its high-dimensional objective space. Since on average more than 30 % of the generated solutions were non-dominated, a huge archive was needed to reflect the whole range of possible efficient solutions. In this situation it is difficult to maintain an appropriate selection pressure towards the real trade-off surface. Therefore we chose a strong elitist approach, i.e. all parents were drawn from the archive. This was not harmful in respect to premature convergence as the archive always exhibits enough diversity. On the contrary, the solutions have even shown to be too diverse to make recombination of distant individuals viable. Finally, a density based selection was necessary to reach a good distribution of alternatives to all regions of the potential trade-off surface, where the parents were sampled with a probability reciprocal to their estimated density instead of just applying a rank-based selection scheme based on the densities. Future enhancements of the algorithm could include a scheme to combine both density and preference information in the selection process.

References

1. Bäck, T., Hammel, U., and Schwefel, H.-P.: Evolutionary computation: Comments on the history and current state. IEEE Transactions on Evolutionary Computation 1(1), pp. 3-17, 1997.
2. Fonseca, C. M. and Fleming, P. J.: An overview of evolutionary algorithms in multiobjective optimization, Evolutionary Computation 3(1),1-16.
3. Horn, J.: Multicriteria decision making. In T. Bäck, D. B. Fogel, and Z. Michalewicz (eds.), Handbook of Evolutionary Computation. Institute of Physics Publishing, Bistol, 1997.
4. Laumanns, M., Zitzler, E., and Thiele, L.: A Unified Model for Multi-objective Evolutionary Algorithms with Elitism. In A. Zalzala et al., eds., Congress on Evolutionary Computation (CEC 2000), volume 1, pages 46-53. IEEE Press, Piscataway NJ, 2000.
5. Ludmann, J.: Beeinflussung des Verkehrsablaufs auf Straßen: Analyse mit dem fahrzeugorientierten Verkehrssimulationsprogramm PELOPS, Schriftenreihe Automobiltechnik, Forschungsgesellschaft Kraftfahrwesen mbH Aachen, 1998
6. Ludmann, J., Neunzig, D., Weilkes, M., Wallentowitz, H.: The effectivity of new traffic-technologies and transportation-systems in suburban areas and on motorways. International Transactions in Operational Research, Res. 6, Pergamon, 1999

7. Prognos AG: Prognos European Transport Report 2000 - 22 Western and Eastern European Countries 1998-2000-2010. Basel, August 2000.
8. Rubi, V.: Industrielle Nutzfahrzeugentwicklung, Schriftenreihe Automobiltechnik, Forschungsgesellschaft Kraftfahrwesen mbH Aachen, 1993
9. Sandkühler, D.: Simulationstechnische Untersuchung des Fahrverhaltens von mehrgliedrigen Road-Train Sattelzügen, Studienarbeit am Institut für Kraftfahrwesen, Aachen, 1998
10. Sen, P. and Yang, J.-B.: Multiple criteria decision support in engineering design. London, 1998.
11. Wallentowitz, H.: Longitudinal Dynamics of Motor Vehicles, Forschungsgesellschaft Kraftfahrwesen mbH Aachen, 2000