PRINT AND MULTI-MEDIA OPTIMIZATION: AN EVOLUTIONARY APPROACH

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Abstract

The use of reach optimizers in the context of print planning has declined substantially in recent years whereas optimizers have become "standard issue" within much of the television planning community. Some measure of this decline is due to the inherent design limitations of many of these print optimization systems given the complex nature of the print-based reach search space.

This paper begins with reviews of the reach search space's complexity and the techniques conventionally employed by print optimizers in searching this space. Noting the fundamental ways in which conventional optimization techniques are ill-suited to efficiently maneuver in this space, a Genetic Algorithm (GA) based optimization methodology is presented. Generally, GA optimizers hold distinct advantages over traditional approaches when confronted with such complexity. In comparison with traditional approaches, GA optimizers will be shown to offer:

- More cost efficient schedules for given reach objectives
- More balanced selection of vehicle insertions, particularly in multiple media contexts
- Robust alternative schedule solutions for the same candidate media set
- More flexible goal definition using the same basic search strategy

These advantages will be demonstrated to hold in both print-only and multiple media contexts utilizing both United States local market data available from Scarborough Research and data for Great Britain provided by BMRB International (TGI).

Introduction

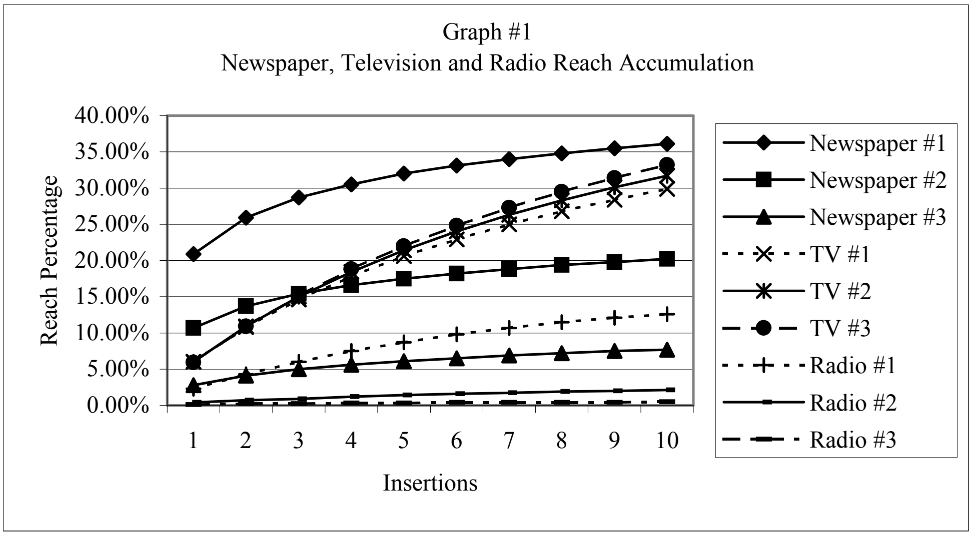
The last decade has witnessed a dramatic growth in the complexity of the media universe. The increase in the absolute number of media vehicles is only one dimension of this phenomenon. Surely as important, if not more so, is the emergence of entirely new media types and channels - cable and satellite television and the ubiquitous Internet.

As the media world has grown more complex, so inevitably has the task of media research. Where once researchers could develop media plans containing two or three media types (e.g., print, broadcast television and radio), currently such plans must include many more media components. Moreover, media researchers face the increasing challenge of rationalizing the proportions of campaign budgets devoted to particular media categories as well as justifying individual media vehicle selections within these categories.

It is as responses to these challenges that this paper and the techniques elaborated in it are intended. The particular focus of this work is the review of a robust optimization technique for developing efficient media schedules, whether they involve vehicles of a single media type or from among multiple media categories. Beyond this, we propose that this and techniques like it have the potential for becoming the means for the more thorough rationalization of the total media allocation process.

The Media Optimization Search Space

The fundamental problem associated with the development of media optimization systems is that the search spaces through which they must navigate toward optimality are non-linear. There are a number of dimensions to this non-linearity, but the most basic is the non-linearity of an individual vehicle's reach accumulation. The accumulation of reach for any individual media vehicle (e.g. magazine, newspaper, radio or television) fails to follow a straight and predictable path. In fact the calculation of reach given most audience measurement methodologies is itself an iterative process (e.g. Beta, Gamma, Hypergeometric).



Graph #1 amply illustrates the non-linear character of reach accumulation irrespective of both media size and type. Note that of the nine media vehicles as measured by Scarborough Research in one of its local market studies, each's reach curve fails to follow a regular path. Note also that the shapes of these individual curves while reminiscent of each other are by no means identical either within or across the three media categories.

While primary, the non-linearity of single vehicle reach is only one aspect of the optimization search space's complexity. Optimization is generally a reach-for-cost problem – the best reach for a given budget, or the lowest cost for a target reach. As such, to the extent to which frequency-based cost discounting is non-linear, the calculation of total cost at a particular insertion level for a particular vehicle is impossible in the absence of explicitly elaborated discount information.

Finally, and maybe most obviously, the accumulation of reach within a schedule of multiple vehicles is complex. In only the rare instance where two or more vehicles share no audience duplication and the insertion levels are at one is the reach of the entire set the sum of the individual vehicles' reaches. Consequently, to determine the overall reach of a multiple vehicle schedule some computation accounting for the duplication among the vehicles is necessary. A distinguishing characteristic of the different formula-based reach models available today is their assumptions as how best to combine individual vehicles given the differing levels of duplication.

The high degree of non-linearity in the media optimization search space has the consequence that it is not possible to find the truly optimal schedule without computing the reach and cost of all possible schedules occupying the search space. Were media reach search spaces linear optimization would require only some relatively straightforward computation. Alas, this non-linearity forces media researchers and applications developers to resort to either exhaustive or heuristic search techniques. It is to a discussion of these that this paper will now turn.

The Optimal Schedule in the Media Search Space

Given the complexity of the media optimization search space, the only way to guarantee that the best schedule (highest reach for a given cost, or lowest cost for a specific reach) has been discovered is to exhaustively search this space. The problem with this approach is that for spaces comprising more than a modest number of vehicles and/or very modest reach or cost targets the number of possible schedules to evaluate becomes computationally untenable.

To see this point consider the task of finding the lowest cost schedule achieving a 70% reach from among the nine vehicles referenced in Chart #1. To put some constraint on this problem assume further that no vehicle should contain more than ten insertions. To naively evaluate all possible schedules would entail computing 11^9 or 2,357,947,691 schedules. Clearly there are ways to reduce this number. For example, any schedule which itself is a superset of a schedule already exceeding the targeted reach (70% in this case) could be immediately rejected. However, even these sorts of reductions are not sufficient to reduce the number of schedule reach computations to a manageable number, and they themselves assume some amount of computational burden.

The Hill-Climbing Search

Given the computational limits on discovering the optimal media schedule through either a naïve or enhanced exhaustive search, a conventional alternative adopted by a number of available print optimizers is one form or another of a hill-climbing search. Broadly stated a hill-climbing search develops a schedule one media insertion at a time. The search begins by evaluating each media vehicle in the candidate pool and selecting the one with the highest reach-per-insertion cost. Successive selections are based upon the marginal reach-per-insertion cost, again from among the pool of vehicles. Thus the term "hill-climbing", for the search procedure climbs the reach-per-cost hill one step at a time. (There are a number of permutations on this technique such as searching for the next insertion by evaluating the next two steps, or stepping up and then stepping back, etc.)

The value of the hill-climbing approach is that the number of reach evaluations is manageable compared with the globally exhaustive (but computationally exhausting) global search technique previously outlined. Using the prior example of nine vehicles with a maximum of ten insertions each, the maximum number of schedules a simple hill-climbing technique evaluates is $9 * 11^2 - 1$ or 1088, a computationally reasonable number.

Schedule sub-optimality is the expense encumbered for the hill-climbing technique's computational efficiency. The basic problem with hill-climbing is that the scope of its horizon is limited to the set of next possible single steps. Simply because immediate available steps are themselves efficient does not mean that they lead toward global efficiency. It is for this reason that hill-climbing techniques are often characterized as "greedy", they seek to maximize short-term efficiency but with no regard to ultimate efficiency. A more formal characterization of this defect is that hill-climbing techniques fall victim to "local optima".

The enhancing permutations of the hill-climbing technique such as those involving evaluation of multiple-steps or step-up/step-down certainly improve on the naïve techniques, but they serve only to reduce the local optima problem not eliminate it. Indeed, the dilemma associated with these enhancements is that they improve only to the extent to which they approach the exhaustive global search scheme. From the perspective of multiple-step or step-up/step-down hill-climbing techniques, the exhaustive search scheme can be understood as a radical or complete variation on either.

The Genetic Algorithm Approach

Non-linear optimization problems arise in a variety of contexts beyond media planning, and as such a broad literature already exists informing the problem at hand. One of the more fruitful inquiries into techniques relevant to this family of problems was begun by John Holland at the University of Michigan beginning in the 1960's and was broadly termed Genetic Algorithms (GA).

As the term implies, evolutionary principles constitute the GA's foundation. While the basic elements of GA's are both few in number and readily comprehensible, testimony to their robustness is found in the panoply of contexts in which they have found useful employment.

Fundamentally, GA's work by first randomly generating, and then crossing-over, mutating and evaluating series of numbers, calculations or rules which constitute potential solutions to the problem at hand. In evolutionary terms the set of individual series forms the *population* which will evolve through successive iterations or *generations*. Each series comprises the *DNA* of a particular population member, with each element of the series being a *chromosome*. The intermixing of series and the mutation of the results embody the process of *reproduction* and evaluation the process of *survival of the fittest*.

The character of the selection of mates for reproduction is a central element of GA's operation. The selection of series for mating and subsequent reproduction is an artifact of the goodness of the series as solutions to the problem at hand. This goodness is measured by a problem-domain specific objective function, the *environment* in evolutionary terms. By design, series embodying better solutions tend to mate with other *fitter* series, producing *off-spring* solutions potentially combining the strengths of both *parents*. Thus, the populations of successive generations possess increasingly improving individual solutions, *fitter members*.

When compared with hill-climbing and global search techniques GA's embody the advantages of each without incurring their respective debilitating costs.

The random quality of the initial GA population and the crossover and mutation strategies insure that all regions of the search space are at least minimally explored thus capturing some measure of the strength of the global search strategy. However, as GA's do not unnecessarily dwell in unproductive regions they possess the computational efficiency of hill-climbing strategies, exactly the efficiency absent from global search.

In contrast to hill-climbing techniques GA's are always evaluating and reevaluating complete solutions and are thus not subject to the deleterious long-term consequences of earlier schedule insertion selections. In fact GA's are distinguished by their resistance to the seductiveness of local optima, a primary weakness of hill-climbing approaches.

Genetic Algorithm Based Media Schedule Optimization – Theoretical Overview

In the context of media optimization the GA approach has a very natural fit. In the systems we have been developing and refining, a set/population of randomly generated schedules is first constructed. Each of these schedules is evaluated against an objective function accounting for the cost efficiency of the schedule with respect to the reach goal (or vice-a-versa with respect to the reach efficiency given a budget goal). Successive generations of schedules are developed by crossover and mutation at rates proportional to the goodness of each schedule as evaluated by the objective function.

Table #1
Genetic Algorithm Schedule Combination

Generation #1
Media Vehicle Insertions

Population Schedules	A	B	C	D	E	F	G	H	Schedule Score
Schedule 1	3	4	7	8	4	2	3	8	90
Schedule 2	5	2	12	3	3	4	0	9	80
Schedule 3	3	5	4	4	7	3	4	6	67
Schedule 4	7	8	6	5	9	7	7	1	55
Schedule 5	3	4	8	6	3	1	5	3	44
Schedule 6	6	6	3	1	5	0	8	4	41
Schedule 7	3	8	6	8	6	3	9	4	35
Schedule 8	5	4	1	6	7	0	2	8	27
Schedule 9	7	3	9	8	3	0	4	6	18
Schedule 10	9	7	0	2	8	0	6	9	9

Schedule Crossovers - Generation #2
Media Vehicles Insertions

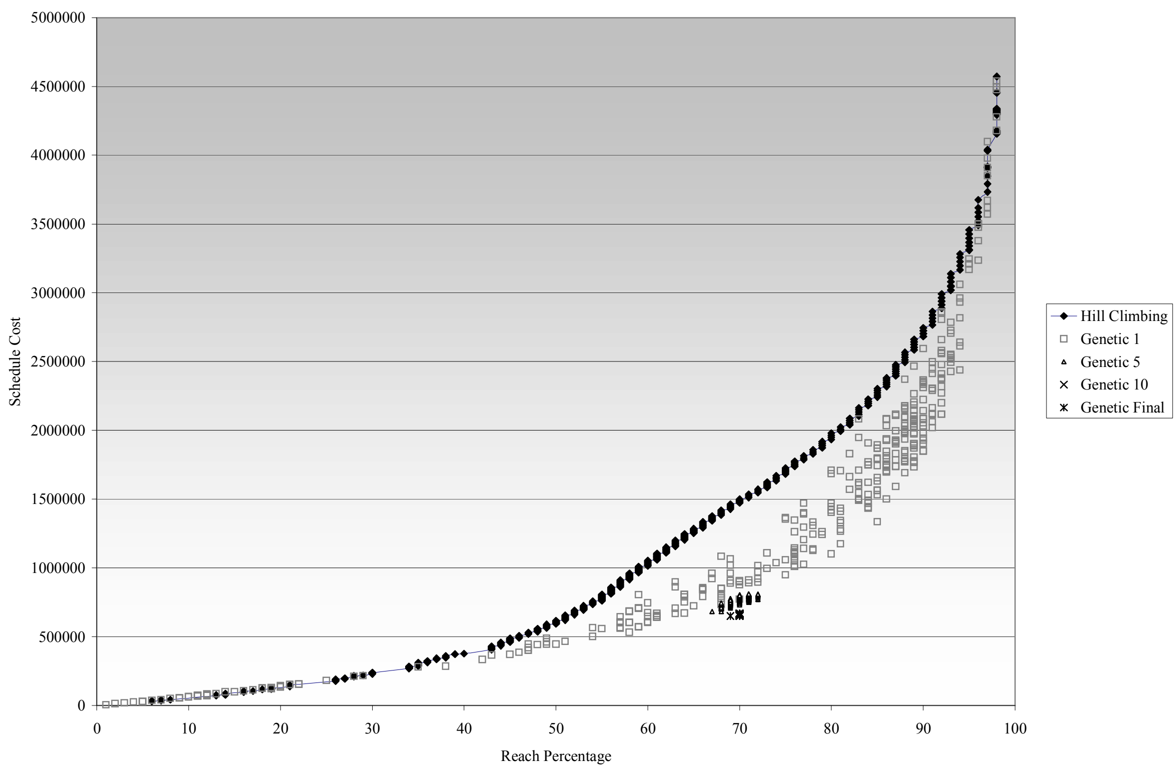
Schedule Combinations	A	B	C	D	E	F	G	H	Schedule Score
Schedules: 1 X 2	3	4	7	8	4	4	0	9	95
Schedules: 1 X 5	3	4	7	8	4	2	5	3	75
Schedules: 2 X 4	5	2	12	5	9	7	7	1	85
Schedules: 3 X 2	3	5	4	4	3	4	0	9	70
etc.									

Table #1 illustrates a hypothetical mating process. Ten initial, randomly generated schedules constitute Generation 1. Each is scored by means of the objective function and combined, sometimes multiple times, with another schedule(s) to create Generation 2. As with the combining of DNA in nature, so to with the combining of schedules, with each *parent* schedule contributing differing numbers of vehicle's insertions to the new *off-spring* schedule. For example, the first pairing involves schedules 1 and 2, schedule 1 contributes insertions for the first five media vehicles, with schedule 2 contributing the final three media's insertions. Thusly this process of mating and the creation of succeeding generations continues until some number of iterations has been reached or a particular generation's most fit member meets certain specified criteria.

As noted previously, that the overall efficiency of the population improves from generation to generation is a fundamental quality of the GA strategy. This quality of steady improvement is the result of the propensity of *fitter* schedules to *mate* and *reproduce* more frequently, a deliberate design feature of GA systems. GA's do not take random walks in search of the elusive optimal point. Neither do they pathologically pursue seductive but ephemoral optima as do hill-climbing techniques. Rather they proceed as a *population* of increasingly robust individuals ceaselessly intermingling and exchanging *genetic* information about the variety of potential paths leading towards a more genuine optimality.

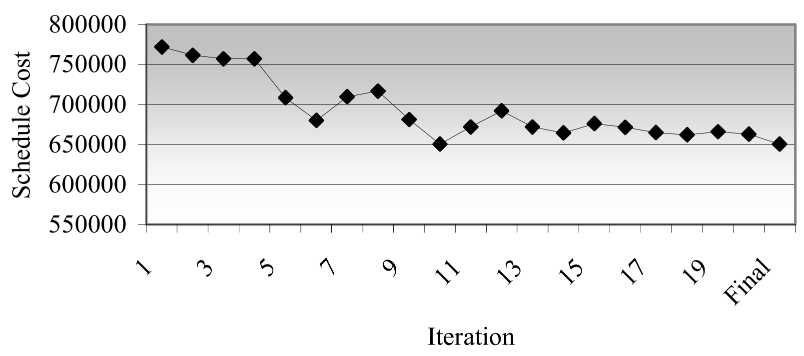
Genetic Algorithm Based Media Schedule Optimization – Evidence in Practice

Graph #2
Genetic Algorithm Optimization Schedule Development - 70% Reach Goal



Graph #2 depicts the continuing improvement of an actual GA media optimization through twenty successive generations. Notice that over the course of successive generations the distribution of the population narrows. Early generations have member schedules with widely varying reaches and costs. As early as generation 5 (Genetic 5) the population is constrained to a narrow reach range, from approximately 68% to 72%. The final population clusters tightly around the 70% reach goal and exhibits the lowest average cost among all twenty generations.

Graph #3
Genetic Schedule Cost Development - 70% Reach Goal



Graph #3 reiterates this from the perspective of cost, with each node in the graph representing the total cost of the most efficient schedule in each of the twenty GA generations.

Experimental Design – Scarborough Data

Scarborough Research conducts syndicated studies in more than 60 major local markets throughout the United States. So as to collect as broad a range of data all the while reducing respondent burden Scarborough employs a methodology incorporating a telephone interview, a retail shopping and activity/lifestyle questionnaire and a personal, seven day television diary. Thus, Scarborough studies provide broad overviews of the media habits (i.e., newspaper reading, radio listening and television viewing), shopping behaviors and lifestyle patterns of individual local market populations.

For the purposes of this analysis data from the 1998 Release II of the Philadelphia market was selected. Philadelphia is a relatively large local market, comprising a relatively diverse population. As appropriate to reaching a diverse population, Philadelphia possesses a broad variety of individual media offerings, possessing fundamentally differing audience sizes and characteristics, from among the three local market oriented media categories. Thus, Philadelphia presents a challenging and informative case for the study of media optimization techniques.

The particular aspects of the analysis that follows are all based on a 41 vehicle candidate set. Included in this set are the three United States national newspapers, five larger city newspapers, nine smaller city/suburban daily newspapers, seven television stations for the "Prime Time" daypart, and 17 radio stations for the "Morning Drive" daypart. The target for this analysis is the adult population (Age 18 plus) for the Philadelphia Designated Marketing Area (DMA).

Experimental Design – BMRB TGI Data

In addition to the local market data from Scarborough, examples were also drawn from the full year 1998 GB TGI survey conducted by BMRB International. The 1998 TGI survey represents all adults of Great Britain with fieldwork conducted between April 1997 and March 1998. The survey consists of c.25,000 adults who are asked a wide range of product, behaviour, lifestyle and print media consumption questions.

For the purposes of examining the effectiveness of a GA optimizer a number of different target audiences and candidate vehicles were selected as described in Table 2 below.

Table #2
BMRB TGI Analyses

Target Audience	Target Audience Counts	Candidate Vehicles
All Adults	Sample: 25,560 Weighted: 46,250 (000)	10 national daily newspapers, 9 national Sunday newspapers, 8 national Sunday colour supplements
All Adults who have purchased a new car in the last 12 months	Sample: 1,331 Weighted: 2,365 (000)	8 magazines, 5 national daily newspapers
All Women	Sample: 14,085 Weighted: 23,762 (000)	48 women's magazines, mixture of monthly and weekly titles.
All Women who spend on average £10 or more per month on skincare products	Sample: 1,398 Weighted: 2,435 (000)	48 women's magazines, mixture of monthly and weekly titles.

The press reach and frequency model used for the TGI data is a formula model called MetherPlus. Developed by Richard Metheringham in the late 1980's for Simmons, MetherPlus is available in the CHOICES press planning software employed throughout the U.S. and the U.K.

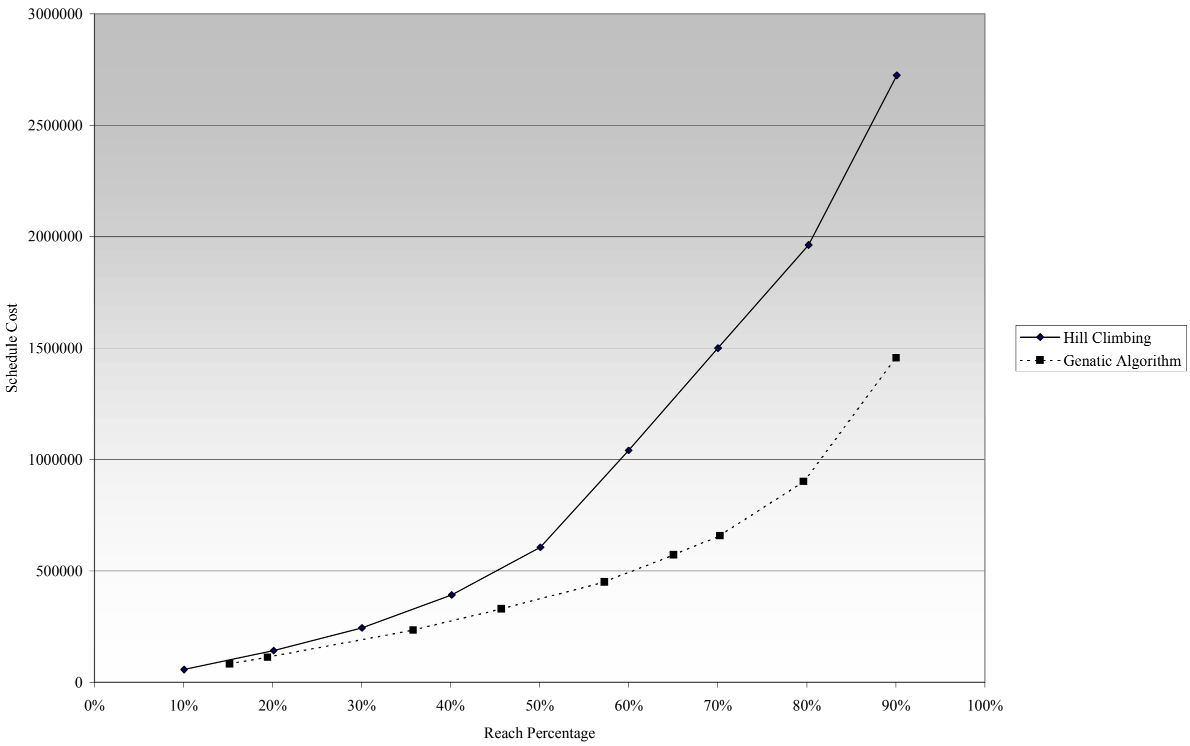
Experimental Design – Optimization Analyses

For the purposes of obtaining a basic overview of the viability of the GA optimization technique when compared with traditional hill-climbing optimizers two series of nine optimizations were performed, one using hill-climbing the other GA. The objective for each of these series was the minimization of cost given a particular reach objective. As such each series was comprised of reach goals beginning at 10% and increasing to 90% in increments of ten percentage points.

Optimization Results

Graph #4 summarizes the results of the optimizations for Scarborough data.

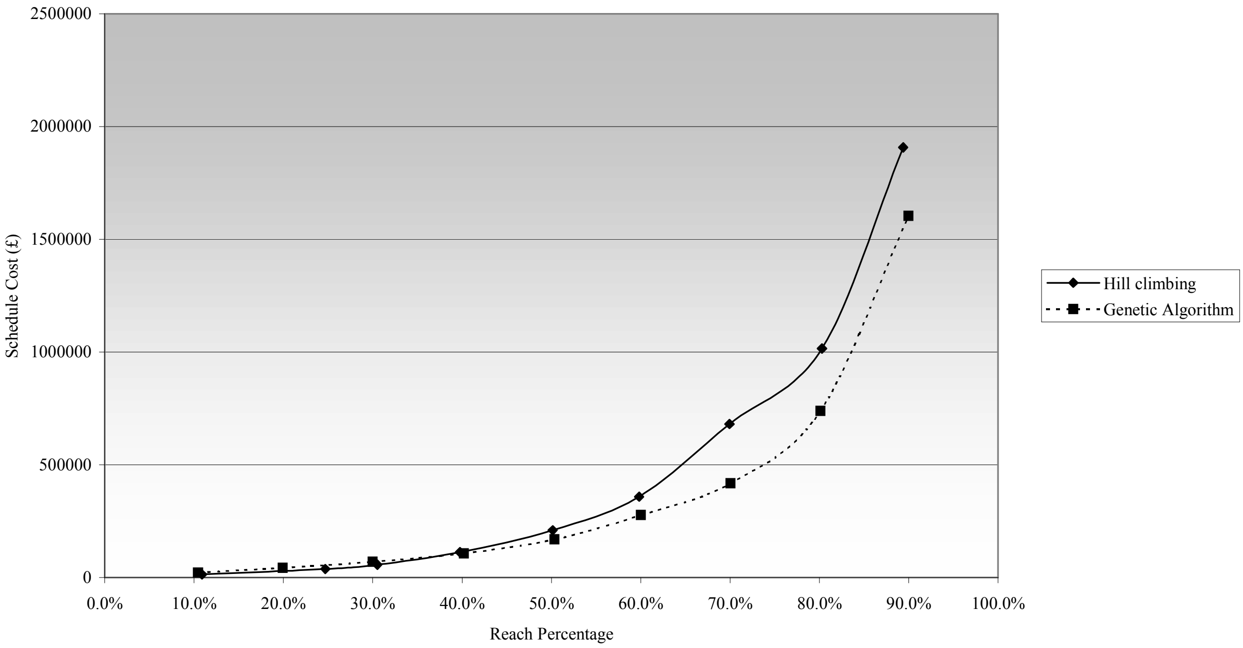
Graph #4
Hill Climbing vs. Genetic Algorithm Optimization - Cost/Reach Efficiency



As is evident from Graph #4, the GA produces more cost efficient schedules at every reach target from 30% through 90%. In cases in the 40% through 90% reach range the GA produced dramatically more cost efficient schedules than did hill-climbing and did so while easily exceeding the specified reach goals.

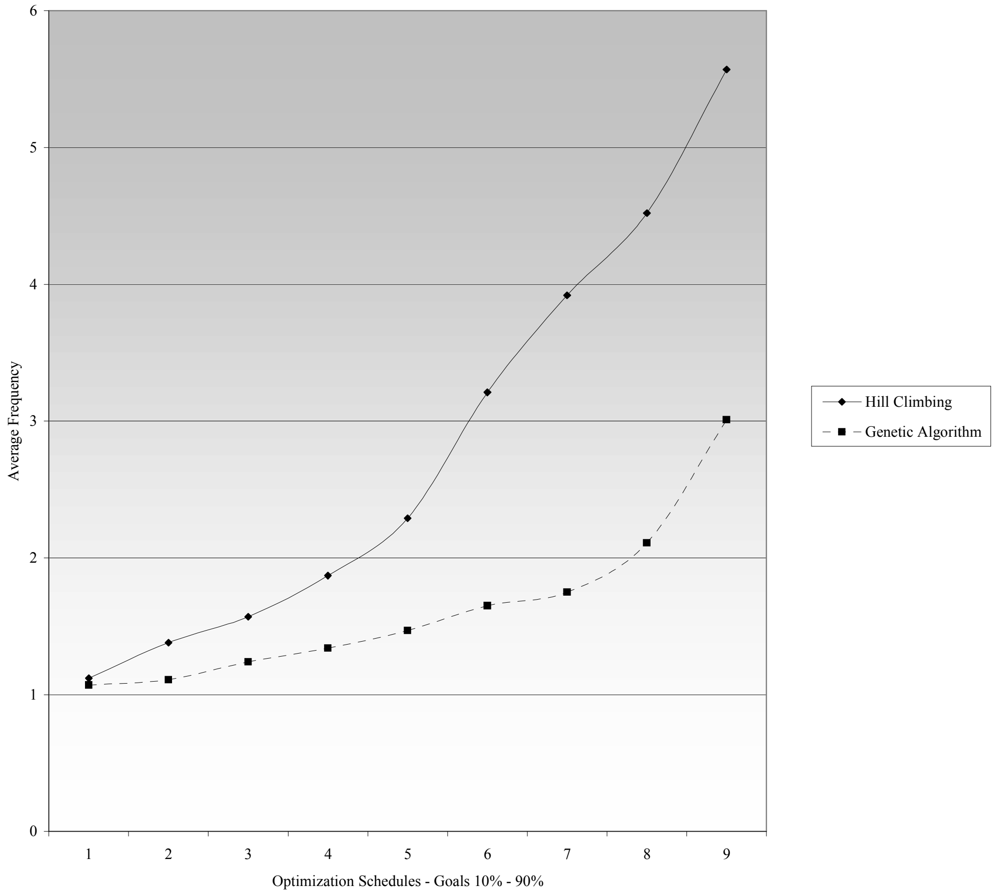
Graph #5 shows results from the TGI data using a target of All Women. A similar pattern emerges with the GA producing more cost efficient schedules at reach points above 40%. Below 40% the reach targets can be achieved using relatively low insertion levels (typically less than 9 insertions) and as such there is little scope in improving these schedules. Whereas in the case of the Scarborough there is a lot more scope in spreading across small, low cost radio insertions.

Graph #5
All Women - Women's magazines



Source: TGI 1988 BMRB

Graph #6
Hill Climbing vs. Genetic Algorithm Optimization - Average Frequency



The relative cost efficiency of schedules developed by GA's is achieved through the strict "focus" on reach embodied in the GA's objective function. Graph #6 plots the average frequencies for each of the nine schedules described above. As is apparent, GA's develop reach while minimizing cost and do so by reducing redundant gross impression development. Thus, the GA consistently attains the reach goals at significantly lower average frequency levels. In cases where it would be desirable to give some measure of weight to frequency, not just reach exclusively, the objective function of the GA could easily be redesigned to accomplish this. What is important to note, in this context however, is the dedicated, maybe even ruthless way in which the GA optimizer focuses on schedule cost efficiency for a particular reach goal, the task for which it was explicitly designed. Once again this is also borne out by the GB TGI data as shown in Graph #7 which shows the number of insertions at each reach point.

One of the consistent objections raised against hill-climbing optimizers is that the schedules they produce are “unnatural” i.e. the schedules exhibit grossly uneven vehicle insertion level patterns. Typically, schedules resulting from hill-climbing optimizations include a disproportionately large number of insertions in a relatively few vehicles and few if any insertions in other vehicles. This is another facet of the relatively high average frequency phenomenon noted previously. Furthermore, this unevenness tends to skew toward larger numbers of insertions in smaller audience vehicles which themselves have relatively low levels of duplication.

Graph #7
Number of insertions - All Women, Source: BMRB International 1998

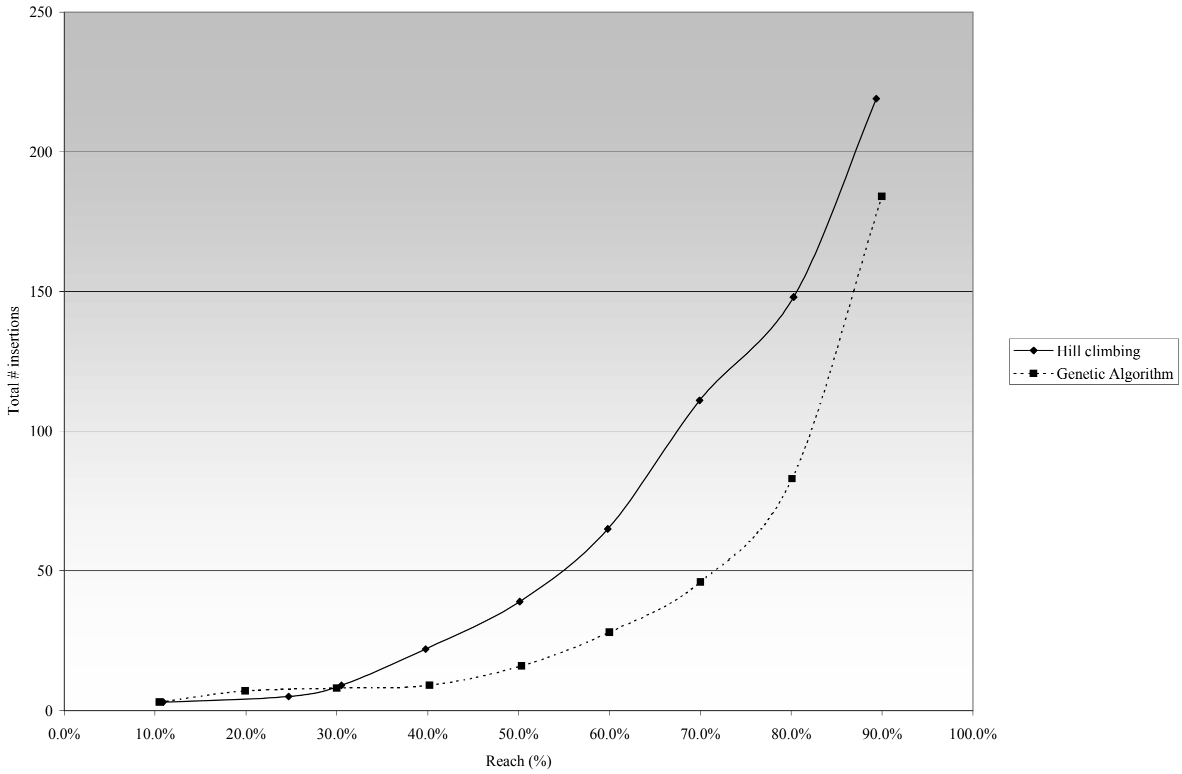
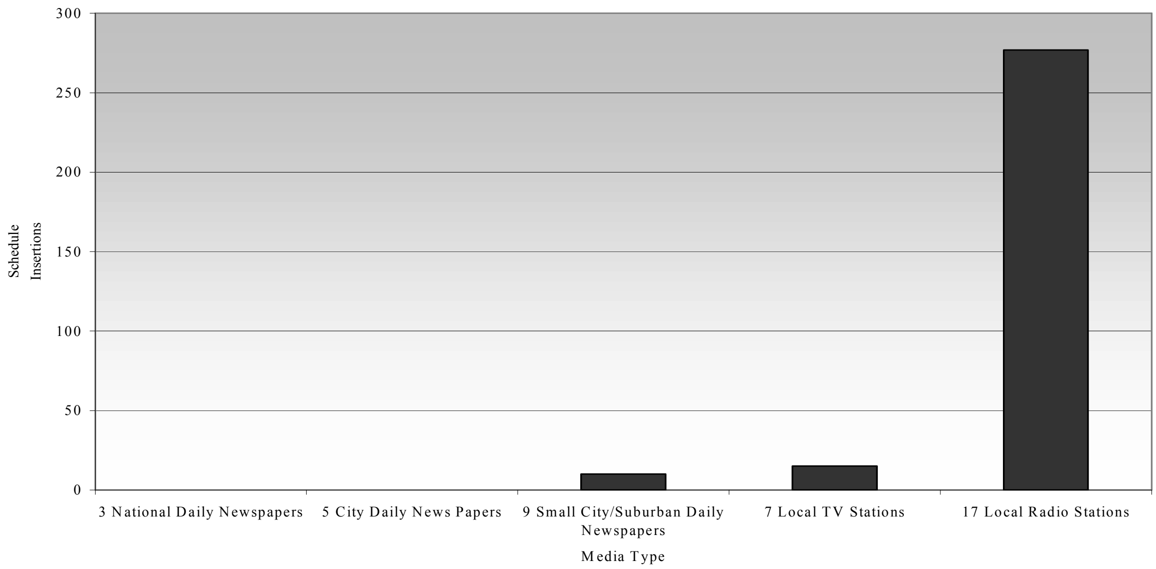


Chart #1
Hill Climbing Optimization Insertion Levels - 70% Reach Goal



Using the same Scarborough media set, Chart #1 shows the number of insertions for each of the five different media types resulting from a hill climbing optimization with a reach goal of 70%. Note that the three national and five larger urban newspapers had no insertions while the 17 local radio stations (having relatively small audiences and low levels of inter-vehicle duplication) had over 250 insertions in total.

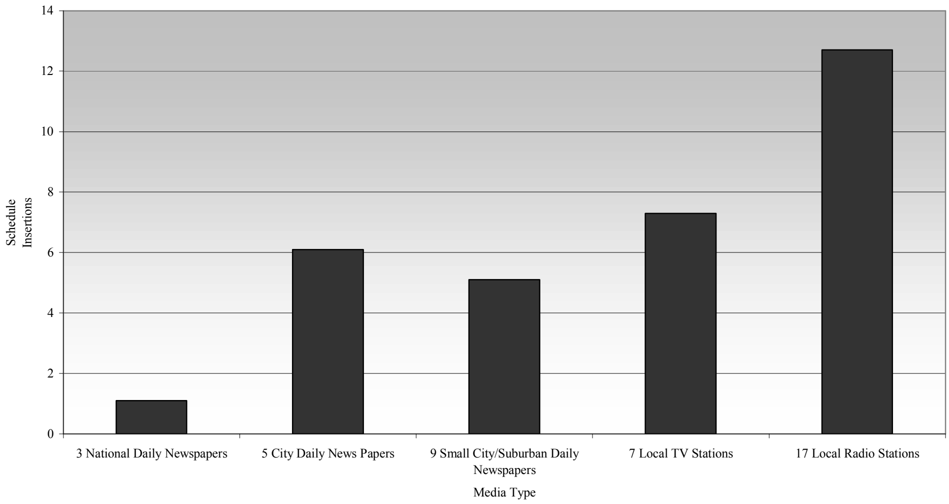
While more research needs to be performed, these disproportionately high insertion levels for radio obtained by the hill-climbing technique appear to derive from two factors.

First, the cost of radio on a single insertion basis is quite low when compared with insertions in vehicles of the other two media types, leading the hill-climbing technique to choose radio insertions first. This is a classic instances of local optima determining the character of the search path.

Second, as persons' radio listening within a daypart is usually constrained to a particular station, comparatively low levels of duplication arise among individual radio vehicles within the daypart. Furthermore, because radio listening is relatively independent of television viewing and print readership, average levels of duplication typically occur between radio and vehicles of the other two media types. Thus the relatively low duplication levels among the radio vehicles render the selection of radio insertions initially relatively efficient when reach alone is the objective – again an example of the dominance of local optima.

Consequently, when in the early stages of its search hill-climbing optimization begins placing insertions in radio other media types become relatively inefficient on a cost-per-incremental-reach basis when compared with other radio vehicles, and are thus not chosen. Further, by the time radio is exhausting its reach potential the relatively higher audience/higher cost media (print and television) may cease to be candidates for inclusion as their incremental reach or cost contributions far exceed the reach or cost optimization goal. Thus the omission of the larger newspapers (national and large urban) from the hill-climbing generated schedule under review.

Chart #2
Genetic Algorithm Optimization Insertion Levels - 70% Reach Goal



In marked contrast to the skewed insertion distribution of the schedule resulting from the hill climbing optimization, the schedule generated by the GA optimizer evidences a much more "natural" insertion distribution. Chart #2 shows the number of insertions for each of the five different media types resulting from a GA optimization with a reach goal of 70%. Note the inclusion of the larger print vehicles at respectable insertion levels in the schedule and the dramatic reduction of the levels of radio, the lower average audience media. As the GA optimizer is insensitive to local optima, the early over-insertion of radio achieved by hill-climbing, did not arise to "distort" the schedule outcome.

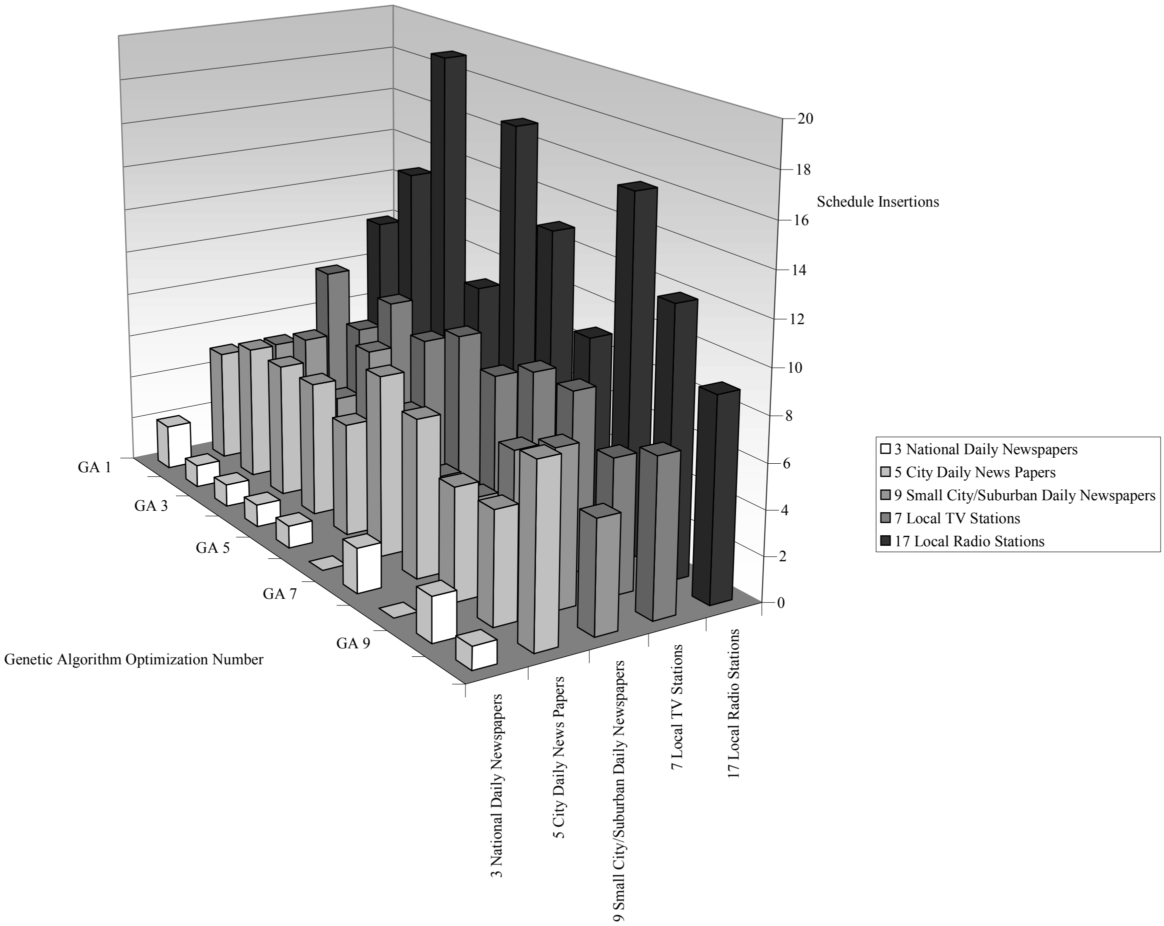
Genetic Algorithm Based Optimization - Issues

While we hope that GA optimization strategies have been shown to be effective on media optimization problems, they are not without issue. One of the most obvious limitations of GA optimizers is that they rarely generate duplicate schedules for the same reach objective given the same media candidates. The reason for this is the extensive and deliberate use of randomness in the generation, crossover and mutation of candidate schedules in the population. It is just such randomness which allows GA optimizers to yield schedules whose efficiencies approach the global optimal, inevitably though randomness yields some measure of non-repeatability.

While the non-repeatability of GA produced schedules is generic and thus unavoidable it is important to recognize that this limitation is not disabling in most circumstances. In fact, media researchers might productively employ a GA optimization multiple times as a part of the same analysis, the better to develop a series of efficient schedule options from which to select a final media plan.

Not withstanding the value of this GA "feature", a review of the variation among a series of GA produced schedules with the same media and reach objective lends a sense of proportion to the extent and magnitude of this issue.

Chart #3
Genetic Algorithm Optimization Insertion Consistency - 70% Reach Goal



Again using Scarborough data, Chart #3 depicts the schedule insertion levels across the five broad media categories for ten different trials of a GA optimization holding the reach goal constant at 70%. While none of the ten schedules is duplicated the general consistency among the insertion levels within each media category is relatively high. In the case of radio where insertion levels appear quite different across the ten schedules, it is noteworthy that the real audience levels resulting from these differing levels are minimal given the relatively small audiences associated with radio.

It is also important to note that the efficiencies of solutions developed by GA and hill-climbing optimization techniques converge under conditions of limited degrees of freedom. The data presented in Graphs #4 (Scarborough) and #5 (BMRB TGI) depict this convergence. Notice that at low end of the curves the GA and hill-climbing achieve reach goals at comparable costs, although the GA usually more readily exceed the reach goals. At the high end of the curves, 80% and 90% while GA's are dramatically more cost efficient, an extrapolation of the GA curve would have it intersecting the hill-climbing curve at the maximum possible reach given the maximum number of allowable insertions.

This confluence occurs at the extremes because it is in exactly those locations where there are relatively few degrees of freedom of choice. At the lower reach goals the hill climbing technique has had few opportunities to exercise choice and thus few opportunities for missteps. In fact, at these lower reach goals local optima approach global optima. Given relatively high reach goals the genetic algorithm has no alternative but to choose high numbers of insertions to achieve the requisite goals. In both instances the selection options are limited and easily exhausted by whichever technique is employed.

Conclusions

We believe that the broad array of evidence – international, multiple media, country-wide and local market -- presented herein makes a strong case for the viability of GA optimization techniques in both single and multiple media planning contexts. While this work is nascent, we consistently find that GA's exhibit a robust efficiency in just those circumstances that confound more conventional media optimization techniques. Our confidence is such that we invite others to join in this investigation and development effort. Irrespective of whether or not these particular techniques and ideas are found intriguing and judged valuable, our broadest hope is that this examination serves to further stimulate interest in and discussion of media optimization techniques generally. Given the ever increasing challenges of further rationalizing and justifying media selection and allocation decisions, rigorous optimization systems should be available to serious media researchers. The charge to media analysis systems designers and developers is to insure the availability and continuous refinement of such tools, whatever the particulars of their design philosophies.

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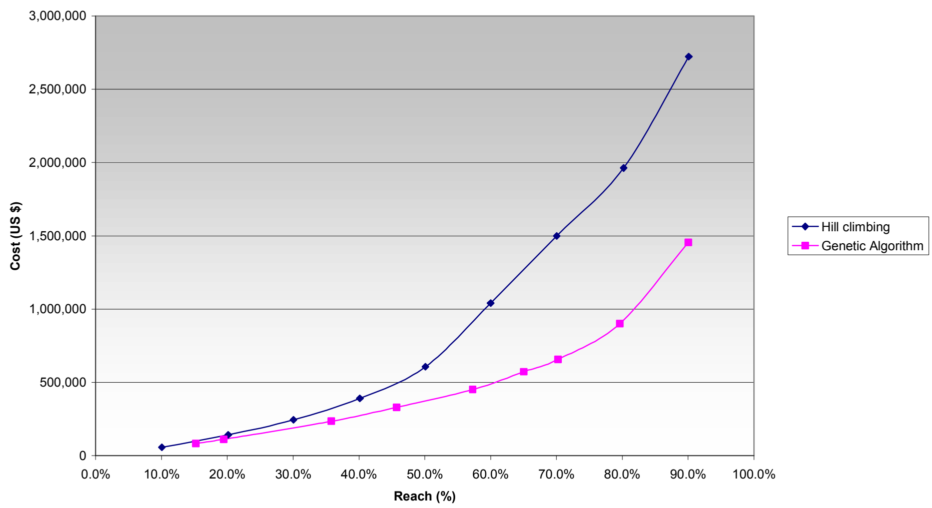
Appendix A - Results for Scarborough multi-media data using a base of All Adults in Philadelphia.

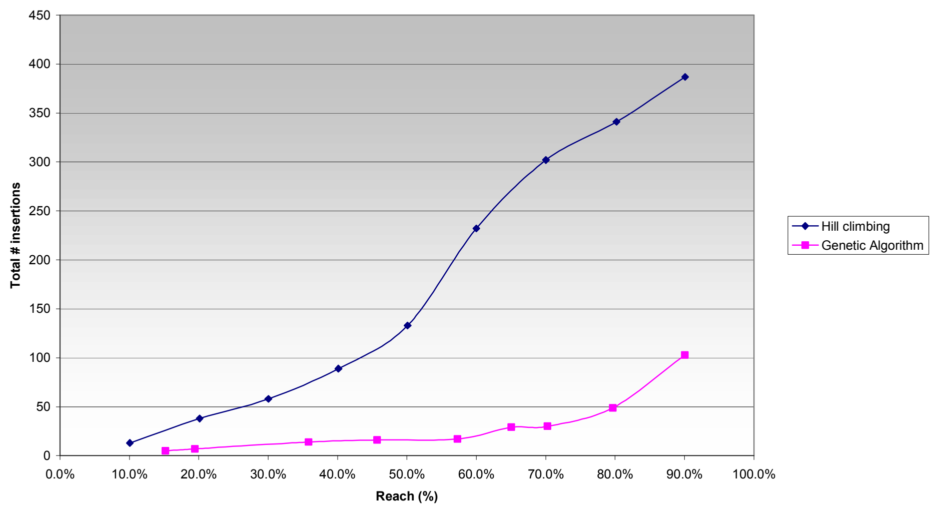
Target description	All Adults
Sample	3,616
Weighted	5,505,140
Source	Philadelphia, Release 2, 1998
Candidate selection	17 Newspapers, 7 Prime Time TV, 17 Morning Drive Radio

	Hill climbing							Genetic Algorithm						
Goals	**Cost (US $)**	**Reach**	**Reach %**	**CPM-Reach (US $)**	**Avg Freq**	**Total vehicles**	**Total inserts/ spots**	**Cost (US $)**	**Reach**	**Reach %**	**CPM-Reach (US $)**	**Avg Freq**	**Total vehicles**	**Total inserts**
Budget for 10% reach	57,300	554,044	10.1%	103.42	1.12	4	13	83,400	836,677	15.2%	99.68	1.07	5	5
Budget for 20% reach	143,300	1,108,236	20.1%	129.30	1.38	7	38	112,500	1,070,509	19.4%	105.09	1.11	7	7
Budget for 30% reach	244,560	1,653,888	30.0%	147.87	1.57	9	58	234,900	1,971,036	35.8%	119.18	1.24	11	14
Budget for 40% reach	392,300	2,209,898	40.1%	177.52	1.87	11	89	330,140	2,516,805	45.7%	131.17	1.34	11	16
Budget for 50% reach	606,500	2,758,192	50.1%	219.89	2.29	12	133	450,900	3,154,236	57.3%	142.95	1.47	13	17
Budget for 60% reach	1,041,500	3,303,329	60.0%	315.29	3.21	17	232	572,580	3,581,325	65.1%	159.88	1.65	20	29
Budget for 70% reach	1,499,850	3,855,767	70.0%	388.99	3.92	22	302	657,870	3,867,311	70.2%	170.11	1.75	23	30
Budget for 80% reach	1,962,960	4,415,656	80.2%	444.55	4.52	27	341	901,910	4,385,168	79.7%	205.67	2.11	29	49
Budget for 90% reach	2,723,700	4,960,168	90.1%	549.11	5.57	33	387	1,456,210	4,958,043	90.1%	293.71	3.01	36	103

Scarborough Data - All Adults



Total number of insertions



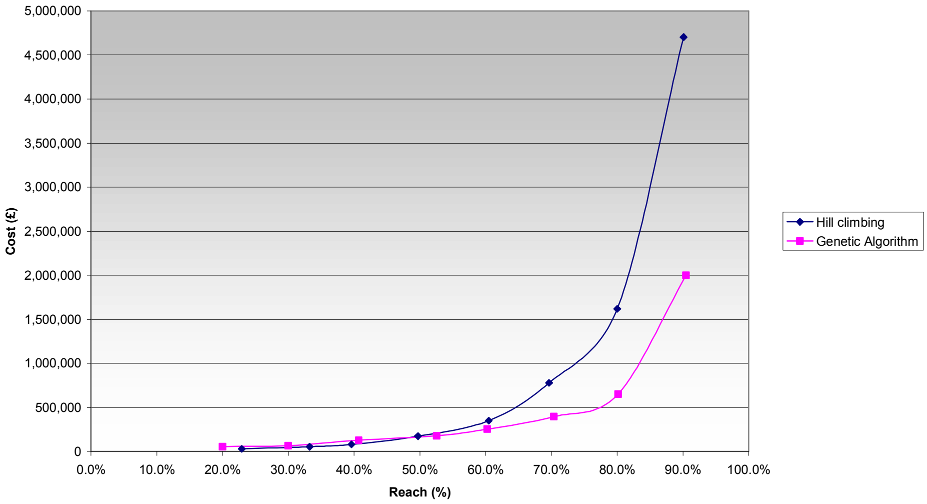
Appendix B – Results for BMRB GB TGI data using a base of All Adults.

Results for 10% reach were unobtainable due to high coverage figures for each magazine

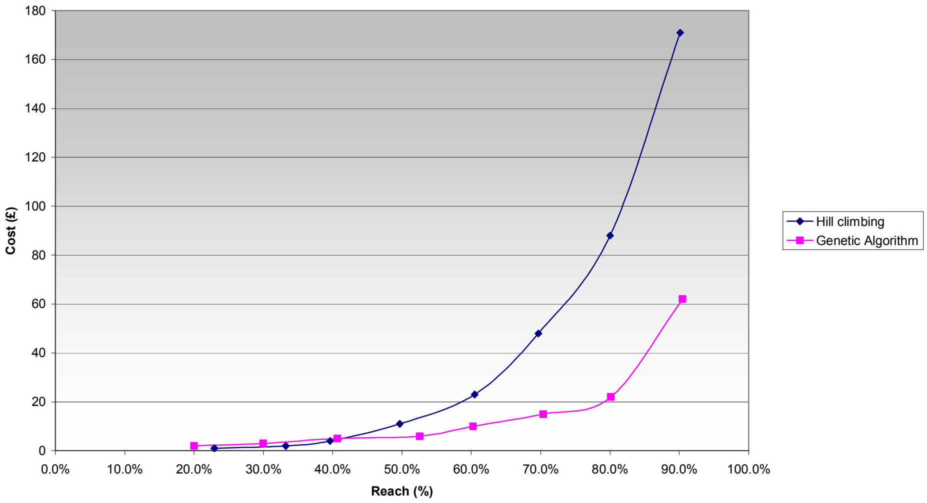
Target description	All Adults
Sample	25,560
Weighted	46,250
Survey	TGI 1998
Candidate selection	10 National Daily Newspapers; 9 National Sunday Newspapers; 8 National Sunday Colour Supplements

	Hill climbing						Genetic Algorithm					
Goals	**Cost (£)**	**Reach**	**Reach %**	**CPM-Reach (£)**	**Total vehicles**	**Total inserts**	**Cost (£)**	**Reach**	**Reach %**	**CPM-Reach (£)**	**Total vehicles**	**Total inserts**
Budget for 10% reach												
Budget for 20% reach	31,500	10,604	22.9%	2.97	1	1	56,600	9,252	20.0%	6.12	2	2
Budget for 30% reach	53,950	15,375	33.2%	3.51	2	2	67,500	13,862	30.0%	4.87	3	3
Budget for 40% reach	80,950	18,319	39.6%	4.42	4	4	128,192	18,823	40.7%	6.81	5	5
Budget for 50% reach	174,350	22,988	49.7%	7.58	7	11	179,850	24,305	52.6%	7.40	6	6
Budget for 60% reach	350,542	27,982	60.5%	12.53	11	23	253,352	27,868	60.3%	9.09	10	10
Budget for 70% reach	779,704	32,222	69.7%	24.20	14	48	395,200	32,542	70.4%	12.14	15	15
Budget for 80% reach	1,621,004	37,007	80.0%	43.80	20	88	651,860	37,065	80.1%	17.59	21	22
Budget for 90% reach	4,704,064	41,677	90.1%	112.87	26	171	2,000,686	41,847	90.5%	47.81	27	62

All Adults - National Daily Newspapers/Sunday Newspapers



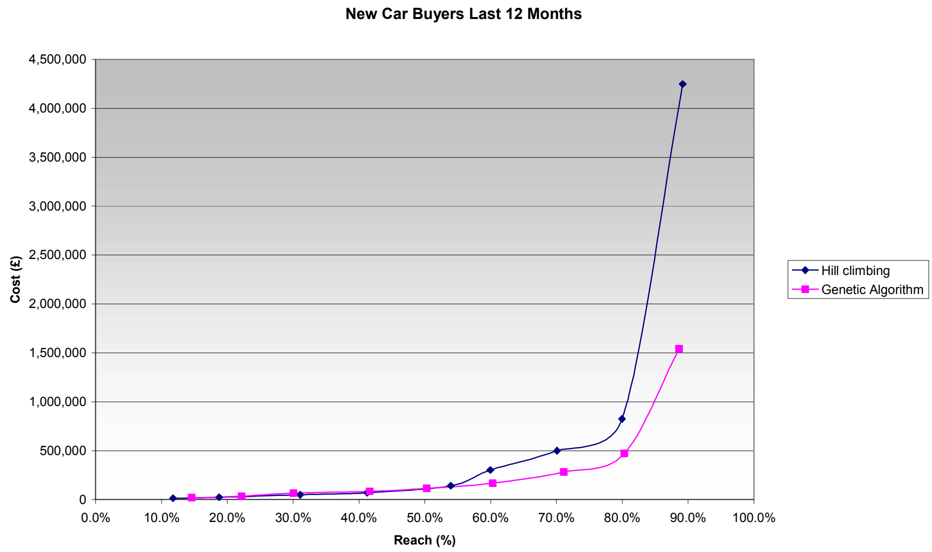
All Adults - National Daily Newspapers/Sunday Newspapers

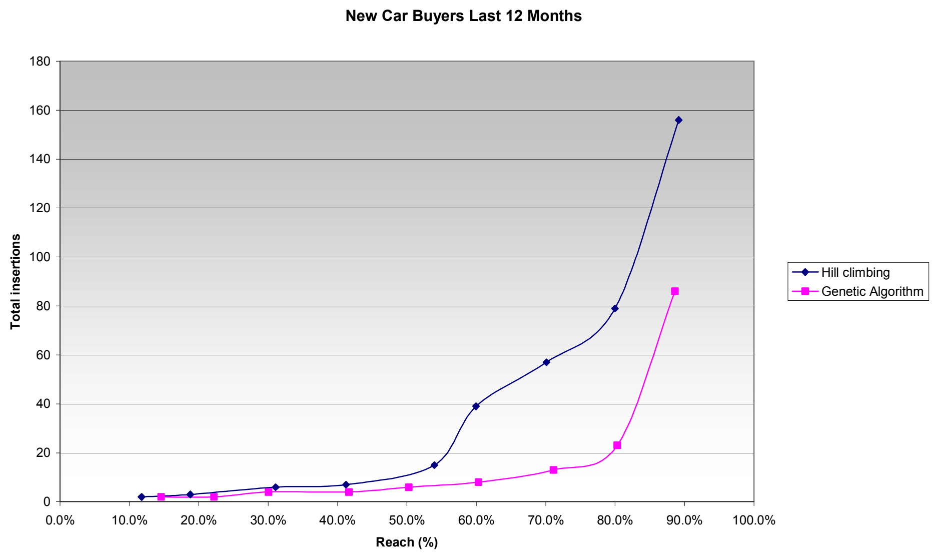


Appendix C – Results for BMRB GB TGI data using a base of All Adults who have purchased a new car in the last 12 months.

Target description	All New Car Buyers
Sample	1,331
Weighted	2,365
Survey	TGI 1998
Candidate selection	8 magazines; 5 Daily Newspapers

	Hill climbing						Genetic Algorithm					
Goals	**Cost (£)**	**Reach**	**Reach %**	**CPM-Reach (£)**	**Total vehicles**	**Total inserts**	**Cost (£)**	**Reach**	**Reach %**	**CPM-Reach (£)**	**Total vehicles**	**Total inserts**
Budget for 10% reach	13,900	278	11.8%	50.00	2	2	18,812	345	14.6%	54.53	2	2
Budget for 20% reach	23,700	444	18.8%	53.40	3	3	34,550	525	22.2%	65.81	2	2
Budget for 30% reach	48,997	735	31.1%	66.66	6	6	66,485	711	30.1%	93.51	4	4
Budget for 40% reach	70,297	975	41.2%	72.10	7	7	84,460	985	41.7%	85.75	4	4
Budget for 50% reach	141,647	1,276	54.0%	111.02	8	15	114,472	1,189	50.3%	96.28	6	6
Budget for 60% reach	301,822	1,418	60.0%	212.87	8	39	167,947	1,426	60.3%	117.77	8	8
Budget for 70% reach	500,870	1,658	70.1%	302.13	9	57	282,819	1,682	71.1%	168.14	11	13
Budget for 80% reach	824,014	1,891	80.0%	435.76	11	79	472,019	1,899	80.3%	248.56	13	23
Budget for 90% reach	4,249,284	2,109	89.2%	2014.93	13	156	1,542,424	2,096	88.6%	735.89	13	86



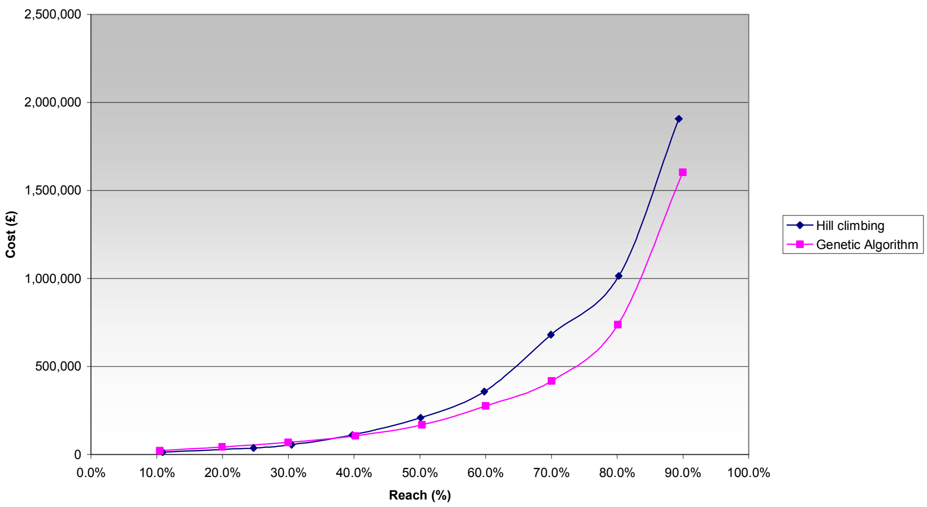


Appendix D – Results for BMRB GB TGI data using a base of All Women.

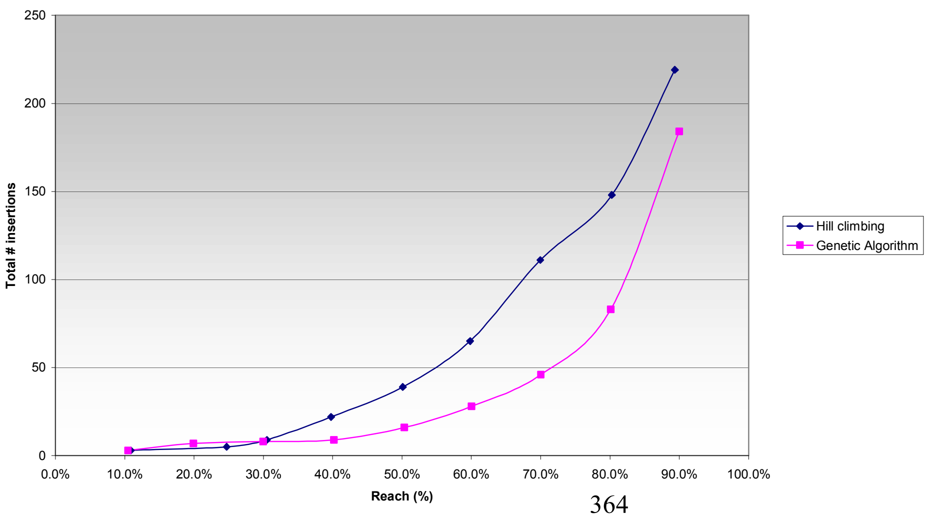
Target description	All Women
Sample	14,085
Weighted	23,762
Survey	TGI 1998
Candidate selection	48 Women's magazines

	Hill climbing						**Genetic Algorithm**					
Goals	**Cost (£)**	**Reach**	**Reach %**	**CPM-Reach (£)**	**Total vehicles**	**Total inserts**	**Cost (£)**	**Reach**	**Reach %**	**CPM-Reach (£)**	**Total vehicles**	**Total inserts**
Budget for 10% reach	13,765	2,585	10.9%	5.33	2	3	22,660	2,488	10.5%	9.11	3	3
Budget for 20% reach	37,665	5,870	24.7%	6.42	4	5	43,057	4,738	19.9%	9.09	7	7
Budget for 30% reach	56,475	7,249	30.5%	7.79	6	9	69,575	7,127	30.0%	9.76	8	8
Budget for 40% reach	112,075	9,451	39.8%	11.86	11	22	106,688	9,553	40.2%	11.17	9	9
Budget for 50% reach	210,338	11,912	50.1%	17.66	18	39	169,161	11,962	50.3%	14.14	16	16
Budget for 60% reach	358,390	14,213	59.8%	25.22	26	65	277,094	14,260	60.0%	19.43	23	28
Budget for 70% reach	681,232	16,618	69.9%	40.99	36	111	418,344	16,643	70.0%	25.14	33	46
Budget for 80% reach	1,015,000	19,074	80.3%	53.22	42	148	738,276	19,038	80.1%	38.78	41	83
Budget for 90% reach	1,906,993	21,235	89.4%	89.80	48	219	1,603,595	21,382	90.0%	75.00	46	184

All Women - Women's magazines



Number of insertions



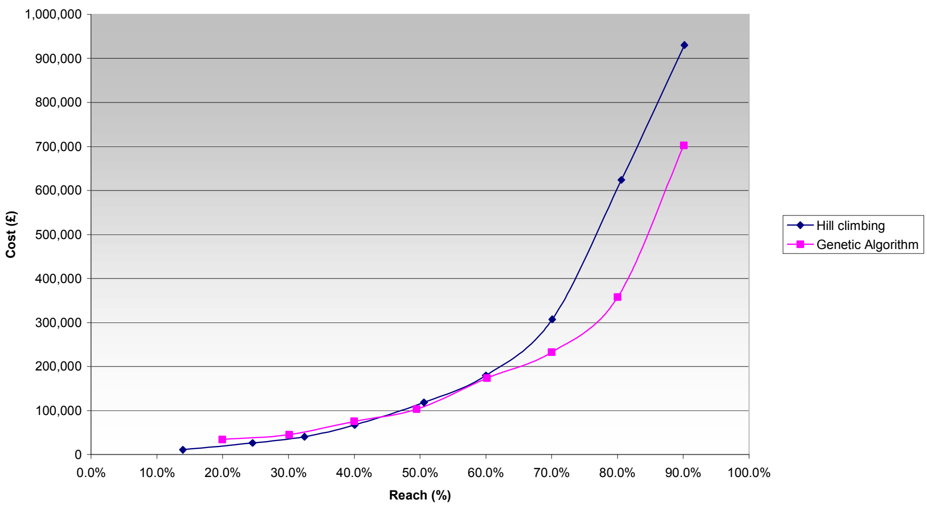
Appendix E – Results for BMRB GB TGI data using a base of All Women who spend on average £10 or more per month on skincare products.

The GA failed to produce a schedule giving c.10% reach, probably due to the relatively high coverage figures for each title

Target description	Women who are heavy skincare purchasers
Sample	1,398
Weighted	2,435
Survey	TGI 1998
Candidate selection	48 Women's magazines

	Hill climbing						Genetic Algorithm					
Goals	**Cost (£)**	**Reach**	**Reach %**	**CPM-Reach (£)**	**Total vehicles**	**Total inserts**	**Cost (£)**	**Reach**	**Reach %**	**CPM-Reach (£)**	**Total vehicles**	**Total inserts**
Budget for 10% reach	11,100	339	13.9%	32.74	2	2						
Budget for 20% reach	26,600	598	24.5%	44.52	4	5	34,756	485	19.9%	71.65	3	3
Budget for 30% reach	40,550	789	32.4%	51.37	5	7	45,650	733	30.1%	62.28	4	4
Budget for 40% reach	67,340	975	40.0%	69.07	8	13	75,380	974	40.0%	77.42	7	7
Budget for 50% reach	118,753	1,232	50.6%	96.39	15	23	103,573	1,205	49.5%	85.95	15	15
Budget for 60% reach	179,648	1,461	60.0%	122.99	17	34	173,773	1,465	60.2%	118.63	20	20
Budget for 70% reach	307,441	1,707	70.1%	180.15	24	57	232,590	1,705	70.0%	136.45	25	25
Budget for 80% reach	623,959	1,963	80.6%	317.92	33	102	358,070	1,949	80.0%	183.75	35	39
Budget for 90% reach	930,451	2,196	90.2%	423.78	43	134	702,422	2,194	90.1%	320.20	42	76

Women Heavy Skincare



Total Number of Insertions