

Alternative Voting Systems in Stock Car Racing

Daniel Eric Smith
Mathematics
Jacksonville State University
desmith@jsu.edu

Aaron Garrett
Computer Science
Jacksonville State University
agarrett@jsu.edu

Abstract

The National Association for Stock Car Auto Racing (NASCAR) is currently the No. 1 spectator sport in the United States. However, the manner in which drivers are ranked to determine the final winner of the championship relies on a somewhat arbitrary point assignment, including bonuses and penalties. In this work, we compare the results of alternative voting methods to determine NASCAR rankings for the Sprint Cup Series. Each of these methods have desirable theoretical properties, and all make use only of the final placement of each driver in each race. We then construct a set of metrics to determine the effectiveness of each of these voting methods when compared to one another and the actual NASCAR scoring system. Finally, we attempt to generate more optimal methods, as defined by those same metrics, using a real-coded genetic algorithm. Our results show that most of the alternative voting methods vastly outperform the actual NASCAR system in terms of those metrics. Likewise, the methods produced by the genetic algorithm outperform even the best of the alternative methods.

1 Introduction

The National Association for Stock Car Auto Racing (NASCAR) is currently the No. 1 spectator sport in the United States [21]. NASCAR consists primarily of three series — the Craftsman Truck Series, the Nationwide Series, and the Sprint Cup Series. At the end of each season, each series crowns a champion. For the Sprint Cup Series, the manner in which a champion is crowned relies on a somewhat arbitrary point assignment, including bonuses and penalties [20].

From 1949 to 1975 NASCAR tried several points systems to determine the champion. One system consisted of two parts. First they assigned 10 points to first place, 9 points to second place, etc. Then these points were increased by 5% of the race purse (i.e., monetary winnings), which may have been different for each race [2]. Other systems counted mileage in addition to assigning points for the drivers finishing position, which would often have been different for each race [2]. Due to the problems with the complicated points system just described, in 1974 NASCAR asked statistician Bob Latford to design a new

points system [17]. His system assumed a maximum field of 54 racers. The first-place driver received 175 points, and each subsequent driver in the top five positions received 5 fewer points than the next highest-ranked driver. The drivers in sixth through tenth place received 4 fewer points than the driver who placed one position ahead of them. From eleventh place until the end of the field, drivers are separated from the next highest-ranked driver by 3 points. The following sequence illustrates this point assignment:

$$175, 170, 165, \dots, 155, 151, 147, \dots, 135, 132, 129, \dots, 3.$$

This points formula also included 5 bonus points for drivers who led at least one lap during a race and an additional 5 bonus points for the driver who led the most laps. This bonus point system was included to encourage drivers to drive more competitively throughout the race so as to make the race more exciting for the spectators [17].

It is relatively common for race teams to violate NASCAR's rules and regulations, either intentionally or unintentionally. With the introduction of the Latford point system, NASCAR dealt with infractions by a monetary fine for the race team. However, the amount of the fines were small in relation to the teams' winnings per race and sponsor revenue, and thus they served as only a minor deterrent [1]. To deal with this, starting in 2002 NASCAR added points penalties on top of the monetary fines [1]. These penalties are deducted from a driver's total points for the season, making it more difficult to win the championship.

In 2004, the Sprint Cup Series season was divided into two segments in order to generate fan excitement. The first 26 races comprise the "Race to the Chase," and the last 10 races are called the "Chase for the Cup" (or simply "the Chase"). For the 2008 season, the twelve drivers with the most points at the end of the first 26 races are entered into the Chase. These twelve drivers have their points adjusted so that each begins the Chase with exactly 5000 points, which ensures that all drivers in the Chase finish above the remaining drivers. Additionally, for every win during the first 26 races, that driver receives an additional 10 points, which rewards drivers for wins during the first part of the season and allows some distinction at the beginning of the Chase.

In an effort to more appropriately reward drivers, the point system has been adjusted several times. As of the 2008 season, the points distribution is as follows: the first place driver receives 185 points, second place receives 170 points, and then the points are reduced by 5 for the next 4 positions. The points drop by 4 for the next 5 positions, and then by 3 for the remaining positions. This sequence is illustrated below:

$$185, 175, 170, \dots, 150, 146, 142, \dots, 130, 127, 124, \dots, 34.$$

The bonus/penalty rules are the same as were described above.

At the end of the season, the driver with the most points is declared the champion. Using the Chase format, it is impossible for a driver who does not make it into the Chase to win the championship. However, all drivers have a

vested interest in competing in every race because all qualifying drivers win a portion of the purse.

In order to study and understand the results from the Spring Cup Series, it is possible to consider NASCAR's season as a voting system. In this system, the drivers represent the alternatives (or candidates), and each race is treated as a voter that ranks the drivers according to their finishing position. In this work, we attempt to evaluate NASCAR's voting system in comparison to other well-known systems which have desirable mathematical properties. We also investigate whether it is possible to devise a more optimal ranking to determine the NASCAR champion.

The remainder of the paper is organized as follows. Section 2 provides the definition of a voting system and discusses specific types, many of which will be considered in this work. Section 3 presents the experimental setup and defines the metrics used to compare the voting systems. In Section 4, we describe and analyze the results of the experiments. Finally, in Section 5 we present our conclusions.

2 Voting Systems

A *voting system* consists of two parts: a ranking of the candidates by the voters and a rule for using those rankings to determine the outcome [7]. In this work, the method of ranking alternatives remains constant for all voting systems. Therefore, we will often use the term "voting system" to refer more specifically to the voting rule mapping rankings to outcomes.

Let $N = \{1, 2, \dots, n\}$ be the set of voters and A be the finite set of alternatives, $|A| = m$. Each voter i ranks the alternatives in A from most preferred to least preferred using a *weak preference ordering*, denoted by \succsim_i . In this way, if voter i prefers alternative x to y , we write $x \succsim_i y$.

In order to have a rational ranking of the alternatives, the weak preference order is required to be complete and transitive [23]. We can derive a strict ordering and an indifference relation from the weak ordering. The strict ordering for voter i is denoted by \succ_i and the indifference relation is denoted by \sim_i .

Each voter has an individual preference order that ranks all the candidates. Let call voter i 's individual preference order p_i . So $p_i = a_{j_1} \succsim_i a_{j_2} \succsim_i \dots \succsim_i a_{j_m}$. The collection of the individual preference orders of the voters is called a profile, $\mathbf{p} = (p_1, \dots, p_n)$. Denote the set of all profiles by P .

There are two types of rules (or voting systems) we will consider: social welfare functions and social choice functions. Our definitions of these functions follow [23].

Definition 1 (Societal Preference Order) *A societal preference order is a complete, transitive, weak preference order of the alternatives that reflects the collective will of the voters under a given voting rule.*

Let R be the set of all societal preference orders of the alternatives in A .

Definition 2 (Social welfare function) *A social welfare function is a mapping $f : P \rightarrow R$.*

Definition 3 (Social choice function) *A social choice function is a mapping $f : A \times P \rightarrow 2^A$.*

Recall that 2^A is the power set of A . Note that one difference between social welfare functions and social choice functions is that social welfare functions return a complete transitive ranking of the alternatives and a social choice function returns a set of “best” alternatives.

Perhaps the most obvious social choice function is the pairwise voting method [6]. In pairwise voting, each alternative is compared to every other alternative using the simple majority rule. If an alternative defeats every other alternative, then it is declared the winner. While simple to understand, this method can suffer from the problem of *cycles*. A cycle is an intransitive ranking of the alternatives [23]. The simplest cycle involving the three alternatives a, b, c is $a \succ b$, $b \succ c$, and $c \succ a$.

We applied the pairwise voting method to the NASCAR 2008 season results. This approach resulted in cycles and was therefore abandoned in favor of voting methods that were social welfare functions. The social welfare functions we considered can be divided into two types: Condorcet methods and scoring functions [23].

A *Condorcet winner* is an alternative that defeats all other alternatives in pairwise comparisons. Any method that chooses the Condorcet winner, when it exists, as the winner of the vote is called a *Condorcet method*.

A scoring function, on the other hand, is defined as follows. Let every voter have a strict individual preference order¹ Each alternative receives s_j points for each voter who ranked it in j th place in that voter’s individual preference order. The points for each alternative are summed, and the alternative is ranked according to its total points in the societal preference order, where more points corresponds to higher rank. The only condition that the s_i ’s must satisfy is

$$s_1 \geq \dots \geq s_n, \quad s_1 > s_n.$$

2.1 Condorcet Methods

Define the *pairwise matrix* $P = (p_{ij})$ such that p_{ij} represents the number of voters who prefer alternative i to alternative j . Also, define the *matrix of majorities* as $M = (m_{ij}) = P - P^T$.

2.1.1 Maximin (MM)

Let $\hat{m}_i = \min_j m_{ij}$ be the row minimum for row i . The alternatives (which may be singular) with the i^{th} largest row minima are ranked in (or tied for) i^{th} place.

¹In the case of modern NASCAR racing, this criterion is satisfied because it is essentially impossible to have a true tie at the end of a race.

2.1.2 Ranked Pairs (RP)

Find the largest and second largest entries in M . Add these ranking to an initially empty directed graph G where the vertices represent the candidates and the edges represent the relationship “has greater majority than”. Find the next largest entry and add the ranking to G . If this creates a cycle discard this ranking. Continue on through the entries from largest to smallest, repeating the process of adding rankings and checking for cycles.

If at any step in the process of adding alternatives to the graph we encounter a tie in M , we follow the following procedure. Randomly select a voter’s individual preference order and use this ranking to resolve the tie. If the alternatives are tied in the selected individual preference order discard this individual preference order and select another voter’s individual preference order. Continue the process of selecting individual preference orders until the tie is resolved. If, after using all voters individual preference orders, the tie has not been eliminated, randomly select one of the alternatives as the winner [26].

2.2 Scoring Function Methods

2.2.1 Simplified NASCAR Voting System (SNV)

This method is the same as NASCAR’s actual method except all bonuses and penalties are ignored, along with the Chase format. This means that all 36 races have equal weight.

2.2.2 Reduced Simplified NASCAR Voting System (RSNV)

This method is the same as the simplified NASCAR system above except the points are linearly adjusted so that last place receives only 3 points, rather than 34. As mentioned in the Introduction, the original point distribution was based on the fact that there could be up to 54 drivers in a race. In modern NASCAR races, the number of drivers per race is fixed at 43. So, from a historical perspective, this seems to be a valid alternative points system.

2.2.3 Borda Count (BC)

In this method, the alternative ranked in first place is assigned 43 points, with each place decreasing by 1 point until the last place alternative, who receives only 1 point. It is important that last place receive at least 1 point because it allows a differentiation between last place and those who receive no votes (i.e., those who fail to qualify), all of whom receive 0 points.

2.2.4 Nauru Borda Variant (NBV)

In this method, the scoring vector is constructed such that the i^{th} place candidate receives $1/i$ points. All candidates who receive no votes likewise receive 0 points.

2.3 Properties

Many different voting systems have been devised over the years. In order to compare these different systems, various properties have been proposed that are generally considered to be desirable in a voting system. We consider nine of the most important of these properties below. In this work, we require each voting system under consideration to satisfy the first five properties, while the remaining four are optional. Table 1 classifies each voting method according to whether it satisfies these optional properties.

2.3.1 Required Properties

Property 1 (Anonymous) *A voting system is anonymous if, in the event that any two voters swap ballots, the societal preference order does not change.*

The Anonymity property ensures that the voters are treated equally by the voting system.

Property 2 (Neutral) *A voting system is neutral if, in the event that every voter swaps alternatives x and y in their individual preference order, then x and y are swapped in the societal preference order.*

The Neutrality property ensures that the alternatives are treated equally by the voting system.

Property 3 (Monotone) *Suppose that for a given profile \mathbf{p}_1 candidate x is ranked in the i^{th} spot. Let \mathbf{p}_2 be the same as \mathbf{p}_1 except some voter has moved x up in their individual preference order. A voting system is monotone if the ranking of x is at least i using profile \mathbf{p}_2 .*

The Monotonicity property ensures that, if an alternative receives more support, it does not hurt his ranking in the societal preference order.

Property 4 (Non-dictatorship) *There is no voter such that the societal preference order is always the same as his individual preference order regardless of the other voters individual preference orders.*

The Non-dictatorship property ensures that no one voter should be the sole decider of the outcome of an election.

Property 5 (Unrestricted Domain) *A voter can rank the alternatives in any complete transitive order.*

The Unrestricted Domain property allows voters the freedom to rank the alternatives in any rational order.

2.3.2 Optional Properties

Property 6 (Weak Pareto Principle (WPP)) *If every voter prefers alternative x to y , then the societal preference order prefers x to y .*

The Weak Pareto Principle ensures that unanimity among the voters is reflected in the final result.

Property 7 (Condorcet Winner Criterion (CWC)) *If a Condorcet winner exists then the Condorcet winner is ranked first in the societal preference order.*

Definition 4 (Condorcet Loser) *An alternative is a Condorcet loser if it is defeated by all other alternatives in pairwise comparisons.*

Property 8 (Condorcet Loser Criterion (CLC)) *If a Condorcet loser exists then the Condorcet loser is not ranked first in the societal preference order.*

The Condorcet Winner Criterion ensures that an alternative that is preferred in all “head-to-head” contests is also the winner of the full election. Similarly, the Condorcet Loser Criterion ensures that an alternative that is rejected in all “head-to-head” contests cannot be the winner of the full election. These criteria are similar to the Weak Pareto Principle in that they attempt to ensure that “local” unanimity is reflected in the “global” outcome.

In order to define the consistency property we need a definition.

Definition 5 (Choice set) *Let f be a voting system and \mathbf{p} be a profile. The choice set is defined as $C(f(\mathbf{p})) = \{x \in f(\mathbf{p}) : x \succsim y \forall y \in f(\mathbf{p})\}$.*

Property 9 (Consistency) *Let the set of voters, V be divided into two nonempty subsets V_1 and V_2 , $V_1 \cap V_2 = \emptyset$, with profiles \mathbf{p}_1 and \mathbf{p}_2 respectively. Let the profile for the entire set of voters be \mathbf{p} . A voting system is said to be consistent if $C(f(\mathbf{p}_1)) \cap C(f(\mathbf{p}_2)) \neq \emptyset$ then $C(f(\mathbf{p})) = C(f(\mathbf{p}_1)) \cap C(f(\mathbf{p}_2))$.*

The Consistency property essentially states that if voters are split up (arbitrarily) into two groups that each hold separate elections, and if both groups elect the same alternative, then the combined set of voters should also elect that same alternative.

3 Experimental Setup

The results of each race in the 2008 NASCAR Sprint Cup Series are available online at [22]. This information was collected and converted to a MySQL database for ease of processing. The accumulated data was comprised of 36 races (voters) and 71 drivers (candidates). Recall that only 43 drivers compete in each race. This means that the non-competing drivers are all ranked as tied for 44th place for that race.

	WPP	CWC	CLC	Consistency ^a
Pairwise	Y	Y	Y	N
MM	Y	Y	N	N
RP	Y	Y	Y	N
SNV	Y	N ^b	N ^c	Y
RSNV	Y	N ^b	N ^c	Y
BC	Y	N	Y	Y
NBV	Y	N	N ^c	Y

^a See [28].

^b See [6].

^c See [18].

Table 1: Optional properties of voting systems

Each of the voting methods was implemented in Java and designed to operate on two interfaces, presented in Listings 1 and 2, respectively. Each voting method was implemented to take a `List` of `Voter` objects and a `List` of `Candidate` objects and to return a `List` of `Set` objects containing `Candidates` representing the complete, transitive ranking of those candidates, where candidates in the same set are considered to be equivalent (i.e., tied) under the voting system. The implementation for each voting method was tested against a set of hand-solved problems to ensure correctness.

```

public interface Candidate {
    // The id uniquely identifies the candidate.
    // It is used by the voter to determine which
    // candidate is currently under consideration.
    public Object getId();
}

```

Listing 1: The Candidate Interface

```

public interface Voter {
    // When a voter casts a vote, it is essentially
    // providing a ranking of the candidates,
    // 1 to n, where n is the number of candidates
    // and 1 represents "most preferred".
    public int castVote(Candidate c);
}

```

Listing 2: The Voter Interface

3.1 Metrics

In order to compare the different voting methods to one another, a set of metrics was devised. Each metric makes use of a calculated statistic that we believe should correlate well to the final rankings of each driver, given a fair and comprehensive voting system. These statistics help us to measure the driver’s ability to start well, race well, and finish well. There were twelve statistics considered in this work, each of which is outlined below. While all of these statistics are important, it is most important in stock car racing to finish well, followed closely by racing well.

1. Start Well
 - (a) Number of Starts (S)
 - (b) Average Start Position (AS)
 - (c) Number of Poles (P) — A driver wins a pole when they have the fastest qualifying time.
2. Race Well
 - (a) Laps Led (LL)
 - (b) Laps Completed (LC)
 - (c) Quality Passes (QP) — A quality pass is defined as “passing a car running in the Top 15 while under a green flag” [22].
3. Finish Well
 - (a) Average Finish Position (AF)
 - (b) Number of Wins (W)
 - (c) Number of Top 5 Finishes (T5)
 - (d) Number of Top 10 Finishes (T10)
 - (e) Number of Top 15 Finishes (T15)
 - (f) Number of Top 20 Finishes (T20)

For each of these statistics, the linear correlation was calculated between the drivers’ statistic values and their ranks as determined by a voting system. The degree of linear correlation present for each statistic when using the NASCAR rankings can be seen in Figure 1. In this figure, each x-axis corresponds to the driver’s rank under the NASCAR system, and each y-axis corresponds to that driver’s statistic value.

More formally, let V represent the voting system under consideration, and let S be the set of statistics s_i where $1 \leq i \leq 12$. Then a metric $M_{s_i} : V \rightarrow [-1, 1]$ is defined as

$$M_{s_i} = \text{corr}(s_i, R_V)$$

where R_V is the societal preference order for voting system V .

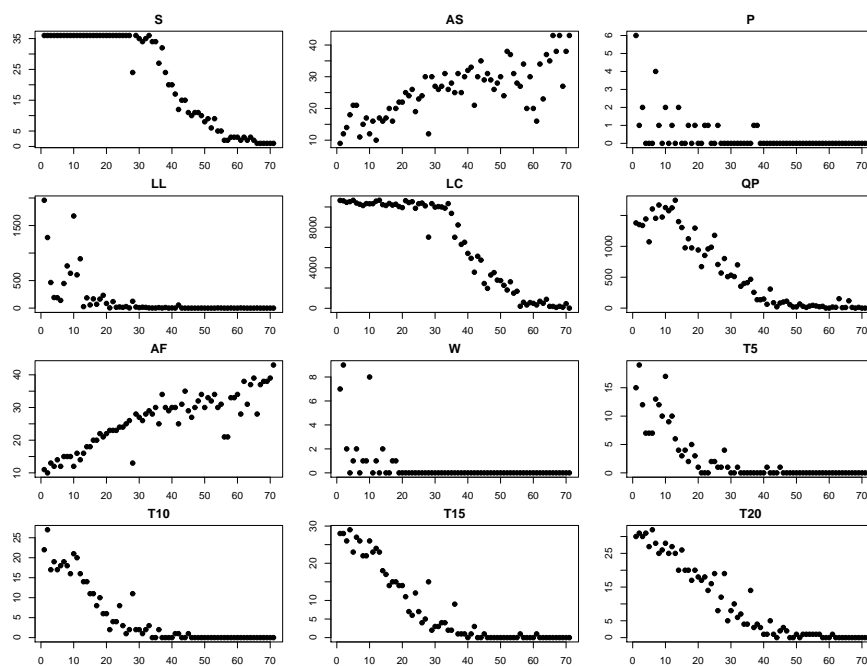


Figure 1: Scatterplots comparing NASCAR rankings (x-axis) to driver statistics (y-axis)

3.2 Evolutionary Optimization

In addition to the seven voting methods (NASCAR, MM, RP, SNV, RSNV, BC, NBV) described above, we were also interested in determining whether a stochastic optimization system could produce a more optimal ranking, where optimality was defined by the mean squared error across the metrics above. Evolutionary computation [9, 11, 12, 25] has been shown to be a very effective stochastic optimization technique [3, 19]. Essentially, an evolutionary computation attempts to mimic the biological process of evolution to solve a given problem [8].

Evolutionary computations operate on potential solutions to a given problem. These potential solutions are called *individuals*. The quality of a particular individual is referred to as its *fitness*, which is used as a measure of survivability [8]. Most evolutionary computations maintain a set of individuals (referred to as a *population*). During each *generation*, or cycle, of the evolutionary computation, individuals from the population are selected for modification, modified in some way using *evolutionary operators* (typically some type of recombination and/or mutation) to produce new solutions, and then some set of existing solutions are allowed to continue to the next generation [12]. Looked at this way, evolutionary computation essentially performs a parallel, or beam, search across the landscape defined by the fitness measure [24, 25].

According to Bäck et al [3], the majority of current evolutionary computation implementations come from three different, but related, areas: genetic algorithms [14–16, 27], evolutionary programming [3, 11, 13], and evolution strategies [4, 11]. Each area is defined by its choice of representation of potential solutions and/or evolutionary operators. For this work, genetic algorithms (GAs) were used to produce two additional final rankings. The first approach evolved a scoring vector that was used to generate a final ranking. The second approach simply evolved the ranking itself.

3.2.1 Evolutionary Scoring Vector (ESV)

When considering scoring vector voting systems such as Borda Count, the components of the scoring vector greatly influence the final outcome. This experiment attempted to evolve a scoring vector, rather than using either the Borda, Nauru, or NASCAR standard vectors. To accomplish this, a real-coded GA [10] was used to evolve a fixed-size population of individuals. Each individual was represented by an array of 71 real values (one value per driver) in the range $[0, 1]$. However, the values for the final 28 elements of this array were fixed at 0 in keeping with NASCAR’s 43-driver race.

The GA used a population size of 50, tournament selection [15] (with a tournament size of 5) for parent selection, steady-state replacement [15], blend crossover [10] with a usage rate of 1.0 and an α value of 0.5, and adaptive Gaussian mutation [8] using the “one-fifth” rule [4] with a usage rate and mutation range of 1.0 and an initial mutation rate of 0.1. The GA was allowed to perform 20000 fitness evaluations in order to produce an optimal scoring vector.

The parameters for the GA were determined experimentally by exhaustively testing all combinations from a small set of parameter values. The parameter values that were tested are shown in Table 2. These values were tested by using each combination of values to create 10 GAs. Each of the 10 GAs was allowed to perform 10000 fitness evaluations to produce an optimal scoring vector. The parameter set that produced the lowest average fitness across its 10 scoring vectors was determined to be the optimal set.

Parameter	Values Tested
Population Size	10, 50 , 100, 500
Tournament Size	2, 5 , 7, 10
BLX- α	0.01, 0.1, 0.25, 0.5

Table 2: Potential GA parameter values (optimal values in bold)

To determine the fitness, each individual was first sorted in descending order (in order to comply with the definition of a scoring vector), and then the sorted values became the scoring vector for all 36 races, producing a final ranking of the drivers. The final ranking was then used in the calculation of the twelve metrics. The mean squared error (MSE) across 9 of those 12 (all but M_{LL} , M_W , and M_P) was calculated and used as the fitness for that scoring vector. Those three metrics were excluded from the fitness calculation because their underlying statistics were not particularly correlated to the rankings in the NASCAR system, which was treated as the standard by which to measure the evolutionary approaches. Therefore, it seemed “unsportsmanlike” to allow the GA to exploit the weaknesses of the NASCAR system.

3.2.2 Evolutionary Ranking (ER)

In addition to evolving a scoring vector, it is also possible simply to evolve a ranking of the candidates. In this case, a random key-based GA [5] was used to evolve a fixed-size population of individuals. Each individual was represented by an array of 71 real values in the range $[0, 1]$ which were used to determine the particular permutation represented by the individual as described in [5].

The GA used a population size of 500, tournament selection (with a tournament size of 7) for parent selection, steady-state replacement, uniform crossover (with a usage rate of 1.0), and Gaussian mutation with a usage rate and mutation range of 1.0 and an initial mutation rate of 0.1. The “one-fifth” rule was also used here to adapt the mutation rate during the evolutionary process. These parameters were determined experimentally through trial-and-error to provide adequate performance.

In order to speed up the search and ensure that the GA had relatively good individuals in the initial population, it was seeded with 12 permutations corresponding to the rankings derived from sorting the drivers according to the 12 statistics. For example, one solution in the initial population would be

composed of the drivers sorted in descending order according to their number of top 5 finishes. The remaining 488 initial solutions were randomly generated. The GA was allowed 5000 fitness evaluations to produce an optimal solution. The measure of fitness used here was the same as that used in the ESV.

4 Results

The six traditional voting methods (MM, RP, SNV, RSNV, BC, NBV) were applied to the 2008 Sprint Cup Series race results. Each evolutionary approach (ESV and ER) was run 21 times due to their stochastic nature. For each run, the MSE across the 9 most informative metrics (as described above in terms of the fitness values and here denoted MSE_9) was calculated. The median for each evolutionary approach (in terms of the MSE_9) was chosen as the representative for comparison to the other eight methods. The median was chosen, instead of the average, because the median across an odd number of runs exists, whereas an average almost certainly would not.

The rankings generated by MM produced 14 groups of tied drivers, with only one driver of the 71 not involved in a tie. All top 10 finishers with MM were split into 4 groups of ties, while the bottom 27 drivers were all tied to one another. While NASCAR has a system in place for breaking ties (relying on wins, top 5 finishes, and top 10 finishes), the sheer number of multi-way ties generated by MM makes it ill-suited as a voting system for NASCAR. Additionally, even using an arbitrary ordering among tied groups, MM performed worst on all metrics except M_{LL} , M_W , M_{T5} , where NASCAR's performance was worst. For these reasons, MM was excluded from the remainder of the analysis. The results of the remaining voting methods in terms of their metric values are presented in Table 3.

4.1 Traditional Approaches

First, it is obvious from Table 3 that there is no metric on which NASCAR wins. Likewise, NASCAR has the poorest MSE_9 . Furthermore, brief investigation shows that NASCAR is the poorest performing system, losing 7 of the 12 metrics including M_{T5} , M_{T10} , and M_{T15} and performing second-to-last on M_{T20} . Given that these four can be considered some of the most important metrics and the fact that NASCAR fails to be best at any metric, under this analysis NASCAR is the worst of all methods considered.

A more competitive system is RSNV, which has the second-best MSE_9 among the traditional approaches. Careful analysis of the metric values shows that this method has overall good performance, excelling in M_{QP} , M_{AF} , and M_{T15} . In fact, RSNV performs worst on M_{LC} , where it is superior only to NBV. In all other metrics, RSNV has middling performance. This is interesting given that RSNV is more faithful to the original NASCAR points system developed by Latford [17].

Metric	Traditional						Evolutionary	
	NASCAR	RP	SNV	RSNV	BC	NBV	ESV	ER
M_S	0.9314	0.9261	0.9314	0.9263	0.9274	0.9164	0.9126	0.9056
M_{AS}	0.7621	0.7675	0.7633	0.7753	0.7707	0.7842	0.8086	0.8493
M_P	0.4644	0.4702	0.4630	0.4608	0.4587	0.4601	0.4688	0.4760
M_{LL}	0.5583	0.5842	0.5745	0.5755	0.5683	0.5852	0.5817	0.5896
M_{LC}	0.9358	0.9313	0.9362	0.9310	0.9321	0.9184	0.9155	0.9060
M_{QP}	0.9176	0.9210	0.9214	0.9217	0.9211	0.9214	0.9244	0.9268
M_{AF}	0.8886	0.8738	0.8902	0.9021	0.9006	0.9014	0.9181	0.9079
M_W	0.4477	0.4660	0.4689	0.4689	0.4630	0.4772	0.4668	0.4655
M_{T5}	0.7249	0.7386	0.7304	0.7331	0.7282	0.7456	0.7443	0.7478
M_{T10}	0.8301	0.8357	0.8309	0.8353	0.8335	0.8355	0.8416	0.8396
M_{T15}	0.8779	0.8810	0.8791	0.8834	0.8823	0.8794	0.8893	0.8845
M_{T20}	0.9241	0.9250	0.9251	0.9284	0.9285	0.9219	0.9312	0.9241
MSE_9	0.02332	0.02240	0.02273	0.02150	0.02212	0.02095	0.01906	0.01808

Table 3: Absolute value of metric values for voting systems. Best performers among traditional systems are in bold font.

The traditional system with the best performance in terms of MSE_9 is NBV. Recall that MSE_9 does not take into account M_W , a metric on which NBV performs best. However, while NBV outperforms the traditional systems on 4 of the 12 metrics, it also performs poorest on 3. In terms of the most important metrics (i.e., those dealing with finishing well), NBV performs best on two (M_W and M_{T5}) but also performs worst on one (M_{T20}).

NBV’s lack of consistency among the most important metrics, especially when compared to RSNV, makes it difficult to judge which of the two is the strongest traditional method. In this case, we believe that RSNV is, in fact, the better traditional voting method despite NBV’s better MSE_9 due to the following observations. First, RSNV and NBV both perform best on two of the “finish well” metrics. Second, NBV also performs worst on one of the “finish well” metrics, while RSNV has solid performance across the board.

4.2 Evolutionary Approaches

Referring again to Table 3, ESV outperforms the traditional methods in terms of MSE_9 . Additionally, it performs best on 7 of the 12 metrics, including 4 of the “finish well” metrics (M_{AF} , M_{T10} , M_{T15} , and M_{T20}). However, it has the poorest performance on M_S and M_{LC} , though these metrics are not as important.

The evolved scoring vector for the median ESV solution is presented in Table 4 where each column consists of the finishing position and its corresponding points. Notice that the top five positions are all awarded the maximum points. Similarly, the bottom three positions are awarded no points and the

four rankings above those are essentially zero (< 0.006). These phenomena are not specific to this particular ESV solution. In fact, 16 of the 21 scoring vectors shared these ties among the top five and bottom six positions. An additional interesting property that 15 of these 16 vectors share is a significant (> 0.2) drop from fifth to sixth position. The outlier here had a drop of approximately 0.1, which might also be considered significant.

1	1	11	0.550629	21	0.211528	31	0.095984	41	0
2	1	12	0.523209	22	0.155195	32	0.062242	42	0
3	1	13	0.415069	23	0.146498	33	0.061457	43	0
4	1	14	0.346342	24	0.135846	34	0.057626		
5	1	15	0.339517	25	0.129487	35	0.042437		
6	0.777694	16	0.274140	26	0.129398	36	0.032284		
7	0.682524	17	0.231148	27	0.109394	37	0.005509		
8	0.641936	18	0.230285	28	0.108901	38	0.002730		
9	0.618978	19	0.229221	29	0.103898	39	0.001846		
10	0.565181	20	0.216167	30	0.098653	40	0.000463		

Table 4: Median ESV scoring vector

The median evolved ranking produced by ER outperformed all other methods (Traditional and ESV) in terms of MSE_9 . In order to determine statistical significance, a Mann-Whitney rank sum test was performed on the MSE_9 values produced by ESV and ER on each of the 21 runs. The test confirmed a statistically significant difference in the median values with $p < 0.0001$.

In addition to having the lowest MSE_9 , ER had the best performance on 5 of the 12 metrics, though only one was in the “finish well” category (M_{T5}). Interestingly, ER performs worse than even ESV on M_S and M_{LC} . In contrast, however, ESV has the best performance overall on M_{AF} , M_{T10} , M_{T15} , and M_{T20} , which are very important metrics. For these reasons, we believe that ESV is the best approach voting system overall.

Table 5 shows the best and worst systems in relation to each metric.

5 Conclusions

In terms of conclusions, it is first important to understand that, under a different voting system, the drivers may have applied different racing strategies during the 2008 season. For instance, if NBV (which heavily emphasizes wins) had been used to determine the champion, then drivers near the top of the ranking might have made riskier decisions in order to gain even a single position. Any analysis of a different NASCAR scoring system would encounter the same issue, which we do not believe to be significant enough to invalidate these results.

Metric	Traditional		with ESV		with ESV & ER	
	Best	Worst	Best	Worst	Best	Worst
M_S	SNV	NBV	SNV	ESV	SNV	ER
M_{AS}	NBV	NASCAR	ESV	NASCAR	ER	NASCAR
M_P	RP	BC	ESV	BC	ER	BC
M_{LL}	NBV	NASCAR	NBV	NASCAR	ER	NASCAR
M_{LC}	SNV	NBV	SNV	ESV	SNV	ER
M_{QP}	RSNV	NASCAR	ESV	NASCAR	ER	NASCAR
M_{AF}	RSNV	RP	ESV	RP	ESV	RP
M_W	NBV	NASCAR	NBV	NASCAR	NBV	NASCAR
M_{T5}	NBV	NASCAR	NBV	NASCAR	ER	NASCAR
M_{T10}	RP	NASCAR	ESV	NASCAR	ESV	NASCAR
M_{T15}	RSNV	NASCAR	ESV	NASCAR	ESV	NASCAR
M_{T20}	BC	NBV	ESV	NBV	ESV	NBV

Table 5: Best and worst systems compared by metrics

The results of the top 15 positions under each method are presented in Table 6. From this table, it is immediately obvious that the rankings of the drivers in the top 15 positions remain relatively stable across the different methods. It is also interesting to note that all alternative methods rank Carl Edwards as the champion, whereas NASCAR crowned Jimmie Johnson the champion.

We have shown that the most successful traditional voting method is RSNV. One consequence of applying this method to the NASCAR season is that it would make it easier for drivers who fail to qualify in some races to remain competitive. This is because RSNV only rewards slightly more those who finish last in a race compared to those who fail to qualify. It is interesting to note that ESV, with its numerous zeroes for the bottom finishers, shares this same feature.

When considering evolutionary approaches, we have shown that ESV is competitive in terms of MSE_9 and is dominant on the most meaningful metrics. We have also shown that the most common form of the ESV scoring vector has zeroes in the bottom-most positions. Use of such a vector would likely cause races to be less disruptive (in terms of accidents and cautions for debris), given that the drivers in the last positions have no incentive to compete against one another.

When considering the effects of bonuses and penalties on RSNV, it was discovered that these devices have a negligible impact on the final standings. First of all, Carl Edwards, despite being penalized 100 points, still has the most points under RSNV, beating out Jimmie Johnson by 16 points. Second, in the top 35 drivers, 22 remained in the same position despite the bonuses/penalties. Furthermore, of those 13 drivers who did change position, 5 shifted by two

	NASCAR	RP	SNV	RSNV	BC	NBV	ESV	ER
1	Johnson	Edwards	Edwards	Edwards	Edwards	Edwards	Edwards	Edwards
2	Edwards	Johnson	Johnson	Johnson	Johnson	Ky Busch	Johnson	Gordon
3	Biffle	Ky Busch	Ky Busch	Ky Busch	Harvick	Johnson	Ky Busch	Johnson
4	Harvick	Harvick	Harvick	Harvick	Burton	Biffle	Gordon	Ky Busch
5	Bowyer	Biffle	Burton	Burton	Ky Busch	Stewart	Biffle	Earnhardt
6	Burton	Earnhardt	Biffle	Biffle	Biffle	Hamlin	Harvick	Hamlin
7	Gordon	Hamlin	Earnhardt	Earnhardt	Bowyer	Burton	Burton	Biffle
8	Hamlin	Gordon	Bowyer	Bowyer	Earnhardt	Earnhardt	Earnhardt	Kenseth
9	Stewart	Kenseth	Gordon	Gordon	Gordon	Gordon	Hamlin	Harvick
10	Ky Busch	Burton	Stewart	Stewart	Stewart	Kahne	Kenseth	Stewart
11	Kenseth	Bowyer	Hamlin	Hamlin	Hamlin	Harvick	Stewart	Burton
12	Earnhardt	Stewart	Ragan	Ragan	Ragan	Bowyer	Bowyer	Bowyer
13	Ragan	Ragan	Kenseth	Kenseth	Kenseth	Kenseth	Ragan	Ragan
14	Kahne	Kahne	Kahne	Kahne	Kahne	Ku Busch	Kahne	Kahne
15	Truex	Truex	Truex	Truex	Truex	Ragan	Truex	Truex

Table 6: Top 15 positions for each method

rankings and the other 8 shifted by only one ranking. To put the impact of bonus points into perspective, the maximum bonus points earned in the top 35 positions was 195 with a median of 40. In contrast, the maximum point differential among the top 35 positions was 196 with a median of 61. This would indicate that the manner in which bonus points are currently allocated does not produce a meaningful difference in the final rankings.

If NASCAR were to modify the bonus points in order to make them more influential, there is a possibility that the system could be manipulated by the following strategy. It is possible to receive bonus points for leading a lap while under caution. This provides an easy way for poorer drivers to gain points. And since bonus points were originally included to increase excitement during the race by rewarding drivers who were more competitive [17], this entirely contradicts the intended purpose of bonuses.

The research presented in this work has generated very interesting results and has several immediate opportunities for extension. First, it would be enlightening to apply these approaches to multiple seasons in order to better understand and generalize their effects on the final rankings. Also, it would be interesting to modify the ESV and ER approaches so that the M_W metric is factored into the fitness calculation. This would most likely require a scaling or dampening of the impact of M_W on the fitness in order to penalize solutions that have better correlation to wins but poor correlations to the more meaningful statistics.

References

- [1] About.com. Nascar penalties getting serious. <http://nascar.about.com/library/weekly/aa123002a.htm>. Last accessed 24 Dec 2008.
- [2] Kristi Ambrose. The nascar points rating system. Articlebase <http://www.articlesbase.com/extreme-sports-articles/the-nascar-points-rating-system-603171.html>. last accessed 25 Jan 2009.
- [3] Thomas Bäck, Ulrich Hammel, and Hans-Paul Schwefel. Evolutionary computation: Comments on the history and current state. *IEEE Transactions on Evolutionary Computation*, 1(1):3–17, apr 1997.
- [4] Thomas Bäck, F. Hoffmeister, and Hans-Paul Schwefel. A survey of evolution strategies. In R. K. Belew and L. B. Booker, editors, *Proceedings of the 4th International Conference on Genetic Algorithms*, pages 2–9. Morgan Kaufman, 1991.
- [5] J. C. Bean. Genetic algorithms and random keys for sequencing and optimization. *ORSA Journal on Computing*, 6(2):154–160, 1994.
- [6] Duncan Black and R. A. Newing. *Committee Decisions with Complementary Valuation*, pages 273–330. Kluwer Academic Publishers, 1998.

- [7] Steven J. Brams and Peter C. Fishburn. *Voting procedures*, pages 173–236. North-Holland, 2002.
- [8] Kenneth A. De Jong. *Evolutionary Computation: A Unified Approach*. MIT Press, 2006.
- [9] Kenneth A. De Jong and William Spears. On the state of evolutionary computation. In Stephanie Forrest, editor, *Proceedings of the Fifth International Conference on Genetic Algorithms*, pages 618–623, San Mateo, CA, 1993. Morgan Kaufman.
- [10] L. J. Eshelman and J. D. Schaffer. *Real-coded genetic algorithms and interval-schemata*, pages 187–202. Morgan Kaufman, 1993.
- [11] David B. Fogel. An introduction to simulated evolutionary optimization. *IEEE Transactions on Neural Networks*, 5(1):3–14, January 1994.
- [12] David B. Fogel. What is evolutionary computation? *IEEE Spectrum*, 37(2):26–32, February 2000.
- [13] Lawrence J. Fogel, Alvin J. Owens, and Michael John Walsh. *Artificial intelligence through simulated evolution*. Wiley, New York, 1966.
- [14] Stephanie Forrest. Genetic algorithms: principles of natural selection applied to computation. *Science*, 60:872–878, August 1993.
- [15] D. E. Goldberg. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley Publishing Company, Inc., Reading, MA, 1989.
- [16] J. H. Holland. *Adaptation in Natural and Artificial Systems*. University of Michigan Press, Ann Arbor, MI, 1975.
- [17] Godwin Kelly. Beach races wane, then depalma turns tide. NIE WORLD <http://www.nieworld.com/special/racing/thatwasthen5.htm>. Last accessed 23 Dec 2008.
- [18] Vincent Merlin. The axiomatic characterizations of majority voting and scoring rules. *Mathematics and Social Sciences*, 41(163):87–109, 2003.
- [19] Zbigniew Michalewicz and David B. Fogel. *How to Solve It: Modern Heuristics*. Springer, 2004.
- [20] Mike Mulhern. NASCAR has history of playing with points. Media General News Service, January 8, 2004. Available online at <http://lapbylap.mgnetwork.com/index.cfm?SiteID=mmm&PackageID=30&fuseaction=article.main&ArticleID=4858&GroupID=100>.
- [21] NASCAR. About NASCAR. <http://www.nascar.com/guides/about/nascar>. Last accessed 22 Dec 2008.

- [22] NASCAR. Sprint Cup Series results. http://www.nascar.com/races/cup/2008/rr_index.html. Last accessed 22 Dec 2008.
- [23] Hannu Nurmi. *Comparing Voting Systems*. kluwer, first edition, 1987.
- [24] Stuart Russell and Peter Norvig. *Artificial Intelligence: A Modern Approach*. Prentice Hall, 2nd edition, 2002.
- [25] William M. Spears, Kenneth A. De Jong, Thomas Bäck, David B. Fogel, and H. deGaris. An overview of evolutionary computation. In *Proceedings of the 1993 European Conference on Machine Learning*, 1993.
- [26] Nicolaus Tideman. *Collective Decisions and Voting*. Ashgate, 1st edition, 2006.
- [27] Michael D. Vose. *The Simple Genetic Algorithm: Foundations and Theory*. MIT Press, 1999.
- [28] H. P. Young. Social choice scoring functions. *SIAM J Appl. Math*, 28(4):824–838, 1975.

A Source Code

All Java source code and MySQL database information related to these experiments are freely available at the first author's website, <http://mcis.jsu.edu/faculty/desmith/voting>.