Multiple Worlds Model of Evolution for Demographic Appropriate Radio Playlists

Joseph Alexander Brown
Artificial Intelligence in Games Development Lab
Innopolis University, Innopolis
Republic of Tatarstan, Russia 420500
j.brown@innopolis.ru

Daniel A. Ashlock
Mathematics and Statistics
University of Guelph, Guelph
Ontario Canada N1G 2W1
dashlock@uoguelph.ca

***Abstract*—This study presents an application of the Multiple Worlds Model of Evolution. The goal is to model radio stations in a given market. The model captures listener demographics and maximizes listeners, while securing advertising revenue. Listener preferences for different types of content are set as positive (like) and negative (dislike) integers, allowing surveys of the demographic to act as the model parameters directly. Fitness evaluation is performed with a modeled hour of radio playtime where stations can select between a set of content types and advertisements. Advertisements provide fitness in the form of advertising revenues; however, listeners will only stay on a station which provides content they enjoy. The Multiple Worlds Model is a form of multiple population evolutionary algorithm. It evaluates fitness based on the actions of one member from each population, and has no genetic transfer of information between populations. Each population can thus specialize. In the current study, such specialization is a self-organization of focused (e.g. rock or country) stations via adaption to listener preferences. The model is examined using different numbers of independent populations with even splits among demographic types. The evolved stations show differences in playlists where the profiles differ in their enjoyments and convergence between stations where the listener profiles are similar.**

***Index Terms*—Multiple worlds model, evolutionary computation, agent based modeling, mixed agent types.**

I. Introduction

The Multiple Worlds Model (MWM) is a type of evolutionary algorithm originally developed for *partitioning regressions* [1]. Partitioning regression breaks a set of data points into similar sets, while simultaneously performing symbolic regression on those sets. The quality of the regression drives the partitioning of the data. In addition, for functioning to cluster data, the MWM provides a regression function which has a low error for each one of the resulting data classes. This type of model is therefore simultaneously a classifier and a model. We extend this idea of partitioning classification in this study to the problem of modeling how a group of radio station listeners choose radio stations, resulting in evolution of playlists at the stations. The model allows for the demographics underlying the population to drive the selection of the playlist.

The MWM has been previously applied to bioinformatics. Ashlock and McEachern [2] looked at the interactions of bacterial cultures; the system models each type of bacterium as a separate population, which can interact with others as part of a game. Four actions are available to these models: two cooperative games, an action which is a defection from those cooperative games, and an action which mitigates the effects of non-cooperation, but blocks off some of the benefits of cooperative actions.

Brown [3] examined the application of the Multiple Worlds Model to the discovery of degenerate motifs in DNA, examining base content, motifs in the presence of reverse complementation, and synthetic DNA data generated by self-driving Markov models. A later study [4] applied this method to another synthetic data type, created by self-driving finite state machines as well as biological data drawn from the human leukocyte antigen classes I and II.

Scirea and Brown [5] applied MWM to the creation of music. By seeing each of the worlds as a voice (*soprano*, *alto*, *tenor*, and *bass*) within a four part harmony the evolution creates music which meets with a set of classical compositional rules used by human composers. The music generated could also solve simple composer exercises in which the bass voice is given and the composer must give three other voices which use this base. This is also the first example of member populations in MWM having a collaborative, rather than competitive, model of evaluation.

The use of demographic models for broadcasts has been examined by their industry organizations, most prominently the Nielsen ratings in the United States. These ratings are provided by the viewers. The first method is to issue diaries to list the shows they have seen during the course of a monitoring period. The diaries are issued based on demographic sections of the population. Such modeling has a number of flaws (see [6], [7], [8]); there is an issue with the choice of different demographic groups to how to classify an individual, there is also a response bias (the listeners may not report shows in diaries, or forget to fill one out, or their responses may vary based on memory), and new methods of transmission (such as recording TV for later viewing, downloading shows, cell phone viewings, and tablet devices) are not accounted for in these statistics, even if a broadcast is made live.

People meters, which monitor the shows directly in order to avoid the problem in recall of a viewer [9], have been used. However, such systems do not remove the problems in the lack of modeling new transmission media. There are also accusations that the method is biased by leaving out minority

Question 1: What are your feelings on Country Music?						
-3	-2	-1	0	1	2	3
strong dislike	weak dislike	dislike	neutral	like	weak like	strong like

Fig. 1. Example survey question with response mapped on a Likert Scale

groups in the population [10]. The cost of such technology and monitoring is rather high as well, which could be a contributing factor to these issues in the sample. By moving to a shorter survey based model, a larger sample can be made for a similar cost, and minority groups can be better represented.

Both of these methods also do not measure the responsiveness of a viewer to content which is unseen, and not programmed. Hence, a simulation, which has the ability to present new content, based on a perceived enjoyment of a particular genre of programming would be better suited to situations where new programming is wanted. It allows for a predictive model. The model presented in this paper is such a simulation. It thus presents a novel simulation method to provide predictions of where a market will trend based on surveys of the population.

The model used in this approach is based off a profile of likes and dislikes for various content types. Advertisements are given a strict dislike value which is the same in all profiles. These profiles could easily be drawn from a seven point Likert scale [11], mapping each with a score in the range $[-3, 3]$, as shown in Figure 1.

In order to examine this model, a number of test populations are examined. These are caricatures of listener types for a hypothetical listening group. Examined is the ability for the model to demonstrate plausible radio stations which can model these groups. The first test uses the α's and β's who are listeners diametrically apposed to the other, and enjoy the α and β music respectively. The second tests use listener profiles of a Rocker, Pop, Country, and Talk Caller. These profiles listen to between two and three stations who may play Rock, Top 40s, Country Music and Talk Programs. In both tests the stations play advertisements to increase their fitness.

The remainder of the study is structured as follows. Section II explores the multiple worlds model of evolution which use the idea of adaptive radiation in multiple species to create models; this section also examines the representation of the radio stations. Section III describes the experimental settings used in the explorations of model demographic groups. The results of the experiments are discussed in Section IV. Finally, Section V gives concluding remarks, and explores further directions for this research.

II. Methods

The following section specifies the Multiple Worlds Model (MWM) of evolution and the modeling of the radio stations on which it is tested.

A. Biological Inspirations

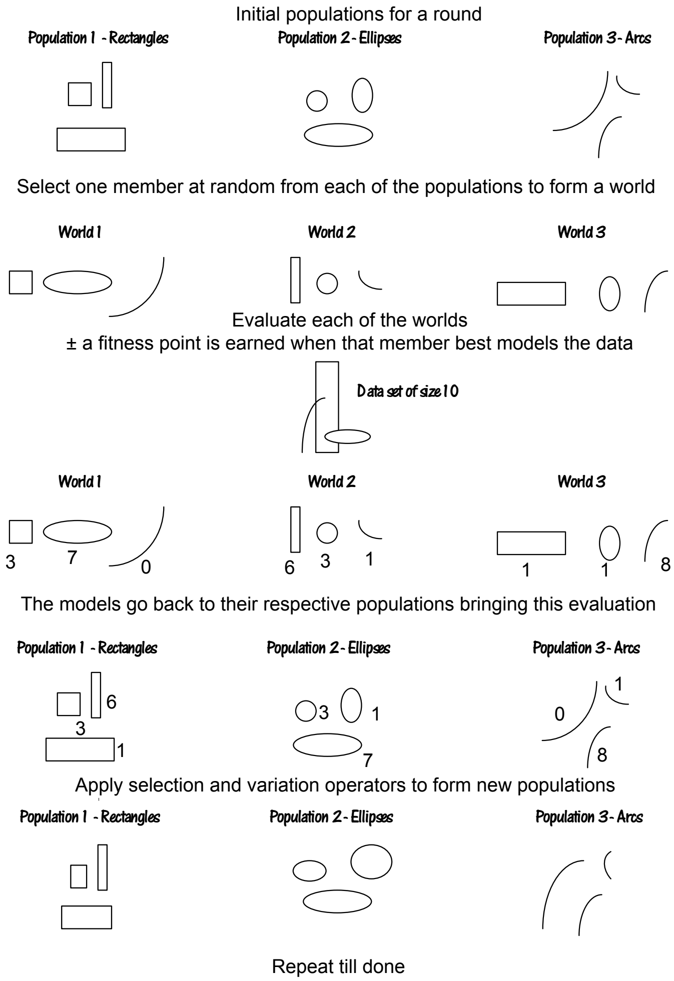
The MWM, as an Evolutionary Algorithm, takes its inspiration from the domain of evolutionary biology. The biological foundation in question is developed from adaptive radiation, demonstrated well by *Geospizinae*, or Darwin's finches. Named for Charles Darwin (who discovered them during the voyage of the H.M.S. *Beagle* (1831–1836)), they were largely ignored initially. Darwin had numerous problems with species misclassification and difficulties with the crew's record-keeping [12]. This led to errors in tracking which island the bird samples had been gathered from. The work of David Lack [13] hypothesized that islands on the archipelago with have only one species of Finch develop a generalized beak — suitable for a number of different food sources. Conversely, islands with multiple species of finch would show divergence in beak shape and specialization; the beak shape and functions, such as a large cracker for nuts or a small tweezer beak for seeds. In extreme cases, beaks developed to manipulate tools and drink blood were evolved. This divergence allows the birds to avoid direct competition over resources with other species. Long term studies (e.g. [14], [15], [16]) with surveys of food types and measurements of phenotypic traits showed that even small yearly variations in food availability can lead to variation.

Furthermore, behavioural modifications can also lead to specialization in food sources through a process of niche partitioning. Hanson in *Feathers* gives an anecdotal account of studying the behaviours of North American bird actions in a forest: "Nuthatches foraged mostly on the trunks, Chickadees dominated the main branches, and Kinglets spend their time flitting about in the side branches" [17]. The MWM aims to use such principles of inter-population competition with intra-population evolution to guide a process of partitioning into models.

This diversity has been seen in studies of mixture vs. monoculture plants in [18], which examined the results of eight years of experimental growth in Jena, Germany. It showed there was an increased interspecific difference to those plants grown in mixture types compared ($P < 0.05$) and intraspecific distance within mixture types on traits was increased ($P = 0.101$). They attribute a difference in relative specific leaf area ($P = 0.073$) and height ($P = 0.074$) to specialization into a niche. While these findings where marginally significant correlations, the authors claim that these traits are representative of relevant niche dimensions, and that further study is warranted looking at the processes of change. [19] examines this study, and the previous mentioned finch studies, to question if such studies can experimentally demonstrate a divergence of species.

B. Multiple Worlds Model

The MWM is applied to situations where a number of distinct agents with interacting roles must be evolved (see Fig. 2). In this model, there are a number of populations where the




```
for some number of generations do
  randomize the worlds
  for all worlds do
    for all datapoints do
      award the point to the model with the best fitness
    end for
  end for
  for all populations do
    Select breeding pairs based on fitness
    Apply Crossover/Mutation
  end for
end for
```

Fig. 2. Demonstration and Pseudocode of the Multiple Worlds system

ideal is for each population to specialize in a role. The role of an agent here is to create a radio station which can maintain itself from advertisement revenue, generated by a population of listeners with differing tastes in content. If there is a natural partitioning of the listeners into preference groups, then the radio stations created by the model should set a playlist to capture these groups. This is an example of specialization leading to a partitioning. If no such partitioning exists, then either a number of stations should fold (leaving a super station) or the stations should split the market by having a group of stations with similar content. This specialization is achieved with the choice of a novel fitness function.

In fitness evaluation, the populations of radio stations are shuffled. The corresponding (first, second, ..., penultimate, last) members of each population are grouped with one member from each population, i.e. a *world*. The score of each station in a world is then computed. In this study, for example, each radio station would be scored on the number of listener-minutes of advertisement it captured during the simulated hour of airtime used for the fitness evaluation. This algorithm is different in theme from spatially structured genetic algorithms such as Island models [20]. First, there is no migration between populations; the population fitness scores are only evaluated for groups of agents, one of each type. Secondly, the evaluation is dependent on taking one member from each population to be a radio station in a world; the populations therefore infuence the fitness of the others. Both of these factors allow the populations to specialize in differing roles, which is an element not present in Island models.

Listener Type	Advert	Top40s	Country	Rock	Talk
Rocker	-1	-3	-2	3	2
Pop	-1	3	-1	1	0
Country	-1	0	3	1	-2
Talk Caller	-1	-1	-1	-1	3

Fig. 3. Listener profiles of a Rocker, Pop, Country, and Talk Caller

C. Representation

There are two groups which will be modeled by this study: radio listeners and radio stations. The listeners are represented as a specification of preferences in the form of numerical value of the enjoyment/dislike of each particular type of music, and a value for the dislike of advertisements. We assume that all listeners start as indifferent to the various radio stations. The radio stations are represented as a list of types of music they will play for a preset interval. An interval in this case could be a programming block, a time period, or the length of a song. Each programming block is deemed to be of a standardized length for the sake of simplicity.

D. Fitness Evaluation

The fitness of a station is defined as the number of advertisements listened to by a set of listeners. The content provided to a listener must be pleasing based upon their unique listener profile. The listeners to a radio station will refuse to listen to a station which only broadcasts advertisements. If they do not enjoy the content, then they are prone to change stations; the change will cost the station advertising revenue, and thus evolutionary fitness. The station must strike a balance between content and advertisement to be most fit.

The listener is defined by a happiness level and a listener profile as shown in Fig 3. The happiness level is how pleased the listener currently is with the broadcast. The profile is a set of likes and dislikes of content types. A classic rocker, for example, might express a large benefit, from listening to classic rock, a small gain from talk (i.e. Shock Jocks), and a sharp decline from Top 40s music. All profiles dislike advertisements; listeners would prefer content. This happiness level is used to determine if a listener will change to another radio station subject to the distribution $C(x) = 1 - \frac{1}{1+e^{-x}}$, as shown in Fig. 4. When happiness is at a value of 0 the listener is indifferent with half a chance to change stations. As the happiness increases to positive six or decreases to negative six, the listener will saturate in terms of like or dislike, and will be certain to stay on or change the channel. Because the listeners do not necessarily have the radio on at any given interval, there is always a null station choice with a constant happiness value of 0. This null station represents the choice of leaving the radio off.

In fitness evaluation, each listener starts on a random part of the dial. There is a number of time steps equal to the programming period of the stations. At the beginning of each time step, each listener generates a random number uniformly distributed in the range $0 \leq x \leq 1$. If this number is greater than the value of their current happiness for that station, they stay on that station. Otherwise, they change which station they are on and continue the process of checking their happiness on a station until they stop on a station. Once they have decided which station they are going to listen to for this programming period, their like for the station is adjusted based on the programming choice of the station for the current time step. If it is an advertisement, then the station receives one point of advertising revenue (fitness).

The fitness of a radio station is the number of ad-revenue scores multiplied by the fraction of advertisements in their total programming block. This model feature represents the tendency of agents to simply not listen to the radio, or perhaps switch to an MP3 device, if they are offended by too many advertisements. This normalization of fitness removes the implausible Nash equilibrium in which all stations go to a constant advertisement format.

E. Subpopulation Collapse

MWM does not need to know the number of correct classes *a priori* when partitioning data or listeners. Instead, the evolutionary model can find a correct number of classes via an emergent model feature called *subpopulation collapse*. Previous studies have show that when the number of worlds selected are greater than the number of supportable models the system moves to one of two states: 1) the two populations converge towards each other and fight over the points in the natural cluster of points, or, 2) one population forces another into an irrelevant position and dominates, the latter having a fitness score tending towards zero. This second case we call a *subpopulation collapse*. Subpopulation collapse is analogous to a biological extinction event; subpopulation collapse for a radio station would be a station which gains little or no revenue because no-one is listening.

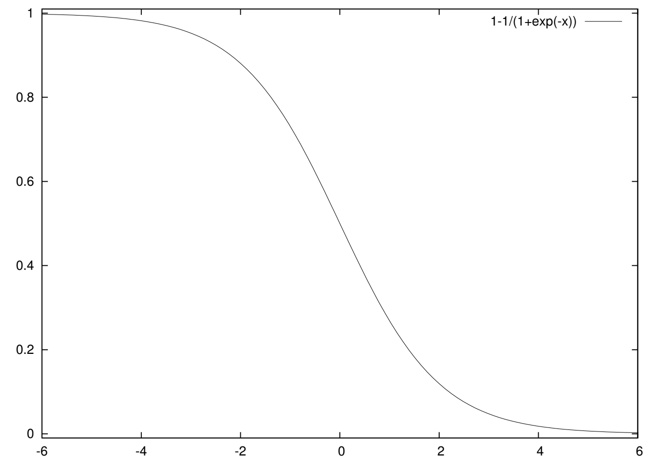


Fig. 4. Graph of the happiness function — $C(x) = 1 - \frac{1}{1+e^{-x}}$ — probability for changing stations lowers as the like a listener increases for a station.

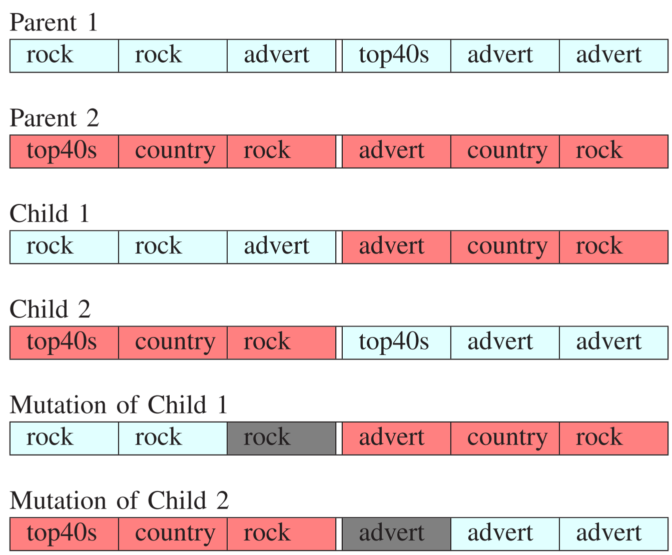


Fig. 5. Example of breeding (crossover and mutation) between the representations of playlists. Parent one is the first radio station playlist of size six in light blue. Parent two is the second radio station playlist of size six in the darker red. A one-point crossover then occurs between the two parents at the third loci creating child one and two. The mutations of the children then happen in child one at the third position and the second child at position four, labeled in dark gray.

III. Experimental Settings

Each populations used contains 100 members. These members consist of a stations playlist of size 60, selected as it is the number of five minute intervals in five hours. Five minutes is long enough to introduce and play song of average length; a distribution of song lengths, created from over 70,000 American songs, has a relatively symmetric distribution in lengths with a mean of 242 seconds, i.e. about 4 minutes [21]. Five hours covers the morning drive time from 5am-10am used by a number of stations in urban centres. Each slot in a playlists is initialized to one of the music types or advertisement with equal likelihood. The listener population is

50 members in total, with 25 being of each of the listener types in the even tests as described below. The selection operation for breeding is a tournament which takes four members of the population, orders them based on their fitness, and replaces the bottom two fitness members with replicates of the top two fitness members. The copies in the bottom two positions then undergo mutation and crossover, e.g. Fig. 5. The crossover operator is a one point crossover; it probabilistically selects one point in the playlist and swaps the broadcast types between the selected positions. The mutation operator randomly assigns a new broadcast type to each time step in the playlist with 10% probability. This occurs for 2500 generations.

IV. Results

In order to allow for a comparison between outputs with multiple stations, there needs to be a way to cluster like stations together. Certain choices would be more likely — such as talk shows for a population with talk callers — the station with higher frequency of the first type of show is used as a standard of placing the stations into classes. Number of adverts in this case is not a good method of classification as the model will often produce stations with the same number of advertisements, and we are interested in seeing if there is behavioural differences.

A. Simple Test — αs and βs

In order to show the partitioning power of multiple worlds a simple example was constructed. In this case we limit the content types to three: Advert, Song A, and Song B. Two profiles were created which are the dual in terms of their enjoyment of the stations, call them listener α and listener β. The mean frequencies of each type are compared:

	Advert	Song A	Song B
STATION α	1.26667	10.3333	0.4
STATION β	1.2	0.366667	10.4333

It is plainly visible from the means, the MWM creates two radio stations. The first appealing to the αs by playing Song A exclusively, and the second appealing to the βs by playing Song B. This simple experiment serves as a certificate that the system is functioning nominally.

B. Two Stations — Even Populations

In all cases the station profiles created show some similar trends. First, there is a length of content which is associated with positive feedback to one of the demographic groups which lasts for at least a quarter of the time. Often, there is then a quick switch into a content type of the other profile right before the appearance of an advertisement; the stations are attempting to get as many listeners as possible before the payoff. After all advertisements of the playlist have appeared, the playlist reverts of a chaotic state. Fitness has already been made or lost at this point and all selections for these locations will produce a playlist of equal fitness. The playlist is therefore epistatic; changes earlier are worth more than later changes. Further, there is an issue in the model that a listener can saturate their happiness by hearing a number of good songs in a row, they "stay on the dial" even for a set of bad content, making later parts of the playlist more chaotic. The mean percentage of each of the play types is presented and commented upon. However, the playlists themselves are far more informative. Figure 6 provides a graphic visualization of the play profiles.

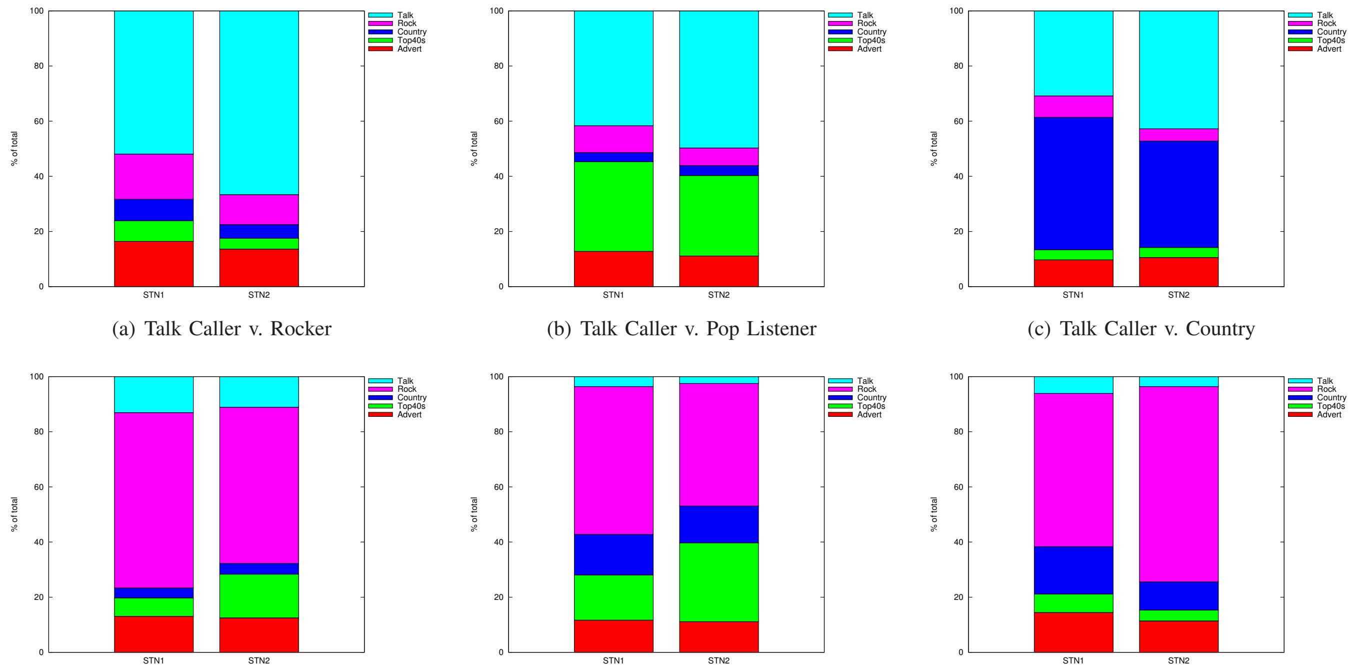
1) Talk Caller v. Rocker: Shock jocks win the day when rockers and talk callers are the population of listeners. The power of talk radio swiftly gains an advantage early on in the playlists, allowing for ads to be played. After advertisements have been played, the epistatic nature of the playlist and the saturation of happiness makes for stations which have a number of unexpected plays of country and top 40s, however in the station with most talk these are reduced. The stations in this model converge in their playlists, as both talkers and rockers both like talk radio. There is no instances of a subpopulation collapse, and the stations are able to coexist.

2) Talk Caller v. Pop Listener: Pop Listener don't mind talk shows, whereas talk callers are offended by anything. Again we observe a large movement towards talk. The Pop Listeners bounce over the dial as the stations fight for dominance in the talk market — leading to playlists of talk right at the start followed by a playlist of talk and top 40s. The top 40s are played in the time step right before an advertisement in order to keep the audience tuned in. There are no instances of a subpopulation collapse; two stations are perfectly happy to share the air.

3) Talk Caller v. Country: Country lovers have a strong dislike for talk, and talk callers dislike from everything else. The advertisement levels between the two diverse groups is reduced compared to the talker v. Pop Listener, and even more than the talker v. rocker. Listeners are moving to a single station and holding position, making it far more profitable to be in a specialized market. There is a single collapse event in the runs, producing a final station with no advertisement revenue. The single focus of the station holds a listener to a station for advertisements without offending.

4) Pop Listener v. Rocker: The stations above once again exhibit a strong like for the same type of music in Rock. Hence, the like for rock presses out the Top 40s music which would offend the audience. The station, unable to play more rock than the other resorts to differentiating itself by the choice of top 40s music. A divergence in the station profiles as the first station aims for more diversity. Station two becomes a rock station, playing only one third of the pop songs, with more allocations of shock jock talkers, who don't offend the Pop listener. Both profiles dislike of Country music has been suppressed to the point of nonexistence, appearing at all due to genetic drift in the population and due to the epistatic nature of the playlist. The final populations show no evidence of collapse, and both stations are relatively profitable.

5) Pop v. Country: An interesting result happens with the Pop and Country in that neither really gets their preferred music. A Pop Listener dislikes country, Country listeners are



(a) Talk Caller v. Rocker

(b) Talk Caller v. Pop Listener

(c) Talk Caller v. Country

(d) Pop Listener v. Rocker

(e) Pop Listener v. Country

(f) Rocker v. Country

Fig. 6. Radio Station Time Allocations — Two Stations

not offended by top 40s but doesn't enjoy it. This explains the higher appearance of Top 40s music in the first station. Both County and Pop listener enjoyment of rock leads to a creation of rock stations. The final populations show two stations which have collapsed, as the rock profile is able to dominate the space.

6) Rocker v. Country: Station one targets rockers and plays half the number of top 40s selections and talk. Station two is able to play more ads by taking more country selections to make up for the offending shock jocks. The shock jocks allow for less rock to be played. The stations do not collapse and both are profitable.

C. Three Stations — Even Populations

Increasing the number of stations in many cases has a settling effect on the playlists into a spectrum between the two demographic groups. Instead of harsh divisions, the middle station is prone to trying to split the difference between the two extreme ends. In cases where the demographics have dislike of the others likes, the selections and breaking into different playlists becomes more pronounced than the two station examples. Figure 7 provides a graphic visualization of the play profiles.

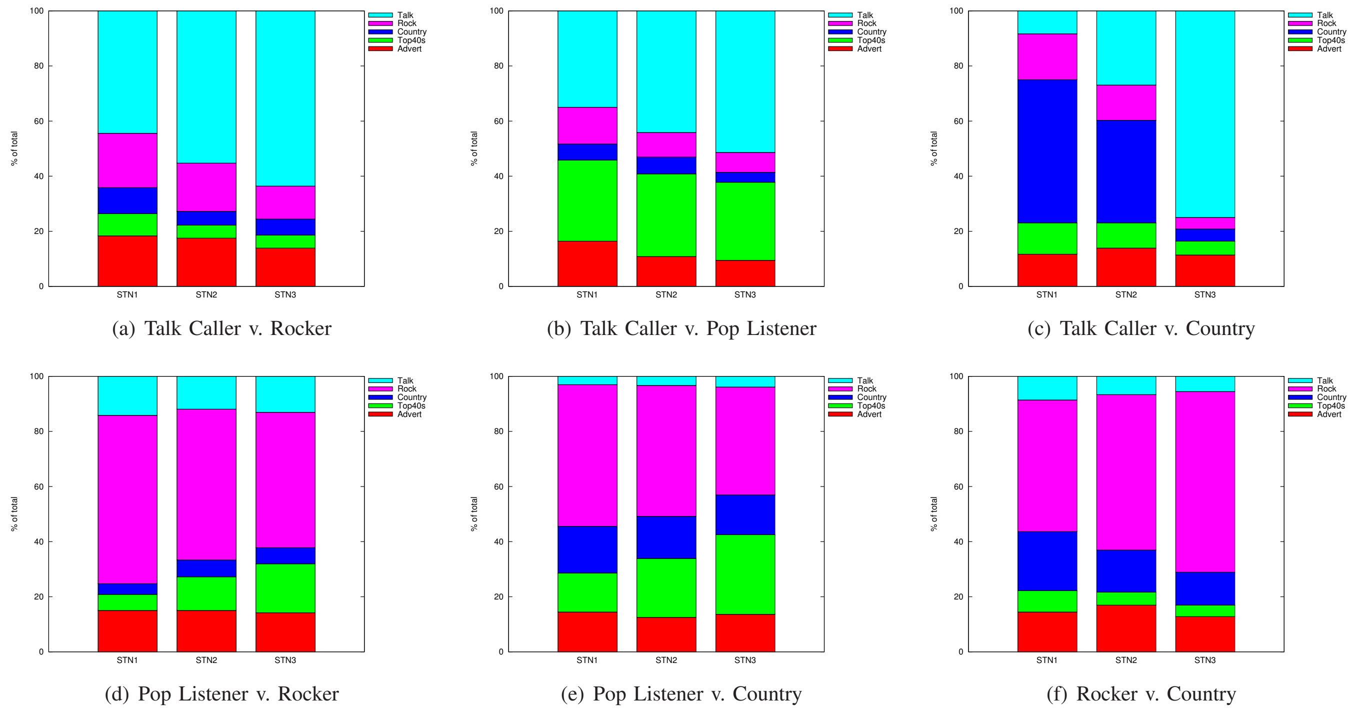
1) Talk Caller v. Rocker: For these stations shock jocks again rule the airwaves. The three stations fighting for the profitable talk and rock markets. Playing rock music is inversely correlated with talk shows, an attempt is being made to specialize for the rockers, to pull them out of the talk only stations. The percentages for stations one and two for Rock and Talk are close to the two station model, Station three using a lower level of talk. There are no instances of collapse similar to the two station model; the demographic is able to support the three stations.

2) Talk Caller v. Pop Listener: As talk decreases, the stations move deeper into country and rock. Station one focuses on a strong mix of rock and talk, moving beyond the bounds set by the two-station model. The three-station model further diverges from the two-station model, as the number of collapses goes up to one. The support for more stations is weakening.

3) Talk Caller v. Country: The talk caller and Country listener are most dissimilar in terms of their likes, and this is evident in the modeling. Station one has progressed to an "all talk — all the time" format. Station three is now a country/rock station. Station two attempts to take the middle ground. This model has no collapse events by pressing to the extremes to capture the listeners.

4) Pop Listener v. Rocker: The Pop and Rockers both end up creating a station with slight differences in the levels of rock and top 40s. Rock dominates the playlist, as both pop listeners and rockers gain enjoyment — talk is not seen to the same extent as in all cases if a talk choice was made, it would have been better to air a rock song. The amount of top 40s is what primarily gives a differentiation from between the stations. No stations are removed from the system as the the sight differences in station values are not enough to collapse a station and the listeners gain enjoyment from all classes.

5) Pop Listener v. Country: The three radio stations model is also pressed into becoming a rock station as both the Pop and Country listener enjoy rock. The stations press apart in



(a) Talk Caller v. Rocker (b) Talk Caller v. Pop Listener (c) Talk Caller v. Country

(d) Pop Listener v. Rocker (e) Pop Listener v. Country (f) Rocker v. Country

Fig. 7. Radio Station Time Allocations — Three Stations

terms of their playing of country and top 40s. Talk shows are pressed off the dial. No subpopulation collapse events occur demonstrating that the demographic is able to support the number of stations.

6) Rocker v. Country: The Country station continues to play talk radio as an alternative to rock selections, with country maintaining a low presence. The number of advertisements increases in the middling station to take on more revenue. The targeted rock station is able to play a smaller number of ads, showing the power which can be had from a single demographic. The three stations have a single subpopulation collapse event showing a convergence in the profiles.

V. Conclusions and Future Directions

In this study we examined the MWM as a representation of radio stations provided to listeners with specific interests; it can model just as easily other broadcast media, such as television and streaming internet programming. Another application can be seen in products where a large number of alternatives or imperfect substitute goods exist; these can be modeled in much the same fashion, with minor changes based on the application desired. For example, a set of restaurants could make investments such as location, price, food style, and atmosphere. A set of consumers would be positioned based on their preferences.

This study shows a simplistic model of the radio stations and listeners, and a number of changes can be made in order to better model the profiles. First, listener enjoyment is based on their entire history with the stations. It would be more realistic to have a memory window. That is a listener will remember perhaps only the last three songs from each station. This would prevent the saturation of listener to either the positive or negative side. Secondly, there is currently no decay in like or dislike over time. The model would be best served to have a decay in the values. Finally, the programming is made in fixed length programming blocks — this should be allowed to change in a more dynamic method, quite often flipping though channels. This would permit an additional level of strategy based on where content block beginnings and endings are placed. The current playlist as a string approach, however, allows for a simple examination of the results produced in order to show the method to be valid.

The introduction of additions to the fitness function allows for a multitude of different studies to be preformed. For example, how to remedy Payola/Plugola, the illegal inducements provided by record companies to stations for playing specific song titles [22], by companies for products to be ‘plugged’ outside of an advertisement block, and political opinions being espoused [23], can easily be introduced and studied in the models. The model could provide a multi-objective fitness to the station for payment from normal ads as well as side payments. In the case of political opinion, another parameter would be assigned to the listener for political affiliation. Countering this would be a probabilistic penalty; fines are received if the Payola/Plugola is discovered by the regulator.

Further, other restrictions, such as the Canadian content regulations [24], can be modeled through the addition of changes to the fitness model and the available contents. The final models would have to contain a set amount of content or a fitness penalty — a fine, would be applied. The selected content would provide less of a increase in like as it appears more often.

The MWM has shown another application of the novel fitness determination taking into account the evaluation of fitness between populations where there is not an exchange in order to partition a space. It is interesting to note that these radio stations are not subject the levels of subpopulation collapse seen in order studies. This study is the first to use a fitness function which is not winner-take-all in terms of a point. In this case, a listener may provide fitness to both stations. Additionally, as the initial starting location on the dial is random, there is a propensity for the stations to be able to keep the listeners that they start with. In previous winner-take-all fitness functions a larger number of collapses are seen. These previous works were also deterministic models. This implies that the model perhaps is too forgiving to bad content, or that the number of listeners was large enough to support a number of radio stations. In order to apply this in the field to real radio broadcasts, case histories and human testing would be required in order to refine the parameters.

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