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SIMULATION AND OPTIMIZATION METHODOLOGY OF PROTOTYPE ELECTRIC VEHICLE

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1. Introduction

In the current time, where energy usage continues to grow, leading to the inevitable depletion of the world's energy resources, there has been an increasing global interest in alternative sources of energy. In recent years, ever more public attention has been paid to the electricity industry, especially in terms of new technologies such as renewable energy plants and low energy consumption devices. Currently, the most promising technologies are hybrid as well as electric vehicles. These are becoming a progressively more important part of the automotive market.

The factors mentioned above has led to the need for developing new design-technological solutions by updating methods of modelling, simulation and optimization for prototyping of electric vehicles. The first two domains are strongly connected. Modelling and simulation of hybrid and electric vehicles have been proceeding extensively during the past decade. A discussion concerning the need for modelling and simulation of electric and hybrid vehicles is presented by Gao et al.. The authors presented an overview of the modelling and simulation of hybrid electric vehicles, with specific emphasis on physics-based modelling.

Ghorbani et al. presented another point of view. This paper considered a simulation and modelling package developed at the University of Manitoba, the so-called REVS, or renewable energy vehicle simulator. REVS comprises several components including electric motors, internal combustion engines, batteries, chemical reactions, fuzzy control strategies, renewable energy resources and support components, which can be integrated to model and simulate hybrid drive trains in a range of configurations. In a book edited by Seref Soylu, modelling and simulation of electric vehicles and their components have been investigated by numerous researchers who work in both the mechanical and control areas of this field. Mathematical models for such devices and their components were proposed to make this reference a guide for everyone who wants to prototype electric vehicles.

Another significant issue that must be taken into account in designing electric vehicles is the optimization of relevant features of every part of the developed system. Such optimization problems are usually formulated for either hardware or software parts of a vehicle and are therefore classified into two groups. The literature indicates that authors more often focus their considerations on the first group of problems.

Many research studies on the design optimization of mechanical elements e.g. suspension system [Šagi and Lulić 2013] and mechatronic devices are available. A comprehensive review on the latest research and development trends in this domain can be found in [Rao 2012]. Recently, more attention has been paid to the second group of problems, in which advanced control methods were mainly developed. A great number of these methods are strongly connected to the problem of fuel saving. Keulen et al. proposed velocity trajectory optimization for hybrid electric vehicles in order to minimize fuel consumption. Their approach enables fuel saving of up to 5% compared, for example, to a cruise controller.

Villagra et al. presents a path and speed planner for automated public transport vehicles in unstructured environments. The proposed method makes it possible to analytically compute a comfort-constrained profile of velocities and accelerations of the electric vehicles. Another path planning method is suggested by Farooq et al., who used a soft computing method, so-called particle swarm optimization, in order to minimize the length of the path and to meet constraints on total travelling time, total time delay due to signals, total recharging time and total recharging cost. Dovgan et al. used multi-objective evolutionary algorithm optimization to find optimal driving strategies taking into account travel time and fuel consumption. Results were compared with driving strategies determined with using predictive control and dynamic programing.

A very interesting approach is shown in [Cook 2007]. The paper considered the simultaneous optimization of either drive train or driving strategy variables of the hybrid electric vehicle system using a multi-objective evolutionary optimizer. The optimization of a driving strategy was also investigated by the authors of this paper in their previous research [Targosz et al. 2013a].

In the present study, some improvements are proposed in the context of the multi-objective velocity optimization for the electric vehicle in structured environments with unknown disturbances. In such a way, this approach allows us to take into consideration no only deterministic situations but also stochastic ones which can be often met in real word environments.

This paper deals with the methodology of advanced simulation model design and its application in the optimization process for prototyping electric vehicles, which can be employed in race car competitions such as the Shell Eco-marathon, Formula SAE and the Greenpower Corporate Challenge.

The paper is organized as follows. In Section 1, a brief introduction to the problem is described. The next section discusses the main important issues in the creation of the simulation model. Section 3 shows the current form of the simulation model that can be used for different purposes. The usefulness of the model is more precisely detailed in Section 4. In Section 5, the authors describe a case study carried out in order to verify the proposed methodology in the case of a prototype of the lightweight electric vehicle. The first example shows verification results that were obtained for a race circuit in Rotterdam, whereas the second example presents performance outcomes for a test circuit in Tychy, Poland. The paper ends with concluding remarks in Section 6.

2. Importance of car simulation model in the project

Designing a vehicle for such specific use as car racing is a difficult task. The Smart Power Team from the Silesian University of Technology carried out the task of constructing racing cars to compete in the Shell Eco-marathon. The race is very specific, because its purpose is driving over a certain distance while consuming the least amount of energy. The final score is given according to the number of kilometres travelled per unit of energy. The best teams achieve almost unimaginable results, exceeding 1000 km/kWh. To achieve such a result consistently, sophisticated technical and organizational solutions must be used, which are not present in other popular motorsports and automotive engineering.

The aim for the designing team is thus clear, i.e., to minimalize energy consumption in given racing conditions. Since the very beginning of the conceptual design for this project, how to assess consecutive concepts of the vehicle and its particular subassemblies and subsystems had been discussed. In other words, how to transfer the task of the current assessment (the idea and detailed design solutions) into a formal optimization task so that at every stage of the designing process, it would be possible to select the best solution from a set of suggested solutions. Also considered had been how to record knowledge acquired while designing for subsequent teams who would continue to take part in the challenge and who could use this knowledge in the best possible way.

The entire project is supported by teamwork, which facilitates work in general and allows to the recording, sharing and storing of current data and designing information. It was also considered whether formal methods of knowledge recording should be used [Skarka 2010]. It was decided to fulfil these needs by using a simulation model of the designed vehicle on the analysed track in

conditions complying with challenge regulations. At the same time, this approach forms a kind of knowledge base concerning the design and the main tools for verification and optimization of design.
At the earliest given opportunity, a multi-module simulation model was created. It should be stressed that the simulation model, which is constantly being developed, was adequate to the degree of vehicle development, as was as the level of team knowledge concerning both the vehicle and the race. Therefore, the initial model created at the start of the project was incomparable to its present version; however, the assumption of the constant development of the simulation model has a significant influence on the assumptions concerning the general form of the model. From the early stages of the project, the division into separate modules covering separate phenomena that could have an influence on the vehicle performance was made. During the project, the following phases of model development were predicted:

- **Elaboration of primary form of the model**
  It was mainly based on the mathematical description of phenomena such as aerodynamic resistance, rolling resistance, etc.
- **Improving particular module models**
  Then, particular modules were developed, based on the obtained results of driving, stand research and test-drives. Special measuring stands were made, i.e., a stand for measuring the engine, a stand for measuring the drive system [Targosz 2013b] etc.
- **Adjusting the model based on rides at the racing track**
  Based on test-drive results at the racing track and during the race, adjusting of parameters was carried out in order to increase its precision.
- **Improving the model based on the results of research at special units**
  A series of verification researches was carried out at highly specialized units and aerodynamic tests were realized at a wind tunnel. The results of this system research were integrated with the simulation model. This allowed greater reliance of the results of the simulation model operation compared to the primary results, which were to a large degree unreliable.
- **Improvement of the optimization method and further adjustment of model parameters**
  A further stage was to adjust the simulation model based on test-drive results on the test track
- **Adjustment of model operation in changing environmental conditions**
  In the consecutive stages, the plan is to adjust the model to changing road conditions and various vehicle parameters.

3. Form of the simulation model

Figure 1 shows a scheme of the simulation model. The model consists of four main subsystems/modules:

- A vehicle model – where the vehicle parameters affecting its dynamics are taken into account. These include basic parameters such as mass, radius, wheel moment of inertia and parameters of the drive unit and transmission unit. In this section of model components, the forces of resistance and the driving force acting on the vehicle in motion are determined.
- A module of the road – in this module, all parameters of the road on which the vehicle is moving are stored, e.g., radius, slope angle and quality of the surface. It is very important to have data about the road, as most of the resistance forces are a function of its parameters.
- A control module – where the control strategy is stored, e.g., reference velocity, time and place of acceleration, etc. In this module, it is also possible to take into account the safety system.
- A module of the weather conditions – where all variables that affect a vehicle are recorded, including air temperature, atmospheric pressure and wind speed and direction;

From the very beginning of creating the model, its modular structure has been assumed, which in future versions of the model refines or defines specified physical phenomena in different ways. This approach allows at an early stage of building a vehicle to verify and optimize certain parameters of the vehicle and to search for direction of changes instead of exact numeric values.

For detailed data, it is necessary to have a larger amount of information. The more accurate and the greater the amount of data, the greater the confidence of the simulation data generated by the model will be.

A good example of such a refined model is the efficiency of transmission unit, which can be taken as constant or can be evaluated as a function of velocity or torque (see e.g., [Targosz 2013b]. In the current form, the model was extended in comparison to the previous version released in [Targosz et al. 2013a] in order to be used for simulating the behaviour of an electric vehicle in structured environments with unknown disturbances. It is very necessary, especially in the case where we assume to have much more adequate and accurate simulation results.

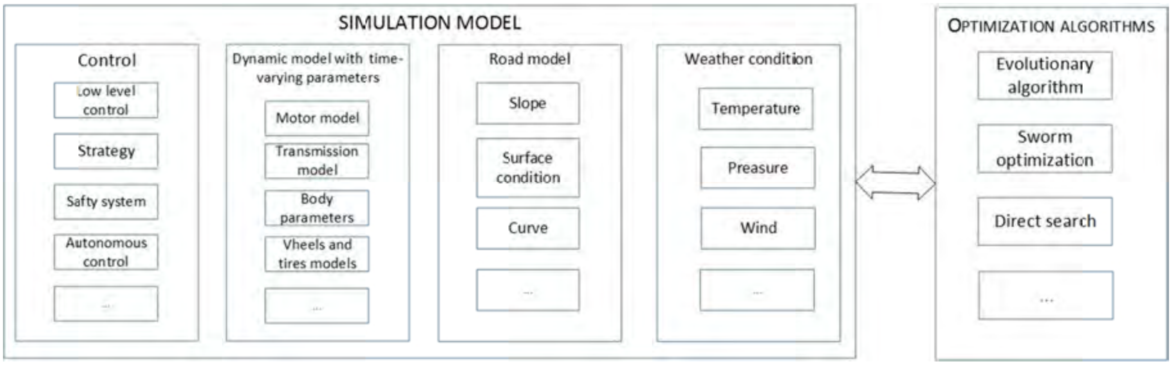

Figure 1. Scheme of simulation model of vehicle

3.1 Model of vehicle

The non-stationary differential equation of the vehicle motion is proposed as follows:

$$m_z\ddot{x} = F_D(t) - \frac{\gamma}{2}Ac_x(t)[\dot{x} + v_w(t)]^2 - c_{rr}\cos[\alpha(t)]mg - \sin[\alpha(t)]mg - c_{tr}(t)\cos[\alpha(t)]mg \quad (1)$$

where m_z is the so-called reduced mass, which is the product of the gravitational mass of the vehicle and the coefficient of reduced masses (rotating masses). In urban vehicles, the influence of the rotating masses of the engine and the transmission unit is often ignored, due to their low impact on the dynamics of the vehicle. The described vehicle is equipped with a freewheeling of back wheel and rotating parts of the motor and transmission unit are periodically triggered; as a result, reduces mass in this model is periodically changed.

The first component on the right side of the equation is the dynamic force $F_D(t)$, which is a quotient of torque and dynamic wheel radius. The value of the torque on the drive wheel is a function of many variables such as motor power, motor efficiency, means of control and total ratio and efficiency of transmission. Another component of the equation is aerodynamic drag, which is the longitudinal component of the resistance of the medium in which the vehicle is moving. It is defined as the product of air density γ dependent on pressure and temperature of the medium, the front area A of the vehicle, the drag coefficient $c_x(t)$ and the square of the velocity of movement of air masses along the body of the car, where $v_w(t)$ is wind velocity. This part of the equation represents an unknown disturbance force. The next component is rolling resistances, where c_{rr} is a coefficient that is dependent on the type of tires, bearing resistance, etc. Another component is the resistance of the hill, which is the component of the gravitational force directed parallel to the surface when the vehicle goes up a hill with a slope $\alpha(t)$. During the curvilinear motion, torsion resisting also acts on the vehicle. Torsion resistance depends on centrifugal force, type of tires, tire pressure, etc. and can be written in the same way as rolling resistance, where $c_{tr}(t)$ is a torsion resistance coefficient.

3.2 Model of route

A description of the track is formed by dividing it into a finite number of elementary sections, O_i, $i = 1, 2, \ldots, n$. Each section can be characterized by a vector $<L_i, R_i, S_i, E_i>$ where:

- L_i [m] is the length of the i-th section O_i,
- R_i [m] is the radius on the i-th section O_i,
- S_i [%] is a slope of the i-th O_i,
- E_i represents a description of the surface condition

Distance of the route is the sum of lengths of each section:

$$D = \sum_{i=1}^{n} L_i \tag{2}$$

These basic data are necessary for the proper determination of the motion resistance in each section of the track. It is assumed that any change of the route features will cause the need to create the next section and a new vector. This approach brings order, which facilitates the modelling of the track in a simulation environment.

3.3 Model of weather condition

Bearing in mind that mobile systems usually move in an open area, a description of the road should have additional parameters like V_{wi} P_i and T_i, where:

- V_{wi} [m/s] is wind velocity
- P_i [Pa] is atmospheric pressure
- T_i [°C] is temperature.

The value of the wind velocity can be calculated using a random process generator; in this way, it is possible to introduce an unknown variable to the model of the vehicle.

3.4 Model of control unit

It has been well-established that the motion controller can be realized in different ways; however, for this paper, three cases were investigated:

- PID regulator with a constant set value of the velocity – a motion strategy can be accomplished by a virtual regulator with different parameter values of P, I and D.
- A binary switch used to accelerate and power on (constant current) the motor if actual velocity is lower than the optimal velocity and to power off if it is higher. The set values of the velocity are calculated by an evolutionary algorithm.
- PID regulator with optimal set values of the velocity determined by an evolutionary algorithm.

The modular form of the model of a control unit allows for verifying the different types of motion controllers of the vehicle. This approach provides the opportunity for testing driving and controlling strategies for electric vehicles where the problem of energy consumption is very important.

4. The use of the simulation model

The primary use of the simulation model was current verification for planned design features during the race and was used to estimate their impact on the race result. This was achieved by supporting simulation experiments with planned alternative design solutions.

For developed and produced structure prior to the race in 2012, there was also a need to develop a strategy for the race and for optimization of driving during the race. It was the second application of the simulation model.

The third application of the simulation model was to identify the parameters of a vehicle that were difficult to determine using the existing methods and where the value of the results did not provide

sufficient certainty [Targosz and Skarka 2013]. Such a typical example was needed to verify the aerodynamic characteristics of the vehicle on the basis of numerical simulation on a simulation model that was previously calculated using CFD tools (Computational Fluid Dynamics).
The fourth use of the simulation model was to determine the optimal design solution in a wider range of variability than that of the race environment in order to adapt and modernize the structure of the possible and changing conditions of the race [Skarka 2014].
The intention is also to use the simulation model to control the vehicle in real time. Below, two main uses of the simulation model during the initial phase of designing and preparing for the race will be described in more detail.

4.1 Verification of design assumptions

Structural assumptions were reviewed on an on-going basis from the determination of the first vehicle concept. They were made using a simulation model to simulate the race on the track. In the conceptual phase of the vehicle design, the simulation model itself also contained basic modules that were based on the basic set of correlations describing the basic physical phenomena, such as physical movement of an object along a specific trajectory, with fundamental forces of resistance activities in a gravitational field. Nevertheless, at this stage, simulations allowed for answering the fundamental questions raised by the project team, such as the impact of the individual resistance components on the final result, or the approximate result achieved by the vehicle when driven in accordance with the strategy developed intuitively, or which of the alternative solutions will yield a better result.
At the stage of preliminary design, the obtained answers to these questions allowed the project team to consciously choose design solutions, which yielded a better result and in the case of achieving comparable results, the solution was to follow other criteria such as, for example, the smallest degree of complexity of construction, or minimizing the cost of construction.
This knowledge allowed us to focus our efforts on features that have the biggest impact on the outcome of the race. In the case of selecting bearing wheels for the vehicle, it turned out that the proposed different solutions for the negligible effect of the rolling resistance of the bearings were abandoned; typical bearings were matched, with the reservation to replace the bearings of the model with low rolling resistance, since the way of bearing has little impact on the outcome.

4.2 Optimal motion strategy

The main aim of any race competition is to drive a vehicle as far as possible using the least amount of energy. All drivers must race a certain amount of laps on the track at an average speed v_{avg} with the minimal energy consumption. The adequate measure of the efficiency of the system is a factor indicating the number of kilometres that the vehicle travels per 1 kWh. In general, the planning of the strategy for completion can be formulated as the optimization problem, in which the best possible trajectory of the linear velocity is sought. As is to be expected, this can be achieved by optimizing the velocity set-points as a function of the distance. The main purpose of the optimization process is to adjust the values of the velocity set-point in different points of the laps in order to minimize a multiple objective function **F**, which can be formulated taking into account the following criteria. The first criterion is correlated with the total energy consumption. The second is associated with the required distance that should be covered during a competition. The last objective is connected to the second one and deals with the set limit value of the travel time that should not be exceeded. Assuming that none of these objectives are in conflict, the optimization task can be written as follows:

$$\begin{aligned} &\text{Minimize} \quad \mathbf{F}(\mathbf{v}_c) = [\mathrm{f}_1(\mathbf{v}_c) \quad \mathrm{f}_2(\mathbf{v}_c) \quad \mathrm{f}_3(\mathbf{v}_c)]^T \\ &\text{subject to} \quad v_{ci}^{(L)} \le v_{ci} \le v_{ci}^{(U)} \quad \text{and} \quad i = 1,2,\ldots,i_{\max} \end{aligned} . \tag{3}$$

where $v_{ci}^{(L)}$, $v_{ci}^{(U)}$ are the lower and upper values of the boundary constraints that should be chosen, taking into account the properties of the electric vehicle; $i_{\max}$ denotes the total number of parts of a race path that is used to digitize the raceway laps.

The optimization problem that described above can be solved in several ways. Generally, multi-objective problems do not have a single global solution and it is reasonable to investigate a set of points, each of which satisfies the objectives f_i. A well-grounded approach to searching for an optimal solution is the global criterion method [Marler 2004] in which objectives f_1, f_2 and f_3 are combined in order to form a single function. One of the most general indirect utility functions in this context can be expressed in its simplest form as the weighted exponential sum:

$$
\begin{aligned}
&\mathrm{U}(\mathbf{v}_c) = \sum_{i=1}^{3} w_i \, \mathrm{f}_i(\mathbf{v}_c) \\
&\mathrm{U}(\mathbf{v}_c) = w_1 \left[1 + \varepsilon_{sim}^{\lambda_1}\right]^{-\lambda_2} + w_2 \left[\mathrm{H}(d_{cv} - d_{sim}) \frac{|d_{cv} - d_{sim}|}{d_{cv}}\right]^{\lambda_2} + w_3 \left[\mathrm{H}(t_{sim} - t_{cv}) \frac{|t_{cv} - t_{sim}|}{t_{cv}}\right]^{\lambda_2}
\end{aligned}
\tag{4}
$$

where H is the Heaviside step function; f_i and w_i indicates the i-th criterion and its importance (the value of the parameter w_i should be chosen arbitrarily from the range [0, 1]); the exponent λ_i determines the extent to which a method is able to capture all of the Pareto optimal points for either convex or non-convex criterion spaces; ε_{sim} [km/kWh] is an estimator of the efficiency of the system calculated on the basis of the total energy consumption in the ride; d_{cv} and d_{sim} [m] is the reference path and the value of the covered distance obtained as a result of the simulation; t_{cv} and t_{sim} [s] represents the set limit value of the travel time and the travel time calculated on the basis of the simulation; $\mathbf{v}_c$ is the velocity vector, where v_{ci} [m/s] is defined for a certain section of the route (the size of this vector depends on the complexity of the route).

The first component of the objective function (2) is responsible for minimizing energy consumption. Two other components are penalty factors, being the limitation that is imposed on the average velocity of the race car. Their goal is to ensure that the vehicle will drive in an assumed manner at the optimum time.

Various types of algorithms can be applied for solving our problem, which has been formulated in the form of (3) or (4). On the one hand, standard optimization methods, e.g., gradient/Jacobian/Hessian-based algorithms cannot be effectively employed in this context, due to the form of the objective function f_2 and f_3 and because of the non-deterministic parts of the simulation model. On the other hand, for these types of problems, stochastic optimization methods in the classic form, e.g., Monte Carlo techniques, are very often not able to find an accurate solution that would guarantee polynomial-time convergence. Because of these reasons, in this paper, the optimal solution (the minimum of the objective function U) was found using evolutionary algorithms (EAs). EAs are known for being methods that solve either single- or multi-objective optimization problems [Deb 2009]. They are based on the natural selection process that mimics biological evolution. In this way, the approximate solutions to this problem can be computed.

5. Verification case study

5.1 Prototype lightweight electric vehicle

The proposed methodology was validated for the case of a prototype of the lightweight vehicle "Mushellka". The vehicle has an electric drive and was designed and built by student members of the scientific association Modelling of Machine Design, working at the Institute of Fundamentals of Machinery Design at the Silesian University of Technology. The vehicle was designed according to the rules of the race for prototype class vehicles and entered in the electric battery category. In the past two years, the vehicle took part in the European edition of the competition, scoring 425 km/kWh in 2012 and 455 km/kWh in 2013.

The vehicle shown in Figure 1 is a three-wheeled self-supporting structure. The vehicle cover is made of composites based on epoxy resin and woven of carbon and aramid fibre. The design of a vehicle and other components has been described in [Sternal et al. 2012].

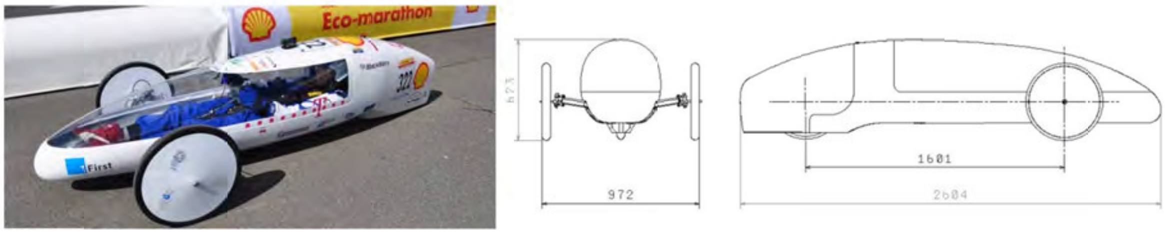

Figure 2. Prototype of electric vehicle Mushellka and overall dimensions of the vehicle

The coefficient c_x =0,23 was estimated as a result of CFD analysis using ANSYS software [Danek 2013]; it was also verified by research at the Institute of Aviation in Warsaw [Wysocki 2012]. The tire rolling resistance coefficient $c_{rr} = 0{,}0014$ was supplied by the manufacturer of the tires. The vehicle uses specially designed Michelin tires, only available to participants of the Shell Eco-marathon competition. The tires have a very low rolling resistance compared to traditional tires.

5.2 Race and test routes

The Shell Eco-marathon competition is held on a street circuit in Rotterdam. One lap is 1630 meters long. Vehicles have to cover ten laps in no longer than 39 minutes. Such requirements impose an average speed of 25 km/h.
The Rotterdam route is a street circuit and therefore, none of the tests can be conducted on dates other than during the event. Trying to find the optimal driving strategy experimentally is also not possible. Thus, to be able to test the vehicle and check strategy, it was necessary to carry out tests using a different route. Driving the prototype vehicle on public roads is prohibited and can be dangerous. Vehicle testing was also carried out on the experimental rides track of the Fiat Auto Poland factory, located in Tychy, in the south of Poland.
AutoCAD Civil 3D allows the user to set the background view of the design space as a satellite photo of the existing terrain. The trajectory of the vehicle path was developed using satellite images. Figure 2 shows a plan view of the path of the drive.

Figure 3. Plan view of the path (AutoCad Civil 3D, Bing Maps)

The vehicle trajectory was determined using the maximum curvature possible that could be obtained on the existing roads. According to drawings in AutoCad Civil 3D, the lengths of straight sections and the lengths and the radius of arcs were obtained. From the satellite view for this area, it is not possible to check information concerning elevation of the roads; therefore, geodetic measurements were taken using GPS technology. The use of such a measurement guarantees the required accuracy to a few centimetres. The measuring points were collected along the axis of the road, with the distance between points amounting to 10 meters. If on the measured route, direction or elevation was changed, the frequency of measurement was increased.

Geodetic coordinates were also imported into AutoCAD Civil 3D and were used to prepare data concerning the route <L_i, R_i, S_i, E_i> that was imported into the simulation environment.

5.3 Parameter settings of evolutionary algorithm

An evolutionary optimization was carried out by means of the MATLAB environment using the Genetic Algorithm Toolbox. The classic evolutionary algorithm was applied to solve the task defined in Section 4.2. Well-known genetic operators for single-objective optimization were used to guarantee convergence to a solution [Deb 2009]. In the first step, heuristic rules, together with the trial and error procedure, were employed to find such values of the evolutionary algorithm's parameters for which the best optimization results would be obtained.

The fitness function was elaborated following eq. (4). The upper and lower values of the velocity set-points and other parameters in eq. (4), such as the exponents (λ_1=2, λ_2=1) and weights (w_1=0.8, w_2=w_3=0.1) were determined arbitrarily by the expert basing the determination on results of a previous study [Targosz et al. 2013a]. Each individual in the population was composed of genes representing the real numeric series of velocity set-points. A random, well-dispersed initial population was created using the feasible population method, whereas fitness scaling was realized applying the rank method, in which the selection of the parents to the next generation was achieved by employing the stochastic uniform method. Two important reproduction options of the algorithm, such as the elite count e_c and crossover fraction p_c were chosen. The first parameter was constant and equal to 2. The second parameter dealt with the fraction of the next generation other than elite children that are produced by crossover. The authors decided to use a heuristic crossover operator. This function returns a child that lies on the line containing the two parents that the distance between the child and the better parent is determined by the user-defined parameter. The value of this parameter was set to 1.2, as was suggested in the literature. The other individuals, i.e., elite and crossover children, are known as mutation children. In this case, the adaptive feasible method was adopted in order to compute them.

The convergence of the evolutionary algorithm is strongly dependent on the population size N and crossover fraction pc. These parameters had critical importance for finding the optimal solution to the problem. Therefore, the convergence of the optimization algorithm was examined for every combination that has been created using elements from the sets N = {5, 10, 15, 20, 25} and pc = {0.4, 0.5, …, 1}. It was assumed that the total number of fitness function evaluations was equal to 500; therefore, should this value be exceeded, the calculation would be cancelled. Therefore, the total number of epochs (NoE) is dependent on the value of N, for example, when N is equal to 5 then NoE is equal to 100, whereas when N is equal to 25 then NoE is equal to 20. For each pair of these values the optimization process was run ten times; following on, the averaging procedure was realized. The averaged results of this step are demonstrated in Figure 3.

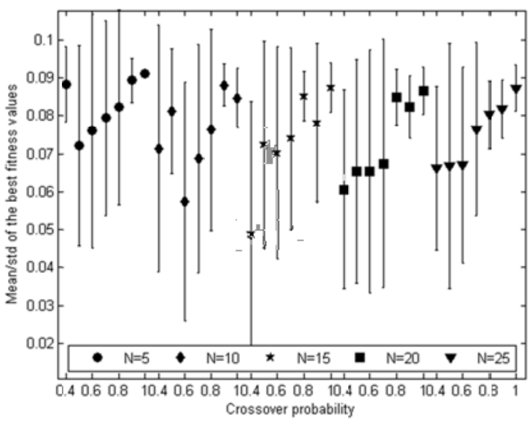

Figure 4. The influence of the relevant features of the evolutionary algorithm on its performance

A plot shows the means and standard deviations of the best fitness results for different values of N and p_c. One can observe that there is a global convergence around the value of 0.05 and it is most frequently obtained, in the average sense, for the case when the population size $N = 15$ and crossover fraction $p_c = 0.4$. However, the value of the standard deviation was not acceptable and the optimization process was in this case often not stable. From a statistical point of view, better results can be seen for the case when N=25 and p_c=0.8, because the repeatability of finding the best solution in this case was higher than in other cases. This pair of parameters has the smallest value of the standard deviation when compared to the rest of those with similar values of the mean of the best fitness results. The authors also carried out several trials for cases in which N was higher than 25, but the results were comparable to those for N=25. Overall, from this experiment, it was concluded that such parameters values (N=25 and p_c=0.8) would be used for further investigations.

5.4 Optimization results

Developing an appropriate strategy has an impact on the level of energy consumption. Figure 4a shows vehicle velocity while driving a route of 3230 meters in 460 seconds. The red line represents velocity of the vehicle using a constant speed strategy and PI regulator. The second case (green line) is a simulation velocity of a car with binary motor switch control and using an evolutionary algorithm to determine the optimal reference speed. The blue line shows vehicle velocity with optimal strategy and control using a PID regulator. Table 1 shows the results of the energy consumption for two different routes. The first is the Rotterdam Shell Eco-marathon race circuit and the second is the FIAT test drive circuit in Tychy.

Table 1. Results of energy consumption

Route	Distance [m]	Travel time [s]	Results [km/kWh] (constant set velocity)	Results [km/kWh] EA strategy	Results [km/kWh] PI control and EA strategy
Rotterdam	1630	2340	460	712	730
Tychy	3230	460	287,5	319,7	330

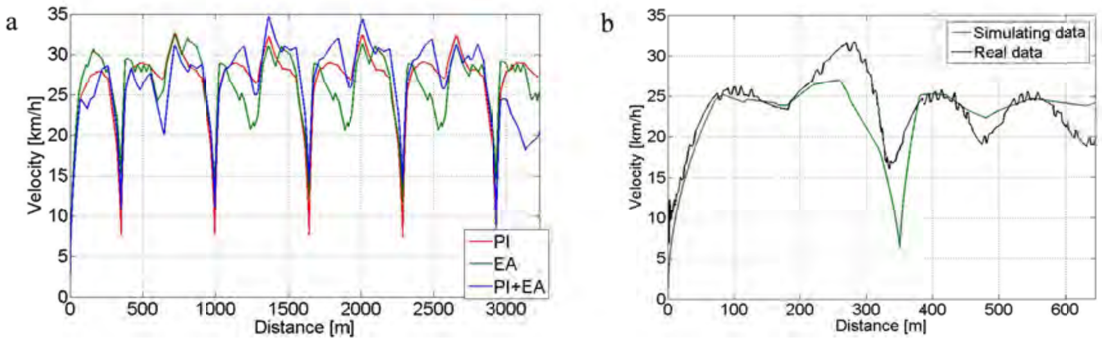

Figure 5. Velocity trajectory

Figure 4b shows real speed (black line) for when the car was driving the first lap on the test track in Tychy, with an average speed of 25 [km/h], as well as realizing motion strategy, which has been determined by the evolutionary algorithm. The driver executed the strategy with a binary switch controller. Information about the position for when the driver would switch the accelerate button was passed using a mobile phone from another person who observed the telemetric data. Telemetric data were collected in real time using a special design telemetric module [Sternal et al. 2012].

The data were compared with the computed strategy. The green line represents a simulation velocity on this lap. The correlation coefficient of the data profile is at the level 0.82. The difference of the

results between simulation and real data obtained during the experiment is associated with mistakes made by the driver, who did not exactly follow the assumed strategy and different weather condition, especially wind speed. In such a case, using the PI regulator and maintaining a predetermined speed may be advantageous.
Simulation studies showed that the use of an appropriate strategy for driving could be beneficial. The presented data illustrates that it is possible to improve the efficiency of energy consumption. Determination of the optimal strategy is needed to improve the result during the Shell Eco-marathon competition. In such a situation, an improvement of a few percent should be considered satisfactory, because it will guarantee a higher rank in the competition. Nevertheless, energy savings should be sought by minimizing the weight and motion resistance of the vehicle, e.g., through optimal shaping of the vehicle body. The best situation is possible when one decides to use a current controller and to realize an optimal strategy. On the one hand, it is very complicated and hard to apply in practise. On the other hand, it could yield significant benefits.

6. Conclusion

The Shell Eco-marathon is an extraordinary challenge that reflects the basic tendencies in the development of automotive technology, i.e., reduction in the energy intensity of automobile transportation. The team from the Institute of Fundamentals of Machinery Design at the Silesian University of Technology have, in order to prepare their car comprehensively and systematically for taking part in this competition, used a simulation model to assess proposed solutions, particularly in terms of impact on the result achieved in the competition, as a basis for the assessment of current activities in the course of the project at all stages of vehicle development.
Currently, the simulation model is being further improved. From a simple initial model, it has become a complex multi-module model, which will be used successfully in the modernization of the existing vehicle; it also being used in the design of a completely new vehicle taking part in a different class in the same race.
The complex simulation model of the vehicle while driving on the racetrack required adjusting to track conditions and environmental conditions, as well as vehicle parameters for every drive it completed. Only such an adjusted model can be used to determine the racing strategy. The research has been developed to test the vehicle, the simulation model and to determine the driving strategy and compliance of the numerical experiment with driving on a racetrack. The test works were carried out on the FIAT test track in Tychy. The obtained levels of energy efficiency differed from the levels obtained during the drives in Rotterdam. The main reasons for this are the fundamentally different driving conditions of the track in Tychy and the track in Rotterdam, mainly in terms of distance and route elevation.
The necessity to ascend requires, on the one hand, the operation of the drive unit outside the range of nominal efficiency and, on the other hand, greater speed changeability, which results in a total increase of air resistance. There was also a significant difference in the surfaces of both tracks. The above-mentioned factors confirmed the significant influence of race and environment conditions on the obtained results. During the research, the impact of driver’s skills on the score was also noted. However, the most important point is successfully implementing the driving strategy. Better repeatability of the ride results require learning to drive such an unusual vehicle and above all, to learn driving strategies for the selected parameters.
Having access to a track on which both structural changes and improved simulation models can be tested on a regular basis provides the opportunity to eliminate design and numerical problems. Adjusting the simulation model to work in the race must be implemented on the target racetrack. It is possible to predict the results of the corrected design of the vehicle without test drives on the track; however, such an approach contains a fairly high degree of uncertainty.

References

Cook, R., Molina-Cristobal, A., Parks, G., Osornio Correa, C., Clarkson, P. J., "Multi-objective Optimisation of a Hybrid Electric Vehicle: Drive Train and Driving Strategy", Evolutionary Multi-Criterion Optimization, Lecture Notes in Computer Science, Vol. 4403, 2007, pp. 330-345.

Danek, W., Gniłka, J., Pawlak, M., "Aerodynamic analysis of wheeled vehicle MuSHELLka", Modelling and optimization of physical systems, 17th International Seminar of Applied Mechanics, Ustroń, 13.09-15.09.2013, Katedra Mechaniki Teoretycznej i Stosowanej. Wydział Mechaniczny Technologiczny. Politechnika Śląska. Gliwice: Wydaw. Katedry Mechaniki Teoretycznej i Stosowanej, 2013, pp. 7-12.

Deb, K., "Multi-objective optimization using evolutionary algorithms", Wiley, 2009.

Dovgan, E., Javorski, M., Tusar, T., Gams, M., Filipic B., "Discovering driving strategies with a multiobjective optimization algorithm", Applied Soft Computing, Vol. 16, 2014, pp. 50–62.

Farooq, U., Shiraishi, Y., Sait, S. M., "Multi-Constrained Route Optimization for Electric Vehicles (EVs) using Particle Swarm Optimization (PSO)", Intelligent Systems Design and Applications (ISDA), 2011, pp. 391-396.

Gao, D. W., Mi, C., Emadi, A., "Modeling and Simulation of Electric and Hybrid Vehicles," Proceedings of the IEEE, Vol. 95, No. 4, April, 2007, pp. 729-745.

Ghorbani, R., Bibeau, E., Zanetel, P., Karlis, A., "Modeling and Simulation of a Series Parallel Hybrid Electric Vehicle Using REVS", American Control Conference, 2007, ACC '07, 9-13 July, 2007, pp. 4413-4418.

Keulen, T., van Jager, B., de Foster, D., Steinbuch, M., "Velocity trajectory optimization in Hybrid Electric trucks", In proceeding of: American Control Conference (ACC), 2010.

Marler, R. T., Arora, J. S. "Survey of multi-objective optimization methods for engineering", Struct. Multidiscip. O. 26, 2004, pp. 369-395.

Rao, R. V., Savsani, V. J., "Mechanical Design Optimization Using Advanced Optimization Techniques", Springer Series in Advanced Manufacturing, XII, 2012, p. 320, illus. 34.

Šagi, G., Lulić, Z., "Multi-Objective Optimization in the Conceptual Phase of Vehicle Development", Concurrent Engineering Approaches for Sustainable Product Development in a Multi-Disciplinary Environment, 2013, pp. 559-570.

Skarka, W., "Innowacyjne metody poprawy efektywności energetycznej transportu na przykładzie energooszczędnego bolidu elektrycznego Mushellka startującego w światowych wyścigach Shell Eco-marathon" CaxInnovation, Mechanik 2/2014 CD, 2014.

Skarka, W., "Using Knowledge-based Engineering Methods in Designing with Modular Components of Assembly Systems", In: Marjanovic, D; Storga, M; Pavkovic et al. Proceedings of the Design 2010 11th International Design Conference, Dubrovnik, MAY 17-20, 11TH International Design Conference (Design 2010), Vol. 1-3, Dubrovnik 2010, pp.1837-1846.

Soylu, S., Electric Vehicles, "Modelling and Simulations", Janeza Trdine 9, 51000 Rijeka, Croatia, 2011.

Sternal, K., Cholewa, A., Skarka, W., Targosz, M., "Electric Vehicle for the Students' Shell Eco-Marathon Competition", Design of the Car and Telemetry System", Telematics in the Transport Environment, 12th International Conference on Transport Systems Telematics, TST 2012, Katowice-Ustroń, Poland, October 10-13, 2012, Communications in Computer and Information Science, Jerzy Mikulski (ed.), Springer Berlin Heidelberg, 2012, pp. 26-33.

Targosz, M and Skarka, W., „Synergia metod modelowania konstrukcji na przykładzie projektu Smart Power", Mechanik 2/2013 CD 40, 2013, pp. 1-9.

Targosz, M., "Test bench for efficiency evaluation of belt and chain transmission", Proceedings of XII International Technical System Degradation Conference, Liptovsky Mikulas, Slovakia, 03-06.04.2013, PNTTE, 2013, pp. 142-143.

Targosz, M., Szumowski, M., Skarka, W., Przystałka, P., "Velocity Planning of an Electric Vehicle Using an Evolutionary Algorithm", Activities of Transport Telematics, 13th International Conference on Transport Systems Telematics, TST 2013, Katowice-Ustroń, Poland, October 23–26, 2013, Communications in Computer and Information Science, Jerzy Mikulski (ed.), Springer Berlin Heidelberg, 2013, pp. 171-177.

Villagra, J., Milanés, V., Pérez, J., Godoy, J., "Smooth path and speed planning for an automated public transport vehicle", Robotics and Autonomous Systems, Vol. 60, No. 2, 2012, pp. 252-265.

Wysocki, Z., "Badania bolidu MuSHELLKA. Badania wagowe współczynników aerodynamicznych i wizualizacja opływu", in polish-not published, RAPORT NR 36/BA1/12/D, Institute of Aviation Warsaw, 2012.

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