Design of a Solar Car Strategy using Multi-Objective Optimization

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1 Abstract

Due to the limited amount of energy available for a solar car, proper utilization of this energy is critical during a race. On average, a solar car receives just enough energy from the sun to run a household hair dryer. Using this and energy stored in the batteries, typical solar cars can travel over 400 miles a day. In addition, depending on the sun and cloud conditions, the power from the solar array can vary from 100 Watts to 1500 Watts. Such a limited and temperamental source of energy dictates the use of an in-depth and complicated strategy.

This paper will develop an Evolutionary algorithm that can optimize several criteria that are basically in opposition to each other. The best solution will be selected from a pareto-optimal solution set that is created using an evolutionary process that maximizes the performance of a solar car.

2 Keywords

Solar Car, pareto, optimization, multi-objective, multi-criterion, SPEA, ASC, Ultra-efficient, pareto-optimal, non-dominated, irradiance, evolutionary algorithm, mutation, targeting.
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3 Introduction

The University of Missouri–Rolla Solar Car Team is a multi-disciplinary student organization that designs, builds and races vehicles that run on solar energy. A typical solar car consists of a solar array, a battery pack, chassis and a body. The solar array converts sunlight into electricity, the battery pack is used for storing and retrieving energy when needed. The chassis houses the driver, the battery and other components and the body creates an aerodynamic shell in order to reduce drag.

Most solar arrays can produce around 1200 Watts of power, though some teams can purchase expensive arrays that produce as much as 2000 Watts. Considering that an average household hair dryer uses about 1500 Watts, it is easy to see that energy is a very precious and limited resource. In order to overcome this energy-sparse environment, solar cars typically are ultra-efficient. The University of Missouri–Rolla’s 2001 solar car, Solar Miner III, can travel up to 2020 Miles at 42 MPH using the energy equivalent to just one gallon of gasoline.

With such a small pool of energy, every Watt of power is precious. Especially in race conditions, there is hardly any room for error in energy usage. In order to perform its best, the car needs to use as little energy to go as far as possible the entire race. Several factors influence the performance of the car. Internal factors include aerodynamics, rolling resistance, parasitic losses, solar array power and battery characteristics. External factors include solar irradiance, wind, terrain, driving conditions and media stops. All of these factors will be discussed in the following sections.

4 Problem Statement

The objective of a solar car race, like any other, is to win. The car that can travel from the start to the finish line in the least amount of time is the winner. However, there are several rules that effect the race. First, ALL traffic rules must be obeyed since the race takes place on public roads along with usual traffic. The race proceeds only during a specified time of the day. All the cars start at a specified time of the day and travel for a specified amount of time. The cars must not leave the designated race route and must stop at designated media stops for a predetermined period of time.

Due to safety conditions however, the stopping time at the end of each
race day is flexible. If, for example, the designated stopping time is 6:00 PM, the solar car is allowed to stop anywhere between 5:45 PM and 6:30 PM so as to allow the team to find a suitable spot to pull off the road. The remaining or excess time used determines the starting time of the next day. So, if a car stops at 5:55 PM on a certain day and is supposed to start at 8:00 AM the next day, actual racing time starts at 7:55 AM.

How each of these rules effects strategy is discussed in the following sections.

4.1 Reasons for developing a Strategy

Every team must run their car to minimize the amount of time it takes them to reach the finish line. Therefore, on initial review, it would seem that the car with the fastest average speed would win. Would it not be logical, then, to go as fast as you possibly can? The answer lies in the fact that there is a limited amount of energy available. Solar car strategy can compared to the following problem: You are given a car and asked to drive it as far as you can and getting there as fast as you can. However, you are given only one gallon of gasoline. There are two opposing optimization criteria in this problem. First, you are to go as far as you can and second, you must get there as fast as you can. If you decide to increase you speed, you will not go as far because a higher speed uses more energy per mile. If you wish to maximize the distance traveled, you will have to decrease your speed in order to conserve precious gasoline. This simple multi-optimization problem demonstrates the necessity of using a predetermined strategy during a race.

Under realistic conditions however, there are a multitude of factors that play a role in deciding the strategy for any day in the race. Each of these factors can be broadly classified into internal or external factors. Internal factors are inherent to the solar car and typically do not change over time. External factors belong to the environment which can possibly change over time or due to earlier decisions made in the strategy.

4.2 Internal Factors

An important part of any strategy deals with understanding the problem space. In the case of a solar car, several components of the car itself contribute to determining a strategy. Different components use varying amounts
of energy depending on basic properties of the car and external factors that influence the behavior of the car.

### 4.2.1 Aerodynamics

In a typical automobile, the majority of the fuel’s energy is lost in the process of the car slicing through air as it travels down the road. Solar cars are no exception. This is the reason why most solar cars have an ultra-streamlined shape.

Aerodynamic loss is less important at slow speeds, but is a significant power loss at any speed above 25 MPH.[Carroll] The fundamental equation that represents aerodynamic drag is given by Eq.1

\[ P_A = \frac{1}{2} \rho V^3 AC_d \]  

where \( P_A \) is the power (Watts) lost due to aerodynamic drag force, \( \rho \) is the density of air in \( kg/m^3 \), \( V \) is the speed of the car in \( m/sec \) and \( AC_d \) is the drag area of the car.[Tamai] Typical, \( AC_d \) for a solar car is about 0.1 to 0.15\( m^2 \). This however will be determined empirically.

The density of air varies with altitude by Eq.2

\[ \rho = -3.64 \cdot 10^{-14} h^3 + 3.88 \cdot 10^{-9} h^2 - 1.1 \cdot 10^{-4} h + 1.17 \]  

where \( h \) is the height above sea level in feet.

Notice that the power used by the solar car varies as the cube of its speed. This means that at high speeds, there is a substantial increase in power consumed with a minimal increase in speed. This is the reason why aerodynamics becomes critical at speeds above 25 MPH.

### 4.2.2 Rolling Resistance

Energy is lost as the tires compress and decompress when rolling along the road. Rolling resistance accounts for most of the resistive drag force on the car at low speeds and a significant portion at high speeds. The equation for power lost due to rolling resistance is given by Eq.3

\[ P_R = 1.99 \cdot C_{rr} \left[ 1 + \frac{V}{100} \right] WV \]  

where \( P_R \) is the power, in Watts, lost due to rolling resistance, \( C_{rr} \) is the rolling resistance coefficient, \( V \) is the speed in MPH and \( W \) is the weight in pounds.[Tamai]

6
4.2.3 Solar Array

Once the race starts, the solar array is the only source of energy that the car can receive. It is important to maximize the energy produced by the solar array. A typical array produces around 1200 Watts. However, the power output varies depending on the time of the day, location on the earth, location of the sun with respect to the Zenith (Normal to the surface), altitude and most important of all – cloud conditions.

There are two configurations of the solar array. While under driving configuration, the solar array is at a constant angle with respect to the Zenith. This condition exists during most of the day. While traveling down the road, the solar car is not allowed to tilt the array so its stays relatively parallel to the ground. While under charging configuration, the entire array is tilted towards the sun so the solar array is at a constant angle with respect to the sun.

As the sun travels from one horizon to the other throughout the day, sunlight has to travel varying distances before it reaches the ground. Therefore the amount of power no only depends on the angle between the solar array and the sun but also depends on the angle between the Zenith and the sun. This power is represented by Eq.4 [Carroll]

\[ P_{Array} = P_{max} \cos(\theta) \left( \cos(\phi) \right)^{0.3} \]  \hspace{1cm} (4)

where \( P_{Array} \) is the power output of the array in Watts, \( P_{max} \) is the power produced by the solar array at high noon. \( \theta \) is the angle between the solar array and the sun. \( \phi \) is the angle between the sun and the Zenith which is calculated by Eq.5 [Carroll]

\[ \phi = \frac{\pi}{2} - \left( \frac{\pi}{2} - \phi_N \right) \sin \left( \frac{\pi}{2} - \frac{SR}{DL} \right) \]  \hspace{1cm} (5)

where \( T \) is the current time in military digital (ie. 3:15 PM = 15.25), \( SR \) is the sunrise time in military digital, \( DL \) is the length of the day in military digital time. \( \phi_N \) is the angle of the sun from the Zenith at high noon. \( \phi_N \) is calculated using Eq.6 [Carroll]

\[ \phi_N = Lat - 23.5 \sin \left( \frac{\pi}{182.5} \left( \frac{D - 82}{182.5} \right) \right) \]  \hspace{1cm} (6)

where \( Lat \) is the current latitude in degrees North and \( D \) is the current day of the year(0...366)
While charging, $\theta$ can be approximated to zero as the array is directly pointed toward the sun. Therefore, under charging conditions, the array power output can be approximated to Eq.7 [Carroll]

$$P_{Array} = P_{max} (\cos(\phi))^{0.3}$$

(7)

4.2.4 Battery

If the solar array produces more energy than the car is currently using, this energy is stored in the battery pack. On the other hand, if the solar array is not producing enough energy to go the desired speed, energy is drawn from the battery pack. However, batteries are not 100% efficient and therefore it is desirable to use all the energy from the solar array immediately. The percent change in battery charge is calculated by Eq.8 [Carroll]

$$%C = \frac{PT}{\left( \frac{C}{n^{1/n}} \right)} \cdot 100\%$$

(8)

where $%C$ is the change in battery charge percentage. $P$ is the power drawn in Watts, $T$ is the time period of draw in Hours, $C$ is the Capacity of the battery pack in $Watt \cdot Hours$ and $n$ is the Peukert number for the battery pack.

Therefore, the resulting battery charge percentage can be calculated by subtracting the initial percent charge by the change in percent charge.

4.2.5 Motor Drive System

Solar cars generally use a DC brushless electric motor. These are considerably more efficient than the brushed ones. Moreover, the motor is directly mounted on the wheel so as to eliminate any frictional losses involved in a belt or gear drive train. In general the motor used by most solar car teams is up to 94% efficient. The efficiency does vary with respect to speed but at the time of writing this document, no equation is known that describes this relationship.

4.2.6 Parasitic Losses

There are other components in a solar car that use energy. These include, cooling fans for battery ventilation and electrical equipment, rear vision cam-
era and display as well as $I^2R$ losses in the form of heat through connecting wires.

4.3 External Factors

External factors play an important role in Solar Car racing. Unlike internal factors, external factors cannot be controlled and usually require some sort of probabilistic prediction. These factors need to be continually updated and re-calculated in order to model the car with any desired degree of accuracy.

4.3.1 Irradiance

Irradiance is the amount of sun’s energy per square meter reaching the surface at any given time. It is usually measured in $W/m^2$. Irradiance determines the energy that the solar array provides. It depends on location of the sun, cloud conditions and altitude. Given a certain location on earth and a certain time of day, it is possible to calculate the position of the sun and look up altitude. However, calculating the cloud conditions exactly is impossible. One solution to this problem is to periodically update predicted cloud conditions for the entire day for various points on the race route. A problem with this approach is that the route sometimes follows desolate areas of the country where weather data might be out of reach for long periods of time.

If we do have all the data, we still need to develop a model that maps all the environmental conditions to an irradiance value. This can be done using an Artificial Neural Network. With the multitude of information available on weather conditions and measured irradiance for several years now, it is possible to train a Neural Network to predict, with relative accuracy, solar irradiance at some location.

4.3.2 Wind

The velocity (speed and direction) of wind effects the aerodynamic performance of the car. Generally, the effect of wind is determined by the component of its velocity along the direction of the car’s travel. For example, if the car is traveling at 50 MPH and there is a head wind of about 5 MPH, then the loss in to aerodynamic power would be as though the car was traveling at 55 MPH. At speeds above 40 MPH, this results in a major change
in total power loss since aerodynamic power loss is proportional to the cube of velocity!

As in the case of irradiance, one approach would be to periodically update wind velocity predictions throughout the day for various points along the race route.

4.3.3 Terrain

Change in altitude affects the strategy because the solar car, like any other, requires more energy to travel up-hill when compared to traveling on a flat surface. Moreover, since aerodynamic forces always act in the opposite direction of velocity, the energy lost due to climbing up a hill is always greater than the energy gained from rolling down the same hill. The route varies dramatically in altitude with the highest location being over 7000 ft. and the lowest being at sea-level.

Almost the entire race route has been geographically mapped using GPS data and so we have altitude at any given point on the race. Therefore there is no prediction factor associated with terrain. The power loss due to change in altitude can be approximated using Eq.9

\[ P_G = (1.99)WVsin(\theta_G) \]  

(9)

where \( P_G \) is the power lost due to the incline, \( W \) is the weight of the car in pounds, \( V \) is the speed in MPH and \( \theta_G \) is the angle of incline.

4.3.4 Driving conditions

Driving conditions include speed limits, road conditions and traffic. Though speed limits and road conditions can be acquired before hand, it is difficult to predict traffic conditions. Road conditions affect the power losses due to rolling resistance and speed limits define the maximum speed at various locations. Speed limits are important to strategy because the energy saved by going slower at one point due to speed limits needs to be effectively used elsewhere where speed limits are not a concern.

4.3.5 Media stops

According to race rules, every car is required to stop at designated ‘Media Stops’ for a half hour. This helps foster awareness among the public about
solar technology. Since the car is allowed to charge at a media stop, it is beneficial to have plenty of sun when at a media stop. 

In order to effectively calculate the time of arrival at a media stop, all the speeds prior to it have to be taken in to consideration. While at a media stop, the speed of the car is 0 and the car is in charging configuration.

4.4 Optimization Criteria

Once we are able to calculate the performance of the solar car given any scenario, we need to optimize the speed so as to maximize performance. The following are the yard sticks used to judge performance:

4.4.1 Battery charge

At the beginning of the day, the strategist decides the percentage of battery charge that is needed at the beginning of the next day. A strategy that results in an end battery charge close to or equal to the desired end battery charge would certainly be more desirable than one that is farther away from the desired end battery charge. Therefore, a strategy that minimizes the difference between desired and actual end battery charge is desirable.

4.4.2 Distance

Any strategy’s goal should be to maximize the distance traveled using the same amount of energy. This is usually done by keeping the speed as high as possible and relatively constant through the entire day.

4.4.3 Battery used per Distance

As seen in the earlier sections, different speeds use different amounts of energy. Calculating the battery percentage used per distance traveled determines the efficiency of the strategy. The lower the battery used per distance, the more efficient the strategy. Since charging and discharging the battery is not 100% efficient, a strategy that uses as much of the energy as possible from the array immediately would be better than one that stores the energy and uses it later. This is done by traveling faster during better sun conditions and slower during worse sun conditions through the day.
It is easy to see that the various optimization factors are in opposition to each other. For example, traveling faster increases the distance traveled but also uses more battery and decreases battery used per distance. traveling slower might lower the battery used per distance but also might end up using less battery then desired and not traveling too far. This is a classic case of a multi-optimization problem.

5 Solution development

The objective of the project is to determine the speed that the solar car must travel at any given time during the day so that it is able to travel the greatest distance while not using too much energy. The resultant output would consist of speeds that the car must travel given in user defined intervals. It must also output the most advantageous place and time to stop at the end of the day so as to maximize the gain in solar energy for the next day.

5.1 Multi-objective approach

Unlike some problems, which have a single attribute that we would like to optimize, in solar racing we have to optimize on more than one criteria. Such problems are called Multi-objective or Multi-criteoon problems. In this case, while the algorithm is trying to maximize the distance traveled per day, it is also trying to use a predetermined amount of energy. In Multi -objective problems, there are trade-offs that occur in order to gain the best result. A technique of handling multi-objective problems is called the Strength Pareto technique.[Zitzler 1999]

5.2 Domination and Cover

In contrast to fully order scalar search spaces, like single objective problems, multidimensional search spaces are only partially ordered.[Sbalzarini] In such cases, two solutions are related to each other in only two ways– one solution dominates the other or neither solution is dominated. In a solar car strategy, the criteria for fitness are distance traveled and the difference between end battery percentage and end battery percentage goal, also called the end battery error.
A strategy $a$ is said to dominate another strategy $b$ if $a$ results in a greater or equal distance traveled than $b$ and the end battery error for $a$ is less than or equal to that of $b$ with an additional condition that at least one of the two criterion in $a$ must be better than $b$. This is represented as $a \succ b$. If neither $a \succ b$ nor $b \succ a$ then we say that neither strategy is dominated.

Additionally, we say that $a$ covers $b$ if and only if $a \succ b$ or they both result in the same distance traveled with the same end battery error. This is represented as $a \succeq b$.

5.3 Pareto Sets

A strategy $a$ is said to be nondominated with respect to a set of strategies $X$ if and only if there exists no other strategy in $X$ that dominates $a$. [Sbalzarini]

Let set of all strategies currently being considered be $S$. A element $a \in S$ is called Pareto-optimal if it is nondominated regarding $S$. The set of all Pareto-optimal elements in $S$ is called the Pareto-optimal front with respect to $S$ or Pareto front.

5.4 The Strength Pareto Approach

The Strength Pareto Evolutionary Algorithm (SPEA) was first proposed by Zitzler & Thiele [Zitzler 1999]. It is based on the principles of Pareto-Optimality and dominance presented earlier. The algorithm was slightly modified and implemented as shown below.

1. Generate an initial population based a normal Gaussian number with mean and standard deviation defined by the user. Add them to $S$.
2. Calculate the fitness of each individual in $S$.
3. Select individuals from $S$ for reproduction.
4. Create children using individuals selected.
5. Mutate the children created.
6. Add all children to population.
7. Calculate the fitness of each individual in the population.
8. Use competition to eliminate individuals with low fitness.
9. If maximum number of generations is reached, then stop, else go to step 3.

In step 3 and step 7, a scalar value is assigned to fitness in the following manner.

1. Copy all nondominated strategies of $S$ to a new set $S'$

2. Remove any strategy in $S'$ that is covered by any other strategy in $S'$.

3. Each solution $i \in S'$ is assigned a strength $s_i \in [0, 1) = \frac{n}{N+1}$ where $n$ is the number of strategies in $S$ that are covered by $i$ and $N$ is the size of $S$.

4. The fitness of a strategy $j \in S$ is calculated by summing the strengths of all strategies $i \in S'$ where $i \succeq j$ and one.

$$f_j = \sum_{i, i \succeq j} s_i, f_i \in [1, \infty)$$

(10)

5. The fitness of each strategy $i \in S$ is scaled by an efficiency factor $\varepsilon$ where

$$\varepsilon_i = \frac{EndBatteryError_i}{Distance_i}$$

(11)

Note that fitness of an individual is to be minimized.

Given any generation, the *pareto front* is defined by all the elements in $S'$.

5.5 SPEA with Targeting

Using SPEA, it is possible to converge on the entire Pareto Front for any given problem space. However, we might have certain targets for any of the objective functions. For example, for a solar car strategy, we want the difference between the end battery percentage goal and actual end battery percentage to be zero. It is possible to ‘pressure’ the algorithm to favor individuals closer to the target. This is done by scaling the fitness values for every individual in the population by some power of its distance from the target.[Sbalzarini]

$$f_i = f_i \cdot D_i^q$$

(12)

$D_i$ is the distance of individual $i$ from the target. Parameter $q$ determines the ‘pressure’ exerted towards selecting individuals closer to the target. A low value for $q$ applies less pressure whereas a high value for $q$ applies more pressure.
5.6 Evolutionary Algorithm details

Any evolutionary algorithms consists of initialization, evaluation, selection, mutation and competition. These implementation details are presented below:

5.6.1 Initialization

There are two sets of parameters involved. One determines the behavior of the evolutionary algorithm while the other determines the behavior of each strategy(individual) in the algorithm. The user inputs the following evolutionary parameters from a file:

Pop size: Size of population.(any positive integer)

Child size: Number of children produced. (any positive integer)

Selection Rate: Initial selective pressure. ((0,1])

Selective Pressure: Scale value for initial selective pressure. ((0,1])

Max Generations: Maximum number of generations to be performed.(any positive integer)

The user inputs the following strategy parameters from another file:

Current Time: The current time from which the strategy will begin. It is given in military time.([0,24])

Interval: The time period for each interval for which the strategy is implemented.((0,24])

End Time: The time at which each race day ends in military time.((0,24])

Current Battery: The current percentage of charge left in the battery.([0,100])

End Battery: The percentage of charge to be left in the battery at the end of the day.([0,100])

Minimum Speed: The minimum speed that the car can travel during the day.([0,65])

Maximum Speed: The speed that the car should not exceed during the day.([0,65])
Speed filter: Speed increments which should be considered. This makes speed a non-continuous value as it must be always divisible by the speed filter.([0,65])

Variance: Used in generating a normal random number.(any float)
Seed Speed: Used to generate speed values for initial population.([0,65])

Each strategy is an array of speed values. The size of the array is the number of intervals it takes to go from start time to end time. Each speed in this interval is initialized to a normal random number with mean and variance determined by the user-defined seed speed and variance. Using the solar car model, the distance traveled and end battery charge are calculated.

5.6.2 Evaluation
The population is evaluated using the algorithm discussed earlier. Then the strategies are arranged in decreasing order of fitness. Therefore, the fittest individual will be at the beginning of the array of population.

5.6.3 Selection
The selection process is determined by selection rate \( \eta \) and selective pressure \( \mu \) as follows

1. Look at each individual in the order of the population array.
2. Generate a random number \( r \in [0, 1] \).
3. if \( r \leq \eta \)
   
   (a) Select the current individual for parenthood.
   (b) set \( \eta = \eta \mu \)

5.6.4 Reproduction
A new child is produced from two parents. Both parents must have the same current time, end time, initial battery charge, interval, end battery goal and speed filter. The speed for each interval in the child is randomly selected from one of the parents. This produces a uniform crossover.
5.6.5 Mutation

All the children are subject to mutation. Each interval is given a new speed based on a normal random number with mean equal to the old speed and variance predefined by the user. Then the distance traveled and the end battery percentage is calculated.

5.6.6 Competition

Both the population and newly produced children are put in an array in increasing order of fitness value. Thus the best individuals are at the beginning of the array. Then the best individuals based on pop size are taken into the next generation. The rest are discarded.

6 Experimental results

The following experimental conditions were used for the evolutionary algorithm:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>popsize</td>
<td>100</td>
</tr>
<tr>
<td>childsize</td>
<td>25</td>
</tr>
<tr>
<td>selection rate</td>
<td>0.1</td>
</tr>
<tr>
<td>selective pressure</td>
<td>0.9</td>
</tr>
<tr>
<td>max generations</td>
<td>200</td>
</tr>
</tbody>
</table>

The population was initialized using the following parameters:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting time</td>
<td>9.0</td>
</tr>
<tr>
<td>Ending time</td>
<td>17.0</td>
</tr>
<tr>
<td>Interval</td>
<td>0.5</td>
</tr>
<tr>
<td>Current battery %</td>
<td>100.0</td>
</tr>
<tr>
<td>End battery % goal</td>
<td>50.0</td>
</tr>
<tr>
<td>Minimum speed</td>
<td>0</td>
</tr>
<tr>
<td>Maximum speed</td>
<td>65</td>
</tr>
<tr>
<td>Speed filter</td>
<td>0.5</td>
</tr>
<tr>
<td>Seed speed</td>
<td>40</td>
</tr>
</tbody>
</table>
6.0.7 Targeting

Targeting plays a crucial role in finding the absolute maxima. Though the SPEA algorithm finds the entire Pareto-Front, we clearly are not interested in strategies that do not use the required amount of battery capacity. Therefore we pressure the algorithm to find strategies along the Pareto-Front that result in the difference between battery used and battery usage goal to be close to zero. In Figure 1, the graph on the left shows the population when no targeting is applied. The population is spread out evenly along the pareto-front. At the bottom-left of the front we have individuals who are closer to the end battery goal but do not travel as far. At the top-right, we have individuals who travel farther but use more battery capacity.

The graph of the right has more individuals on the pareto-front closer to the desired target of zero difference between battery usage and battery usage goal. Here the distance \( D \) is the difference between battery usage and battery usage goal and the it is raised to the power \( q = 0.05 \). If the value of \( q \) is increased more of the elements on the pareto-front will be closer to the target.

(a) No target  
(b) Target: Battery error = 0

Figure 1: Effect of targeting
6.0.8 Pareto-front size

The Pareto-Front of each generation determines the progress of the evolutionary algorithm. When the population is initially created, there are few elements on the Pareto-Front. However, soon many of the individuals take positions along the Pareto-Front. At this point, few of the maxima have been found, therefore, the Pareto-Front is huge and very volatile. As the number of maxima found begins to increase, the number of individuals that are not dominated by any of the maxima decreases and hence the size of the Pareto-Front decreases.

![Pareto-Front size](image)

Figure 2: Number of elements on the Pareto-Front

From Figure 2, we see that there are only one or two individuals on the pareto front for the first ten or so generations. In the next 20 generations, this number rockets to almost 50. This is when most of the problem space has
been explored and the individuals begin to converge on the maxima. After
about 30 generations, the size of the pareto-front begins to gradually decrease
until it stabilizes at about 15. This is when most of the population has
converged to a couple of maxima and are fighting for the absolute maximum.

6.0.9 Population convergence

The effects of targeting can also be seen by looking at snapshots of the entire
population at regular generations. As expected, in the beginning, the popu-
lation is random and is spread out far and wide. As the evolution progresses,
the population moves towards its targets until they reach a maxima. It is
important to note in this case that though individuals may be approaching
the same maxima in distance and minima in battery error, they have a dif-
frent set of speeds. This ensures that the population is diverse enough and
does not converge to the same solution.

In Figure 3, we can see that after 40 generations, the population is still
relatively unfit. After 80 generations, the population begins to converge
on the best fitness and almost all of the individuals have high fitness (as
they travel further and are still close to the result battery goal). Plots of
generation 120 and 200 show the population to be almost entirely converged
on the target.

Once the evolutionary algorithm finishes running, the individual that has
the highest efficiency would be the best strategy. Efficiency here would be
calculated as distance traveled divided by battery percentage used.

7 Conclusions

From our experimental results, we can see that the Strength Pareto Evo-
olutionary Algorithm produces excellent results for the multi-optimization prob-
lem of a Solar Car Strategy design. Since the entire pareto population is being
found, there is a higher probability that the population is diverse and that
more peaks can be examined at the same time. However, one short-coming
of the SPEA is that though the population begins to converge to the maxima
quickly, it takes time to find the absolute maximum. This would mean that
in order to find it, more generations are required.
Figure 3: Location of each individual in the population at various generations
8 Future plans

Now, we know that an SPEA can be used to find an excellent strategy for a solar car. However, this is dependent on the quality of our model of the solar car. Accurately modeling the solar car is crucial for the strategy to be useful. After all, the entire model could just be that of an ostrich for all we know. Then the strategy would be of no use whatsoever. Therefore, the next step is to record the characteristic of the car and then adjust the model so that it actually describes the behavior of the solar car. Once this is done, the strategy will be ready to undergo a full scale test. This can be done via several practice runs and evaluations. Only then will the strategy be used in the American Solar Challenge.

References


