Pareto-Optimal Kart Setups for Different Track Types

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Abstract
This project applies multi-objective optimization to find optimal kart setups for Mario Kart 8 Deluxe. Each kart's performance depends on multiple attributes such as speed, acceleration, traction, handling, and mini-turbo. In order to find an optimal setup we used the NSGA-II genetic algorithm to generate diverse sets of Pareto optimal kart combinations. Different track types were taken into consideration such as: curvy, long straight, and off-roading heavy tracks. Different objectives were weighed more heavily depending on statistics which certain tracks tend to favor. Our results demonstrated top 10 kart combinations based on their performance over several track types with balanced trade-offs.

I. Introduction and Problem Statement

Mario Kart is a beloved racing game worldwide where users can create their own kart combos; Racing the karts in various map types to first place. In a competitive game such as Mario Kart, a player's chosen kart combo can impact their gameplay, as each combination brings different stats. The kart's driver, kart, wheels, and glider can affect game stats such as the speed, acceleration, weight, handling, and grip while racing on the tracks. As players, we want to choose kart setups that perform well across different tracks and enhance overall gameplay performance. As kart setups carry different components, choosing the best setup is a multi-objective optimization problem. In this paper we aim to use pareto optimization via NSGA-II algorithm to generate optimal kart setups tailored to different race conditions in Mario Kart 8 Deluxe.

There is no universal best kart combination in Mario Kart that will excel in both different tracks and playstyles. As mentioned, there are different types of tracks that emphasize different attributes. The main three types of tracks we focus on are curvy, long straight, and off-roading heavy tracks. Curvy tracks require better handling and miniturbo, whereas long straight tracks require karts with better speed. Off-roading heavy tracks may have players drive on different textures, therefore requiring better acceleration and traction. As a result, players need to make trade-offs between different kart setups for their objective of winning first place. Taking into consideration different track types and playstyles, different stats are ideal for certain tracks. This makes the process of choosing a kart setup a complex optimization problem without prioritizing just one kart stat.

II. Related Work and Background

Multi-objective optimization (MOO) focuses on finding multiple solutions and best trade-offs when there are multiple objectives involved. MOO focuses not on one solution but a set of solutions called the Pareto Front. In a survey by Marler and Arora (2004), they categorize different optimization strategies based on user preferences. Preferences are organized as follows: a priori (preferences are set before optimization), a posteriori (preferences chosen after results are seen), and no-preference (the algorithm finds preferences). This paper establishes a foundation for optimizing multiple objectives, which would be useful in our case of kart trade-offs on different tracks.

There also is prior work focused on finding best kart setups in Mario Kart, such as *Mario meets Pareto* by Mayerowitz (2025), where pareto optimization is applied as well to kart trade-offs and analysis. Mayerowitz also emphasizes that there is no single kart combination that is optimal with all stats, and offers a pareto front of different builds with different advantages. Mayerowitz focused on stat-based optimization, our project builds upon this by taking into consideration track types.

Our project also utilized the genetic algorithm, NSGA-II (Non-Dominated Sorting Algorithm II). Deb. et al (2002) introduced NSGA-II as an effective method to generate a diverse set of pareto optimal solutions for multi-objective problems.

III. Our Approach

In this project we wanted to build upon previous Pareto optimization work, such as Mayerowitz, but further taking in consideration track types. In order to generate optimal kart setups for different track conditions, we implemented NSGA-II for our multi-objective optimization approach. NSGA-II follows six steps:

1.) Initializes a population by creating random kart setups
2.) Each setup is evaluated by their performance across different stats
3.) Best performing setups are selected
4.) Selected setups undergo crossover and mutation
5.) Next generation is formed from most optimal setups
6.) Process repeats for a selected amount of iterations

By following this process it develops a Pareto front of non-dominated solutions that offer balanced trade-offs with multiple objectives. This algorithm was chosen as it aligns with multiple objectives we aimed to optimize. For example, NSGA-II helped generate multiple setups, which would allow for users to pick a kart combination that fits their playstyle the most. The sorting in each generation was non-dominated, therefore prioritizing setups with strong performance across multiple stats instead of focusing on one. Lastly, it allows for diverse solutions, preventing getting stuck in local optima and encourages more diverse setups.

To implement the algorithm, we first defined our decision variables. The decision variables define the different attributes of a kart build, and would be used to generate and evaluate kart setups. We used four decision variables. Speed, across different terrain types such as ground, water, air, and anti-gravity. Next Handling, which similar to speed was dependent on terrain, impacting how well a kart maneuvers through different terrain. Acceleration, which measured how quickly a kart could reach its top speed after resting or slowing down. Traction, which determined how well a kart would grip to a track. Lastly, Mini-turbo, which is the strength of the mini boost given to the kart after drifting. Each of these variables are independent of each other, and maximizing one stat means minimizing another.

To implement NSGA-II into our approach we used python. The performance data we used for the drivers, karts, wheels, and gliders was from an open-source dataset on Github (jfmario, 2023). Each

kart setup is considered as an individual with its respective four decision variables. Using the data from the dataset we combined the variables to calculate their performance in speed, acceleration, handling, traction, and mini-turbo.
To further optimize our kart combos, we also took into consideration different track types based on their layout and terrain: curvy, long-straight, and offroading tracks. Each track type may favor karts with certain stats over others. In order to evaluate how different karts perform on different track types, heavier weights were applied on certain performance objectives. More specifically, the heavier weights to objectives that were more important for each track type. For example, prioritizing acceleration and mini-turbo for curvy tracks, as the curves require better control and recovery after turning. For long straight tracks, heavier weights were applied for ground speed, air speed, and weight to maintain momentum while driving. As for off-roading tracks, heavier weights were applied in traction, handling, and acceleration to stay stable over different terrain. Applying these weights to the fitness scores allowed us to identify which kart setups were balanced and optimal under different race conditions.

IV. Evaluation and Results

Our NSGA-II algorithm ran for 40 generations, each with populations of 100 kart setups and 200 offspring per generation. From running the algorithm we gained a diverse-set of pareto-optimal kart combinations. Our results are analyzed based on their performance across the three track types. By applying the weighted scores in each setup, we were able to identify which kart combinations favored each of the different track types.

For long-straight tracks, it favored kart combinations that had a heavy-weight driver, and wheels that would enhance speed over acceleration or handling. Long-straight tracks's best kart setups were more fit for all-terrain, and ideally maintained high speed.

Optimal kart setups for curvy tracks had lightweight drivers and wheels that would bring higher acceleration and handling, trading off higher speed and weight. These karts were usually balanced with all stats, but slightly favored acceleration and handling. Curvy tracks ideal karts worked best with sharp turns, maintaining control and for quicker speed recoveries.

Offroading optimal kart setups had lightweight drivers and smaller wheels which offered higher acceleration and handling. These kart types were ideal for recovering speed in tracks with more off-roading areas.

In determining the top 10 kart combos, it was based on their total track score, a combined measurement of their performance across different tracks. In figure 1, it shows a parallel coordinate plot with the top 10 kart combinations. Each vertical axis is a kart stat, and each line is an individual setup. The color of the line represents the total score, therefore darker lines are lower scores and yellow lines are higher scores. A noticeable pattern in the top 10 karts is that the higher performing builds balance their stats, minimizing trade-offs. Figure 2 provides a table of the top 10 combinations shown in figure 1.

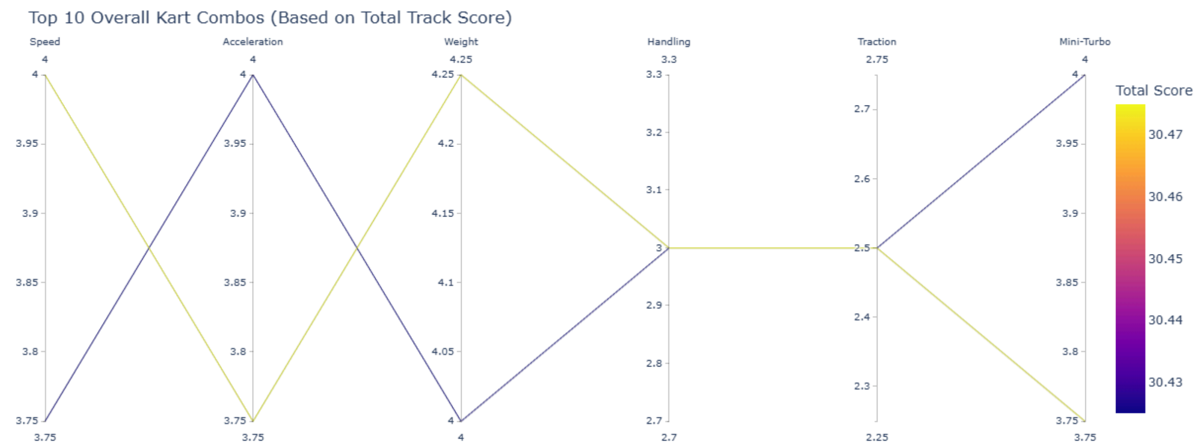

Fig. 1: Parallel Coordinates Plot of Top 10 Best Kart Combos based on total track score

Driver	Vehicle	Tires	Glider	Groundspeed	Acceleration	Weight	Groundhandling	Traction	Miniturbo	Curvy Score	Long Straights Score	Total Score
Bowser	Comet+	Roller	Gold Glider	4	3.75	4.25	3	2.5	3.75	10.125	20.35	30.475
Morton	Comet+	Roller	Wario Wing	4	3.75	4.25	3	2.5	3.75	10.125	20.35	30.475
Bowser	Cat Cruiser	Roller	Plane Glider	4	3.75	4.25	3	2.5	3.75	10.125	20.35	30.475
Bowser	Comet+	Roller	Peach Parasol	3.75	4	4	3	2.5	4	10.8	19.625	30.425
Bowser	Comet+	Roller	Parafoil	3.75	4	4	3	2.5	4	10.8	19.625	30.425
Morton	Comet+	Roller	Hylian Kite	4	3.75	4	3	2.75	3.75	10.125	20.15	30.275
Bowser	Comet+	Roller	Super Glider	4	3.75	4	3	2.75	3.75	10.125	20.15	30.275
Bowser	Comet+	Roller	Waddle Wing	4	3.75	4	3	2.75	3.75	10.125	20.15	30.275
Morton	Comet+	Roller	Cloud Glider	3.75	4	3.75	3	2.75	4	10.8	19.425	30.225
Bowser	Cat Cruiser	Roller	Flower Glider	3.75	4	3.75	3	2.75	4	10.8	19.425	30.225

Fig. 2: Table of Top 10 Best Kart Combos

Overall, the NSGA-II algorithm performed well in generating a Pareto front of diverse kart setups. It helped balance multiple objectives, and identify builds that suited different track types.
However, one constraint we faced is not incorporating different playstyles such as aggressive vs defensive racers. Different kart combinations may be favored by different playstyles, which we did not account for. As well as using simplified track types and not accounting for different surface types such as mud, sand, grass, or water which can also impact gameplay. Despite these limitations, our results show that multi-objective optimization can be used to improve gameplay and strategies for players in Mario Kart.

V. Conclusion and Future Directions

This project offers novel contributions using multi-objective optimization with NSGA-II to find optimal kart setups for Mario Kart 8 Deluxe players by taking into account different track types. By generating diverse Pareto fronts, it can allow for players to pick which setup works best for their playstyle. Our approach showed that balancing multiple objectives can allow for a more strategic gameplay.
In future work, this project can be expanded upon by incorporating more different track surfaces. As well as by running simulations with the top 10 generated kart setups, and testing how different playstyles play a role in picking an optimal setup. Lastly, making the track weights more specifically

tuned to their sharp turns and terrain. Ultimately, this project can provide a foundation for using optimization algorithms to enhance gameplay.

VI. References

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