USING QUEUEING THEORY TO FIND THE OPTIMAL CHARACTER-VEHICLE COMBINATION FOR 150CC MARIO KART WORLD RACES

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SUMMARY

This investigation entailed using Queueing Theory to determine the probabilities of possessing any given number of coins during a race and evaluating the expected overall speed of every possible character-vehicle combination according to its speed increase from its speed attribute for each terrain, its weight-dependent coin effects, the coin possession probabilities, and the effects of its acceleration attribute on the drift and trick boost durations to find the optimal character-vehicle combination for 150cc races in Mario Kart World.

The optimal character-vehicle combinations were found to be a flyweight character (i.e. Swoop, Para-Biddybud, Baby Peach, or Baby Daisy) with the Baby Blooper, with viable alternatives being a flyweight character with the W-Twin Chopper, a solid-focused lightweight character (i.e. Nabbit or Toadette) with the Mach Rocket or R.O.B. H.O.G., a solid-focused featherweight character (i.e. Spike, Goomba, or Baby Mario) with the Baby Blooper, a flyweight character with the Mach Rocket or R.O.B. H.O.G., and a solid featherweight character with the Mach Rocket or R.O.B. H.O.G.. The solid-focused middleweight character (i.e. Mario or Rocky Wrench) with the Baby blooper, being 28th best, is no longer a contender for the best character-vehicle combination.

The results of this investigation demonstrate that speed on solid terrain should be emphasised. The high acceleration attribute and low weight attribute of all six identified best combinations also highlight the importance of maximising the acceleration attribute and minimising the weight attribute when selecting a character and vehicle for racing in Mario Kart World.

All spreadsheets and Python scripts used in this investigation are available in the folder where this report resides.

ACKNOWLEDGEMENTS

Special acknowledgements to my Manufacturing Engineering lecturer in my final year at university for teaching me Queueing Theory, and my best friend and former coursemate for inspiring me to become proficient in Python.

Acknowledgements also to the members of the Mario Kart World community who came before me and made available the data needed for this investigation.

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LIST OF SYMBOLS

$\varepsilon = relative\ speed\ increase$
$s = speed\ attribute$
$c = number\ of\ coins\ in\ possession$
$w = weight\ attribute$
$t = terrain\ identifier$
$\lambda = coin\ collection\ rate\ (\mathrm{min}^{-1})$
$\mu = coin\ dispossession\ rate\ (\mathrm{min}^{-1})$
$r = coin\ reset\ rate\ (i.e.\ frequency\ of\ races)\ (\mathrm{min}^{-1})$
$P = coin\ possession\ probabilities$
$d_1, d_2, d_3, a_1, a_2 = intermediate\ calculation\ variables$
$E = Expected\ overall\ speed\ increase\ relative\ to\ the\ baseline$

NOMENCLATURE

RAW	rails, air, and walls; a terrain in Mario Kart World

1. INTRODUCTION

Selecting an optimal character-vehicle combination is essential for maximising one's chances of winning races in Mario Kart World. Members of the Mario Kart World community have found the performance attributes (i.e. speed, acceleration, weight, and handling) of each character and vehicle and how they interact with the in-game mechanics (e.g. *MK World Builder* [1], *Mario Kart World Stats* [2], and *The Mario Kart World Stratpedia* [3]), including how each coin's effect on the racer's speed depends on the number of coins in possession and the racer's weight attribute, but the probability distribution of the number of coins in possession from 0 to 20 for a racer at any given moment, the effects of the acceleration attribute on the racer's average speed through drift and trick (non-item) boost durations, and, by extension, the expected overall speed for each character-vehicle combination, have yet to be derived until this investigation.

Therefore, this investigation aimed to find the optimal character-vehicle combination in 150cc Mario Kart World races by maximising the expected overall speed while maintaining a reasonable acceleration. This investigation was conducted via the following objectives:

a. Apply Queueing Theory to determine the probabilities of possessing any given number of coins during a race from 0 to 20.
b. Evaluate the expected overall speed of each possible character-vehicle combination, according to its speed increase from its speed attribute for each terrain, its weight-dependent coin effects, the coin possession probabilities obtained from objective {a}, and the effects of its acceleration attribute on the non-item boost durations.
c. Find the character-vehicle combination with the highest expected overall speed.

2. RELEVANT GAME MECHANICS

The background information relevant to this investigation is as follows.

2.1. Speed attribute, coins, and weight attribute

For each terrain, the speed attribute increases the racer's 0-coin speed linearly from a baseline, and coins increase the racer's speed by up to 5% of the racer's 0-coin speed at 20 coins, where the weight attribute determines the rate at which each coin, from the 1st to the 20th, increases the racer's speed (Figure 1) [3].

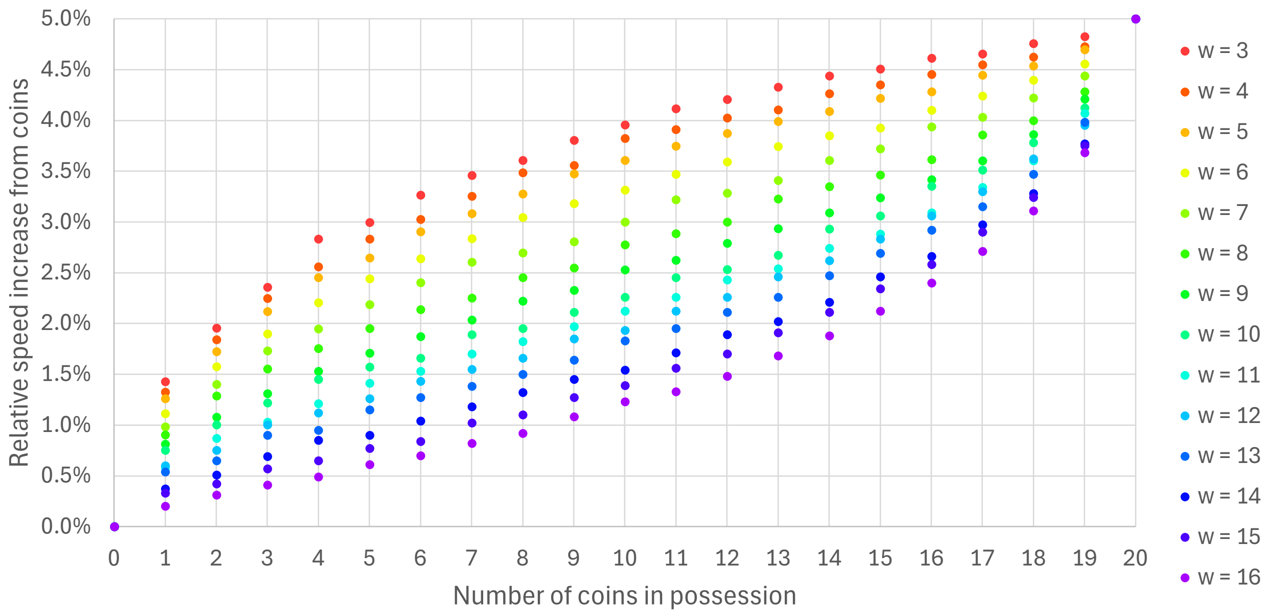

Figure 1. A simultaneous plot of $\varepsilon_{c,w}$ vs the number of coins in possession for $w = 0,1,2,\ldots,13$.

$\varepsilon = relative\ speed\ increase$

$s = speed\ attribute$
$c = number\ of\ coins\ in\ possession$
$w = weight\ attribute$
$t = terrain\ identifier$
(lowercase means specific and uppercase means averaged)

$$\varepsilon_{s,t} \approx 0.312\% \cdot s_t \tag{1}$$

$$\varepsilon_{s,t,c,w} = (1 + \varepsilon_{s,t})(1 + \varepsilon_{c,w}) - 1 \tag{2}$$

There are four terrains in Mario Kart World. They are solid (e.g. asphalt, brick, metal, carpet, wood, ice), grainy (e.g. sand, soil, snow), water, and rails, air, and walls (abbreviated RAW). The solid, grainy, water, and RAW terrains constitute 51.88%, 21.31%, 7.47%, and 19.34% of all roads in Mario Kart World [3]. While the solid, grainy, and water terrains have distinct speed attributes, that for RAW terrain is 13 points across all character-vehicle combinations. These proportions inform the weighted mean speed increase.

$$\varepsilon_{s,T,c,w} = 0.5188\varepsilon_{s,solid,c,w} + 0.2131\varepsilon_{s,grainy,c,w} + 0.0747\varepsilon_{s,water,c,w} + 0.1934\varepsilon_{13,RAW,c,w} \tag{3}$$

2.2. The effects of the acceleration attribute

Meanwhile, the acceleration attribute determines the duration required to get to top speed from zero and the duration of boosts from drifting and tricking [3]. The boost types are mini-turbo, super mini-turbo, ultra mini-turbo, ramp tricks, mid-air or in-water tricks, rail tricks, and charge jumps. Only the boosts from ramp tricks and mid-air or in-water tricks were found to be independent of the acceleration attribute. The acceleration attribute for each character-vehicle combination is constant across all terrains.

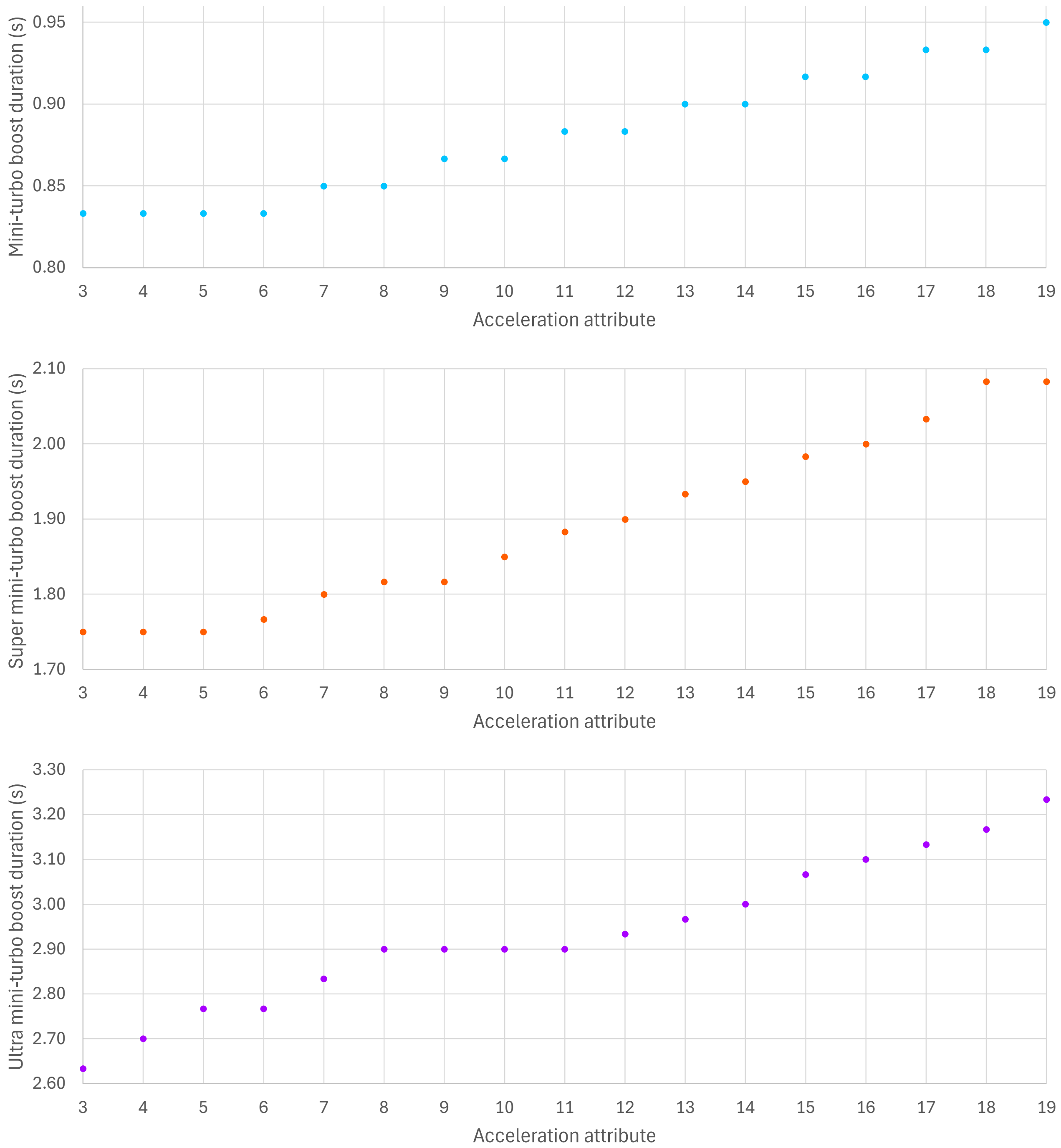

Figure 2. The boost durations for a mini-turbo (blue; top), super mini-turbo (orange; middle), and ultra mini-turbo (purple, bottom) as the acceleration attribute increases from 3 to 19 points.

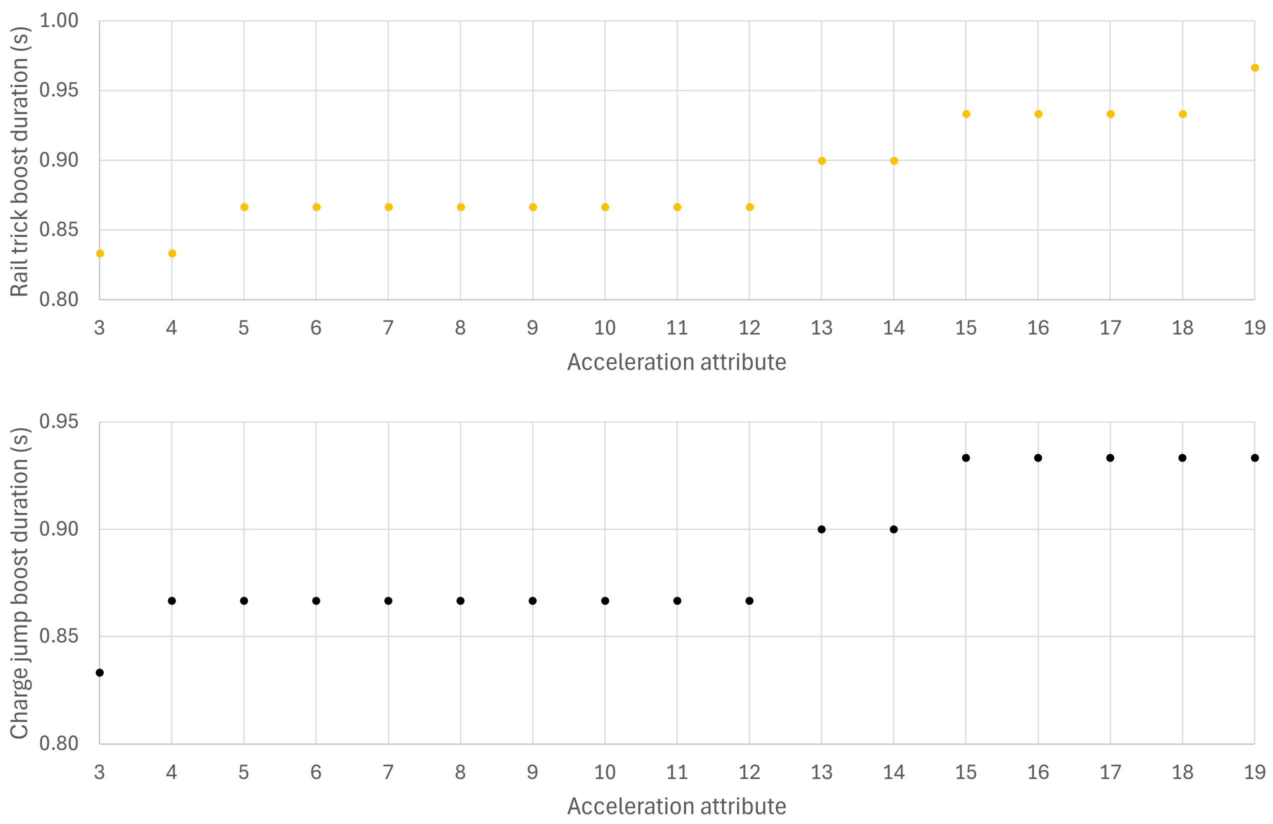

Figure 3. The boost durations for a rail trick (yellow; top), and charge jump (black; bottom) as the acceleration attribute increases from 3 to 19 points.

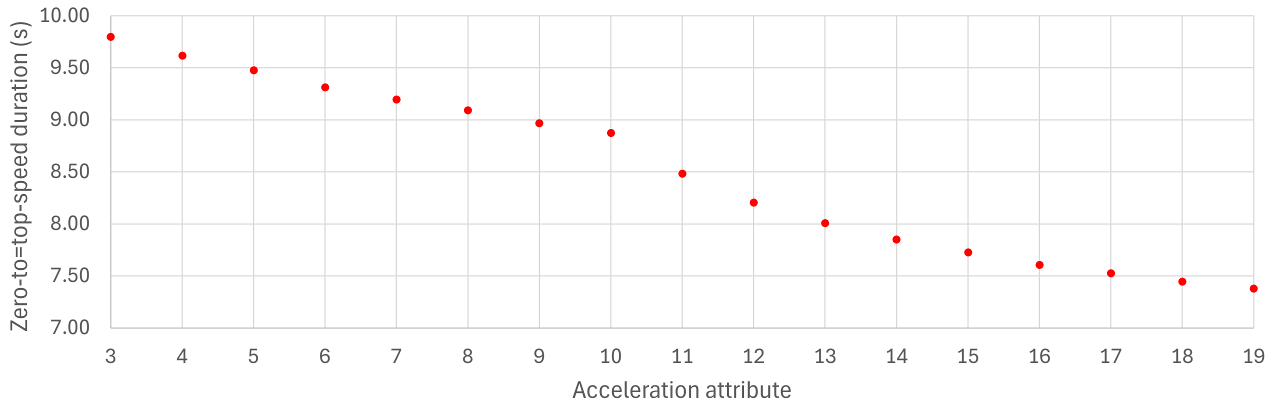

Figure 4. The zero-to-top-speed duration as the acceleration attribute increases from 3 to 19 points.

It was known that the frequency of zero-to-top-speed occurrences is once per race [3].

3. METHOD

The method used in this investigation is as follows.

3.1. The Markov chain of coin possession

In Queueing Theory, each possible number of coins in possession, from 0 to 20, is treated as a state. In this model, collecting coins means moving to a higher state and dispossessing coins, either by being hit by an item, running into an obstacle, falling off track and requiring Lakitu to intervene, or finishing a race and starting a new one, means moving to a lower state. Given that coins are collected one at a time, each mid-race dispossession is 3 coins or the entire possession, whichever is less, and coin possessions reset at the start of each race to between 0 and 5 coins depending on the racer's position, the model of the coin possession probabilities can be illustrated as follows.

$\lambda = coin\ collection\ rate\ (\mathrm{min}^{-1})$
$\mu = coin\ dispossession\ rate\ (\mathrm{min}^{-1})$
$r = coin\ reset\ rate\ (i.e. frequency\ of\ races)\ (\mathrm{min}^{-1})$
$P = coin\ possession\ probabilities$

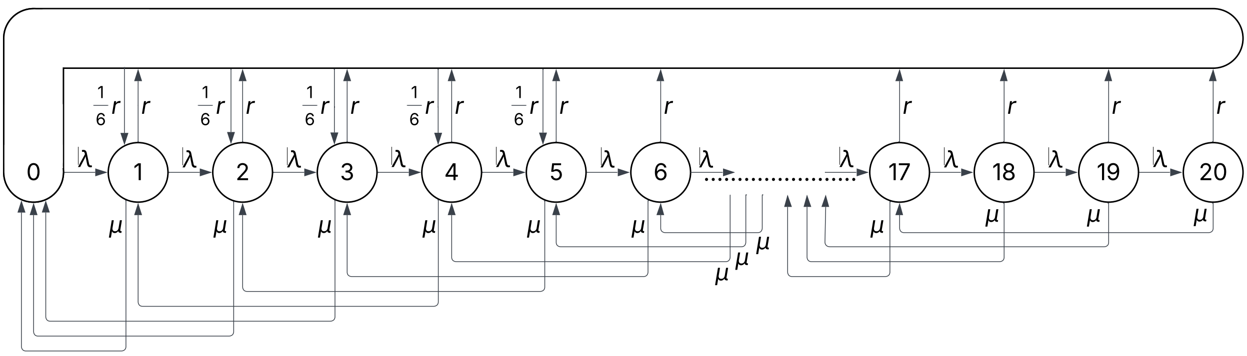

Figure 5. The Markov chain for coin possession in a 150cc Mario Kart World race.

Since the inflows and outflows at each state are balanced for any system at equilibrium, the following equations were derived.

$$-\lambda P_0 + \left(\mu + \frac{5}{6}r\right)(P_1 + P_2 + P_3) + \frac{5}{6}r(P_4 + P_5) + r(P_6 + P_7 + \cdots + P_{20}) = 0 \qquad (4)$$

$$for\ 1 \le c \le 5, \qquad \lambda P_{c-1} - \left(\lambda + \mu + \frac{5}{6}r\right)P_c + \mu P_{c+3} = 0 \qquad (5)$$

$$for\ 6 \le c \le 17, \qquad \lambda P_{c-1} - (\lambda + \mu + r)P_c + \mu P_{c+3} = 0 \qquad (6)$$

$$for\ 18 \le c \le 19, \qquad \lambda P_{c-1} - (\lambda + \mu + r)P_c = 0 \qquad (7)$$

$$\lambda P_{19} - (\mu + r)P_{20} = 0 \qquad (8)$$

$$and\ by\ definition \qquad P_0 + P_1 + P_2 + \cdots + P_{20} = 1 \qquad (9)$$

Substituting Equation 8 into Equation 7 when $\boldsymbol{c} = 19$ yields the following matrix-vector equation.

$$-\left(\lambda+\mu+\frac{5}{6}r\right)\rightarrow d_1,\qquad -(\lambda+\mu+r)\rightarrow d_2,\qquad -(\mu+r)\rightarrow d_3,\qquad \left(\mu+\frac{5}{6}r\right)\rightarrow b_1,\qquad \frac{5}{6}r\rightarrow b_2$$

$$\begin{bmatrix}
-\lambda & b_1 & b_1 & b_1 & b_2 & b_2 & r & r & r & r & r & r & r & r & r & r & r & r & r & r & r \\
\lambda & d_1 & 0 & 0 & \mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & \lambda & d_1 & 0 & 0 & \mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \lambda & d_1 & 0 & 0 & \mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \lambda & d_1 & 0 & 0 & \mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \lambda & d_1 & 0 & 0 & \mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & \lambda & d_2 & 0 & 0 & \mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \lambda & d_2 & 0 & 0 & \mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
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0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda & d_2 & 0 & 0 & \mu & 0 & 0 & 0 & 0 & 0 \\
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0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda & d_2 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda & d_3 & d_3 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1
\end{bmatrix}
\cdot
\begin{bmatrix} P_0 \\ P_1 \\ P_2 \\ P_3 \\ P_4 \\ P_5 \\ P_6 \\ P_7 \\ P_8 \\ P_9 \\ P_{10} \\ P_{11} \\ P_{12} \\ P_{13} \\ P_{14} \\ P_{15} \\ P_{16} \\ P_{17} \\ P_{18} \\ P_{19} \\ P_{20} \end{bmatrix}
=
\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}
\tag{10}$$

3.2. Finding the rates

An hour-long YouTube video of Mario Kart World online gameplay uploaded by Shortcat [4] was watched. The numbers of occurrences of coin collections, coin dispossessions, and drift boosts, trick boosts, and charge jumps of each kind were counted, and the race times were recorded. The coin collection, dispossession, and reset (i.e. the number of races) occurrences were divided by the total racing time to find $\boldsymbol{\lambda}$, $\boldsymbol{\mu}$, and $\boldsymbol{r}$. Similarly, the non-item boost rates were found by the number of occurrences divided by the total racing time.

3.3. Evaluating the expected overall speed

For each of the 480 unique character vehicle combinations (from 20 unique character classes and 24 unique vehicle attribute profiles), after evaluating $\boldsymbol{\varepsilon_{s,T,c,w}}$ for all $1 \le \boldsymbol{c} \le 20$ using Equations 1 to 3, finding the proportion of time spent in non-item boosts by the dot product of the boost rates and boost durations for the separated types, and finding the proportion of time saved from the zero-to-top-speed performance, the expected overall speed increase relative to the baseline during 150cc races $\boldsymbol{E}$ was evaluated using Equations 11 and 12. Finding the optimal character-vehicle combination then required identifying the combination with the highest $\boldsymbol{E}$. ($\boldsymbol{\varepsilon_{nib}}$ was found through manual testing.)

$E = expected\ overall\ speed\ increase\ relative\ to\ the\ baseline$
$\overleftrightarrow{B} = non\text{-}item\ boost\ rate\ column\ matrix\ (\mathrm{min}^{-1})$
$\overleftrightarrow{T} = non\text{-}item\ boost\ duration\ column\ matrix\ (\mathrm{s})$
$nib = non\text{-}item\ boost$
$\tau = average\ race\ duration\ (\mathrm{s})$
$\zeta = zero\text{-}to\text{-}top\text{-}speed\ duration\ (\mathrm{s})$
$a = acceleration\ attribute$

$$\varepsilon_{s,T,c,w,a} = \left(1+\varepsilon_{s,T,c,w}\right)\left(1+\frac{1\ \mathrm{min}}{60\ \mathrm{s}}\overleftrightarrow{B}_{(7\times1)}\cdot\overleftrightarrow{T}_{(7\times1)}\varepsilon_{nib}\right)\frac{\tau}{\tau-\left(\zeta|_{a\,=\,0}-\zeta\right)}-1 \tag{11}$$

$$E = \sum\nolimits_{c\,=\,0}^{20} P_c \cdot \varepsilon_{s,T,c,w,a} \tag{12}$$

3.4. Assumptions and simplifications

This investigation has relied on the following assumptions and simplifications:

- The terrain on which the racer is driving and the number of coins in possession were treated as independent events.
- The terrain on which the racer is driving and whether the racer is in a non-item boost were treated as independent events.

4. RESULTS

First, the following coin collection, dispossession, and reset rates were found (Table 1).

Table 1. The data collected on coin collection, dispossession, and resets [4].

Total number of			Total racing time (min)	λ (min^{-1})	μ (min^{-1})	r (min^{-1})
Coins collected	**Dispossessions**	**Races**				
411	61	20	46.40	8.858	1.315	0.4310

The coin possession probabilities were found to be higher towards 0 coins and at 19 coins or 20 coins (Figure 6). This trend is supported by anecdotal evidence from gameplay, as frontrunning and sandbagging both enable the racer to collect coins easily, chaos in the racer pack in median positions tends to minimise coin possession, and there are no known phenomena to keep coin possession counts away from the extremes.

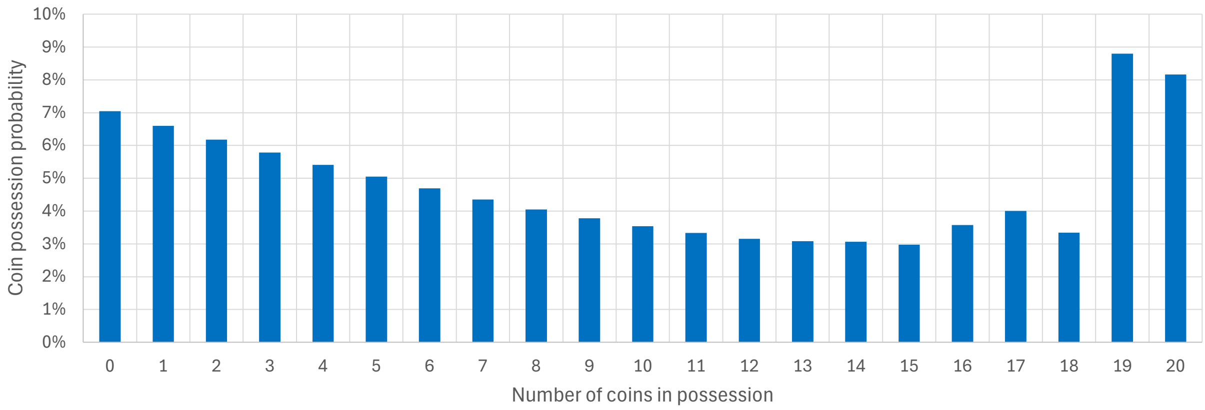

Figure 6. A bar chart of $\boldsymbol{P_c}$ versus $\boldsymbol{c}$.

Then, the following non-item boost rates were found (Table 2). $\boldsymbol{\varepsilon_{nib}}$ was found to be 9%.

Table 2. The data collected on the non-item boost occurrences and rates.

Non-item boost type	Mini-turbo drift boosts			Trick boosts			Charge jumps
	(Basic)	**Super**	**Ultra**	**Ramp**	**Mid-air or in-water**	**Rail or wall**	
Occurrences	134	71	23	233	24	120	16
Rates (min^{-1})	2.888	1.530	0.496	5.022	0.517	2.586	0.345

In light of the coin possession probabilities and the effects of the acceleration attributes on the average racing speed, the optimal character-vehicle combinations were found to be a flyweight character (i.e. Swoop, Para-Biddybud, Baby Peach, or Baby Daisy) with the Baby Blooper at $\boldsymbol{E_{max}} \approx 10.797\%$, with viable alternatives at $\boldsymbol{E_{max}} - 0.100\%$ or above being a flyweight character with the W-Twin Chopper, a solid-focused lightweight character (i.e. Nabbit or Toadette) with the Mach Rocket or R.O.B. H.O.G., a solid-focused featherweight character (i.e. Spike, Goomba, or Baby Mario) with the Baby Blooper, a flyweight character with the Mach Rocket or R.O.B. H.O.G., and a solid featherweight character with the Mach Rocket or R.O.B. H.O.G.. Figure 6 shows their $\boldsymbol{\varepsilon_{s,T,c,w,a}}$ versus $\boldsymbol{c}$ profiles.

Table 3. The attribute profile of the optimal combination and the viable alternatives.

Character Vehicle	Attributes								E (%)
	Speed			Acceleration	Weight	Handling			
	Solid	Grainy	Water			Solid	Grainy	Water	
Flyweight Baby Blooper	10	5	5	16	4	18	14	14	10.797
Flyweight W-Twin Chopper	10	10	10	13	5	14	14	14	10.790
Solid Lightweight Mach Rocket	11	5	5	15	5	19	13	13	10.754
Solid Featherweight Baby Blooper	11	5	5	15	5	19	13	13	10.754
Flyweight Mach Rocket	9	4	4	17	3	19	15	15	10.752
Solid Featherweight Mach Rocket	10	4	4	16	4	20	14	14	10.700

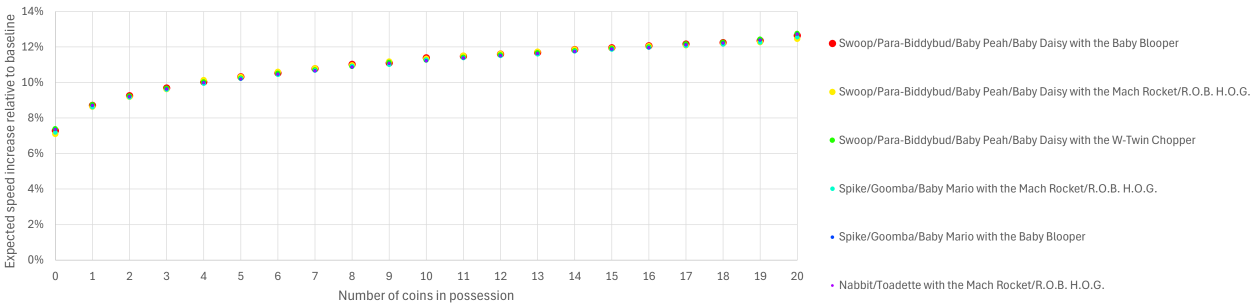

Table 4. A simultaneous plot of the $\boldsymbol{\varepsilon_{s,T,c,w,a}}$ versus $\boldsymbol{c}$ profiles of the optimal combination and the viable alternatives.

The Baby Blooper and Mach Rocket were widely featured in the best character-vehicle combinations because they offered the most speed for minimum weight, the former at 7 points for the speed attribute on solid terrain versus 2 points for the weight attribute and the latter at 6 points versus 1 point. Five out of the six best character-vehicle combinations featured emphasis on the speed attribute on solid terrain, as solid terrain is the most common terrain, excluding RAW terrain, in Mario Kart World. The only exception is the flyweight character with the W-Twin Chopper, being the second-best combination, having 10 points for its speed attribute in all solid, grainy, and water terrains, where the increased 0-coin speeds in grainy and water terrains compensated for its lower acceleration attribute and higher weight attribute.

Unsurprisingly, maximising the acceleration attribute and minimising the weight attribute have also proven crucial in optimising racing performance, as higher acceleration attributes increase the proportion of the time the racer benefits from the 9% speed increase of the non-item boosts, whereas higher weight attributes dampen the ability of coins to increase the racer's speed.

The solid-focused middleweight character (i.e. Mario or Rocky Wrench) with the Baby blooper, being 28th best at $\boldsymbol{E} \approx 10.503\%$, is no longer a contender for the best character-vehicle combination.

5. CONCLUSION

To conclude, by using Queueing Theory to determine the probabilities of possessing any given number of coins during a race and evaluating the expected overall speed of every possible character-vehicle combination according to its speed increase from its speed attribute for each terrain, its weight-dependent coin effects, the coin possession probabilities, and the effects of its acceleration attribute on the drift and trick boost durations, this investigation has found the optimal character-vehicle combination for 150cc races in Mario Kart World.

The results of this investigation demonstrate that speed on solid terrain should be emphasised. The high acceleration attribute and low weight attribute of all six identified best combinations also highlight the importance of maximising the acceleration attribute and minimising the weight attribute when selecting a character and vehicle for racing in Mario Kart World.

The aim of this investigation was achieved successfully.

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