Building a time-optimal power consumption strategy for a solar car

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Abstract. Solar car races are characterized by a long distance and plenty of ways to save and use energy. In this paper an optimization of a power management strategy for solar cars is introduced to minimize the time needed to pass the route of the competition by implementing the hierarchical technique.

1. Introduction

Solar car racing is becoming more and more popular among the universities teams due to complex nature and being environment friendly [1,2,3,4,5]. There are several competitions with long lists of participant teams. The most notable competitions are Bridgestone World Solar Challenge (BWSC), American Solar Challenge (ASC) and South African Solar Challenge (SSC). And while building a great car is a challenge on its own, that is not all about it takes to achieve maximum performance. Power management is a vital part of a solar-car racing. Wrong usage of a very well built car will have a drastic impact on overall team performance.

That is why solar teams are developing their own complex power management strategies. Competitions are characterized by having very long routes, and thus having a large number of input parameters for optimization, that can rarely be seen in other place.

In order to build an optimal power management system, a model of the solar car must be implemented, which includes both its drivetrain and solar panels. By combining the competition track data and a solar car model, a simulation of the race can be performed. And in order to maximize the performance, a time-optimal strategy optimization is needed.

2. The vehicle model

The approach for building a solar vehicle model is based on an idea of an energy balance [4,6,7]. On one hand vehicle draws energy to move itself on the course, on the other – vehicle charges the battery using the solar radiation (and sometimes regenerative braking). Let $E$ be the total energy, consisting of $E^{(-)}$ – energy draw, and $E^{(+)}$ – energy income.

$$E = E^{(+)} - E^{(-)}$$

The energy is stored in the accumulator battery, which is fully charged at the start of the distance. This changes the equation in the following way:
\[ E_i = E_{i-1} + E_i^{(+)} - E_i^{(-)}, 1 < i < n \]
\[ E_0 = E_{\text{battery}} \]
\[ 0 < E_i < E_{\text{battery}} \]

Where \( n \) is the number of track pieces.

At any given time the amount of energy in the system can’t exceed the accumulator capacity, but also can’t be less than zero.

Model inputs could be a vector of speed values or a vector of torque values for each piece of distance, depending on solar car control system.

The model is built by iteratively calculating an amount of energy needed to cover certain part of track and an amount of collected energy from the solar array for every piece of the route at certain time.

2.1. The track

Track data is described by primary and secondary characteristics.

Primary characteristics are geographical:
- Latitude
- Longitude
- Elevation

Secondary characteristics are calculated though the primary ones:
- Length of each track piece
- Elevation change
- Distance to this point
- Sin and cos of slope angle

Track data is characterized by having a very large number of parts (more than 10,000 for WSC).

2.2. Energy draw

There are 3 key parts to energy draw:
- Drag force (\( D \))
- Gravitational force (\( W_x \))
- Friction force (\( R \))

\[ T = D + W_x + R \]

Assuming the constant motion, \( T \) is a sum of forces which impede movement of the vehicle.

Amount of energy needed to cover certain part of the route can be calculated as \( \eta \) is an engine efficiency, \( s_i \) – \( i^{th} \) part of the track:

\[ A_T = \frac{T}{\eta} \cdot \Delta s_i \]

Also, there are some operational losses:

\[ A_{op} = \frac{P \Delta s_i}{V} \]

Where \( P \) is an onboard equipment power, \( V \) – speed of the vehicle.

Total energy draw can be calculated as follows:

\[ A = A_T + A_{op} = \frac{T}{\eta} \cdot \Delta s_i + \frac{P \Delta s_i}{V} = \frac{D + W_x + R}{\eta} \cdot \Delta s_i + \frac{P \Delta s_i}{V} \]
If we are considering the non-uniform motion, an additional component of acceleration losses is included:

\[ A_{\text{acc}} = M_{\text{dyn}} \cdot \frac{\Delta \xi}{r} \cdot \frac{1}{\eta} = \left( \frac{\text{mar} + \left( J_{\text{wheel}} + J_{\text{motor}} \right) a}{r} \right) \cdot \frac{\Delta \xi}{r} \cdot \frac{1}{\eta} \]

Therefore, total energy draw will be as follows:

\[ A = \frac{1}{\Delta \xi} \int \left( A_x + A_{dp} + A_{acc} \right) ds \]

2.2.1. Drag force. The drag force depends on vehicle speed (V), atmospheric density expressed through environmental conditions (an air temperature (T), an air pressure (p) and a gas constant \(R_A\)), and aerodynamic characteristics of the solar car: a frontal area (\(S_{\text{front}}\)) and a drag coefficient (\(C_D\))

\[ D = \frac{1}{2} \rho V^2 S_{\text{front}} C_D = \frac{p}{R_A T} \frac{1}{2} V^2 S_{\text{front}} C_D \]

2.2.2. Gravitational force. Gravitational force is calculated through the mass of the vehicle (m) and a sin of a slope of the track (\(\alpha\)).

\[ W_g = mg \sin \alpha \]

2.2.3. Frictional force. Friction force is calculated through two friction coefficients (\(\mu_1\) and \(\mu_2\)), latter of which is multiplied by the speed of the vehicle, a vehicle mass and a cos of a track slope.

\[ R = mg \mu \cos \alpha = mg \left( \mu_1 + \mu_2 V \right) \cos \alpha \]

2.3. Energy income
Energy income can be calculated using several different approaches:
- Statistical approach
- Model approach
- Live weather forecast

Statistical approach uses averaged data from previous years to provide the solar radiation data.

Model approach relies on computing an amount of solar radiation for certain point in time and space [8].

While both statistical and model approach can give you some intel about environmental conditions, weather forecasting will for sure provide more accurate data.

Either way, after obtaining the environmental data we can calculate the possible energy income by using given data and solar panels characteristics (area and efficiency) and integrating the result over time.

2.4. Merging energy income and energy draw
As it was said above, a vector of speed values or torque values acts as an input for the model. It doesn’t really matter which of them is used, as one can be calculated through another for certain electric motor. Using this vector we can calculate the amount of energy needed to pass each part of the route.

Also, since we are using speed as input, and the length of the track pieces is known, a time needed to pass each part of the route is also calculated. After getting the calculated times, we can bond spatial data with time data. This allows us to calculate the power income for every point in time and space.
After the calculation of both parts of the energy balance equation, the overall travel time can be obtained. Energy restrictions can be checked, since the amount of energy for every part of the route was saved. That means two basic checks: \( \min(E) > 0 \) and \( \max(E) < E_b \).

Note that additional features can be added, like charging stops.

On the figure 1 you can see an energy-distance plot of a simulation results. There are three graphs:
- Power use
- Power income
- Total power in system

By looking at them, we can see that car starts with charged battery; vehicle consumes more power, than it gets from the sun, but still makes it to the end of the route without violating the energy restrictions. Spikes in energy income can be seen as a result of pre-programmed charging stops for compliance with WSC rules, when at the start and at the end of the race day vehicle doesn’t move and only charges from the sun.

![Figure 1. Energy(distance) plot of simulation results.](image)

### 3. Optimization

There are several approaches to selecting an optimal power management plan for solar cars, but most of them use heuristics, therefore they all can be improved [9-15].

As the events like WSC, ASC, etc. are all races, the main objective is to finish the event in the least possible amount of time. That means that the time must be the criteria to optimize the model. Taking total time as an output of the model, and a vector of speed/torque values \( S \) as an input, model could be optimized.

\[
f_{\text{time}}(s_1, s_2, s_3, \ldots) \rightarrow \min
\]
But this is the moment when problems start to show up. Since the track itself is split into several thousands of pieces, the input vector for the model will be of the same size. Having to change thousands of parameters during an optimization, the task will be very complex and computationally intensive.

Moreover, to comply with energy restrictions a penalty function was added.

\[
 f_{\text{time Const}}(s_1, s_2, s_3, \ldots) = f_{\text{time}}(s_1, s_2, s_3, \ldots) + k^* \min\left( f_{\text{energy}}(s_1, s_2, s_3, \ldots) \right)
\]

There are several things to be done to ease the task.

3.1. Track pre-processing

The amount of input variables can be greatly reduced by performing a track analysis. Reducing the number of track pieces can be done in several different ways. Track can be simplified based on information of track point’s elevation and distance to the point.

3.1.1. Keep only extremum points. The easiest thing to do is to keep only the extremum points in the elevation-distance representation of the track. By using this method, the number of track pieces can be reduced up to three times. That being said, quality of track representation suffers a lot when using this type of operation.

3.1.2. Merge similar slopes. Slightly more advanced technique is to merge track neighbouring pieces with equal or nearly equal slopes in the same elevation-distance representation by comparing the slope angles. This method can reduce the number of track parts up to two times when using reasonable criteria of similarity, but the track representation quality is a lot better than in the simplest method.

3.2. Optimization workflow

Even with the most extreme track pre-processing, the amount of input variables is still too big for the task to be solved in a reasonable time. To overcome this problem, a hierarchical approach was suggested.

Instead of solving one optimization task with large number of parameters, a set of smaller optimization task could be solved.

![Figure 2. Hierarchical optimization workflow.](image)

For example, processed track consists of M pieces. Instead of running an optimization task on all M inputs, task can be reformulated in a hierarchical way. Input parameters are divided into N groups. M is significantly larger than N. N is selected so that the number of input values for the optimization task remains reasonable. For each parameter in the same group, input value will be the same. That means that input vector will be like \( (s_1, s_1, s_1, s_2, s_2, \ldots, s_N, s_N, \ldots) \) instead of \( (s_1, s_2, s_3, \ldots, s_M) \). When optimizing, all the values in the group change simultaneously, like it is only 1 parameter. Once
optimization on set of \((s1,s2,...,s5)\) is done, the amount of energy at the start and at the end of each group is calculated using the optimized values. Then \(N\) optimization sub-tasks are ran, each in their own group with the start and end energies taken from previous step as a separate optimization task. First subtask is ran on set of \((s11,s12,..s1N)\), second – on set of \((s21,s22,..,s2N)\), etc. Hierarchical optimization process can be seen on figure 2 for \(N=3\).

Also note that optimization sub-tasks are independent, and therefore can be run in parallel, speeding up the whole optimization workflow.

4. Conclusion and future work
An approach was proposed for optimization of the solar car strategy with large number of input parameters without the use of heuristics. Without the hierarchical approach calculations of this accuracy are not likely possible. The vehicle model can be adapted to other types of vehicles, including the optimization by the time or distance criteria. The approach is set to be tested during a solar car racing competition on a basis of a Polytech Solar team.

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