Augmenting System Dynamics with Genetic Algorithm and TOPSIS Multivariate Ranking Module for Multi-Criteria Optimization

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Abstract

System Dynamics like other simulation methodologies is basically descriptive, in that it does not search for optimized set of policy variables. To render it an optimization capability one may augment it with a Genetic Algorithm (GA) input machine with a multi criteria objective function evaluator such as TOPSIS. Starting from a random population of policy variables, different simulation run will be performed one for every member of the population. Using GA operators and the evaluation motor a new population of policy variables will be constructed. The procedure is automatically repeated until the best combination of policy variables is formed. This paper presents this as an idea and gives an example of how this can be performed in practice.

Key words: System Dynamics, Genetic Algorithm, Optimization, TOPSIS

1- Introduction

Simulation in general is a descriptive methodology. It is not an optimization methodology. To search for an optimized solution one has to make several simulations to find the best set of decision variables. It is therefore left to the discretion of the decision maker to judge and choose the best solution. System Dynamics (Forrester, 1961), like other simulation methodologies, is descriptive as well, in that it does not directly search for optimized set of policy variables. It is however possible to enhance and make it into an optimization methodology.

To render it an optimization capability one may augment it with a Genetic Algorithm (GA) input machine coupled with a fitness function evaluator. Use of Genetic Algorithm and other optimization heuristic techniques such as simulated annealing and taboo search have already been used in conjunction with System Dynamics (Sterman, 2000). The fitness function, for GA, would be a single variable function if there is a single output. When we have multiple outputs to the model, we have to deploy a multivariable evaluator to rank the outputs. This can be derived from on any sort of multi-criteria decision making method, depending on the nature of the situation on hand. One such multi criteria objective function evaluator can be TOPSIS, suggested in this paper. The idea was first presented in a Ph.D. theses the author was advisor to (Afshar, 2003).

Starting from a random population of policy variables, different simulation run will be performed one for every member of the population. Using GA operators and the TOPSIS evaluation motor a new population of policy variables will be constructed. The procedure is automatically repeated until the best combination of policy variables is formed. This paper presents this as an idea and gives an example of how this can be performed in practice.

2- Genetic Algorithm

Genetic Algorithm (GA) is a search optimization technique emulating the process of natural evolution. The technique was first introduced by JohnHolland in 1960's. His book, *Adaptation in Natural and Artificial Systems*, written on the subject is very much worth reading (Holland, 1975). It has then after acquired a vast area of applications in diverse fields, e.g. oil pipe line operations optimization, image processing, medicine, job shop scheduling and control. Goldberg gives a very good account of the technique in his book, *Genetic Algorithm in Search, Optimization and Machine Learning* (Goldberg, 1989). Michalewicz also gives a very good presentation of unconstrained and constrained optimization techniques for complex problems in his book, *Genetic Algorithm plus Data Structures equals Evolution Programs (*Michalewicz, 1992).

Starting from a population of random elements the algorithm deploys operators similar to the genetic operators e.g. cross over, mutation and reproduction to gradually improve the population towards the optimum point. A fitness function evaluates the members of the population, at each iteration, and rank the members based on their fitness values. The generation of the next population is formed following these fitness values. Figure 1 shows a typical GA.

3- TOPSIS

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a multi criteria decision technique, used to rank alternatives. TOPSIS, as indicated in Olson (2003), was initially introduced by Hwang and Yoon (1981), Lai *et al.* (1994) and Yoon and Hwang (1995).

TOPSIS has been used in many applications including, financial investment decisions, selecting manufacturing processes, and to compare company performances and financial ratio performances within a specific industry (Olson, 2003).

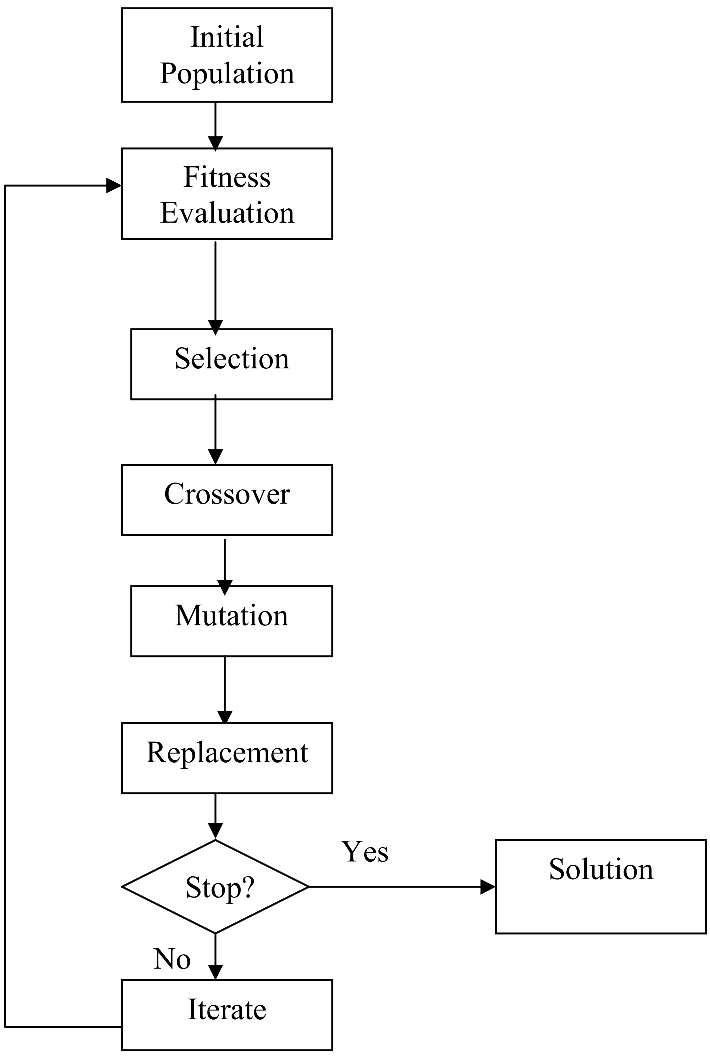

Figure 1: A Typical Genetic Algorithm

The idea behind this technique is that the selected alternative should be closest to the best situation and farthest form the worst one. It hence ranks the alternatives based on their distance from the beat and worst alternatives on hand.

TOPSIS assumes that each criterion wants to be either maximized or minimized. Therefore the ideal positive and negative values of each criterion are identified, and each alternative judged against this information. Each criterion is weighted based on its utility to the decision maker. The procedure followed in TOPSIS is given below as adopted from Olson (2003).

(1) Obtain performance data for n alternatives over k criteria. Raw measurements are usually standardized, converting raw measures x_{ij} into standardized measures s_{ij}.
(2) Develop a set of importance weights w_k, for each of the criteria. The basis for these weights can be anything, but, usually, is *ad hoc* reflective of relative importance. Scale is not an issue if standardizing was accomplished in Step 1.
(3) Identify the ideal alternative (extreme performance on each criterion) s^+.
(4) Identify the nadir alternative (reverse extreme performance on each criterion) s^-.
(5) Develop a distance measure over each criterion to both ideal (D^+) and nadir (D^-).
(6) For each alternative, determine a ratio R equal to the distance to the nadir divided by the sum of the distance to the nadir and the distance to the ideal,

$$R = \frac{D^-}{D^- + D^+}$$

When applied to the proposed SD/GA/TOPSIS model for optimization purposes TOPSIS can be invoked to rank the members of the GA population in each iteration.

4- Putting System Dynamics, GA and TOPSIS together

Figure 2 shows how the modules of the hybrid SD/GA/TOPSIS model are related. The model basically contains a GA input module, a core SD simulation module and a ranking TOPSIS module. The way the model works is explained below.

Step 1- The core of the hybrid model is the System Dynamics model already constructed and tested.

Step 2- The list of policy variables of the SD model is given.

Step 3- The list of the output variables of the SD model is also given.

Step 4- The GA input module initializes with a population of input members. Each member of the population corresponds to a set of policy variables. These are set at random at the beginning, within a feasible range for each variable. Each policy variable corresponds to a criterion, when invoking TOPSIS in Step 6. The weight for each variable is also set for TOPSIS.

Step 5- For each member of the GA population a separate System Dynamics simulation is run. The outputs are recorded accordingly.

Step 6- TOPSIS is invoked. Each set of outputs are ranked using the TOPSIS module.

Step 7- It is checked to see if near optimum solution is found or if the number of simulation runs has exceeded the set limit to stop.

Step 8- Using appropriate GA operators a new population if formed

Step 9- Step 5 onward is repeated.

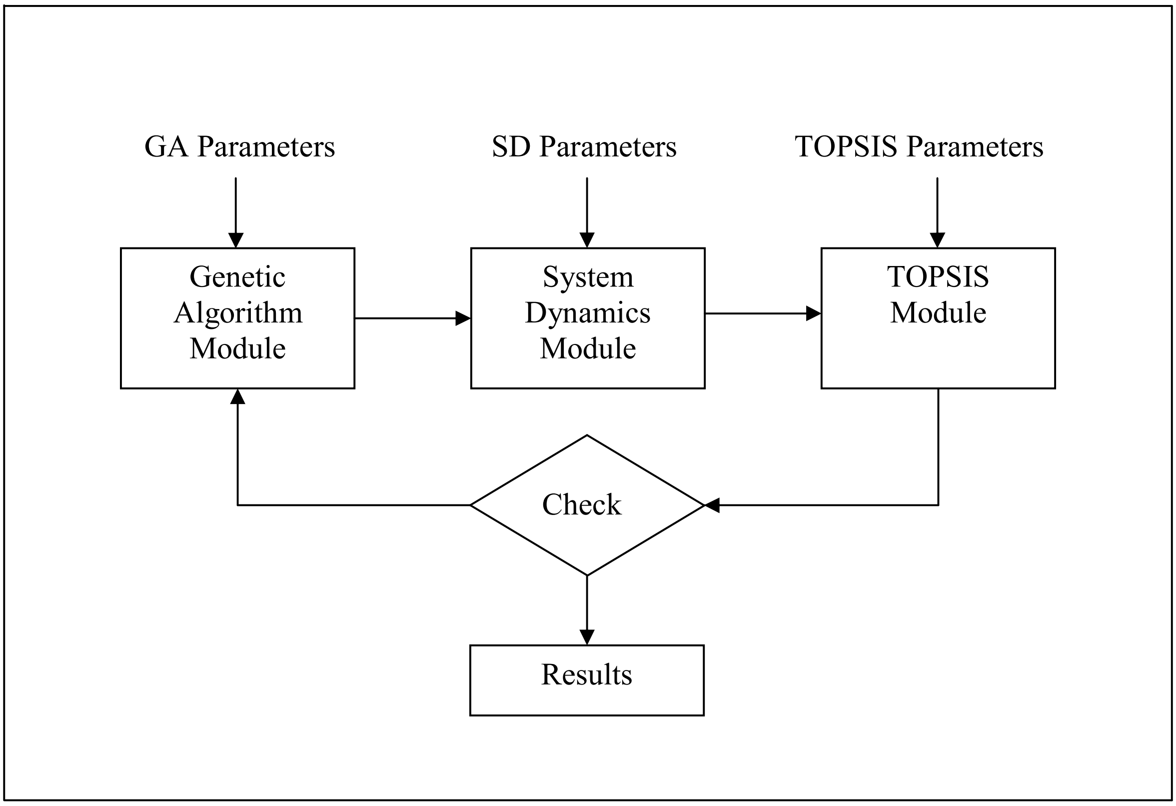

Figure 2: The Hybrid SD/GA/TOPSIS Optimization Model

5- An Example to Test the Idea

In this section we shall explore how the idea can be applied in practice using a hypothetical case. The example is a Production and Inventory Model. Production rate is depended on the number of projects received by the marketing department and the production capacity of the factory. Products produced are delivered to the market by trailers. (Figure 3).

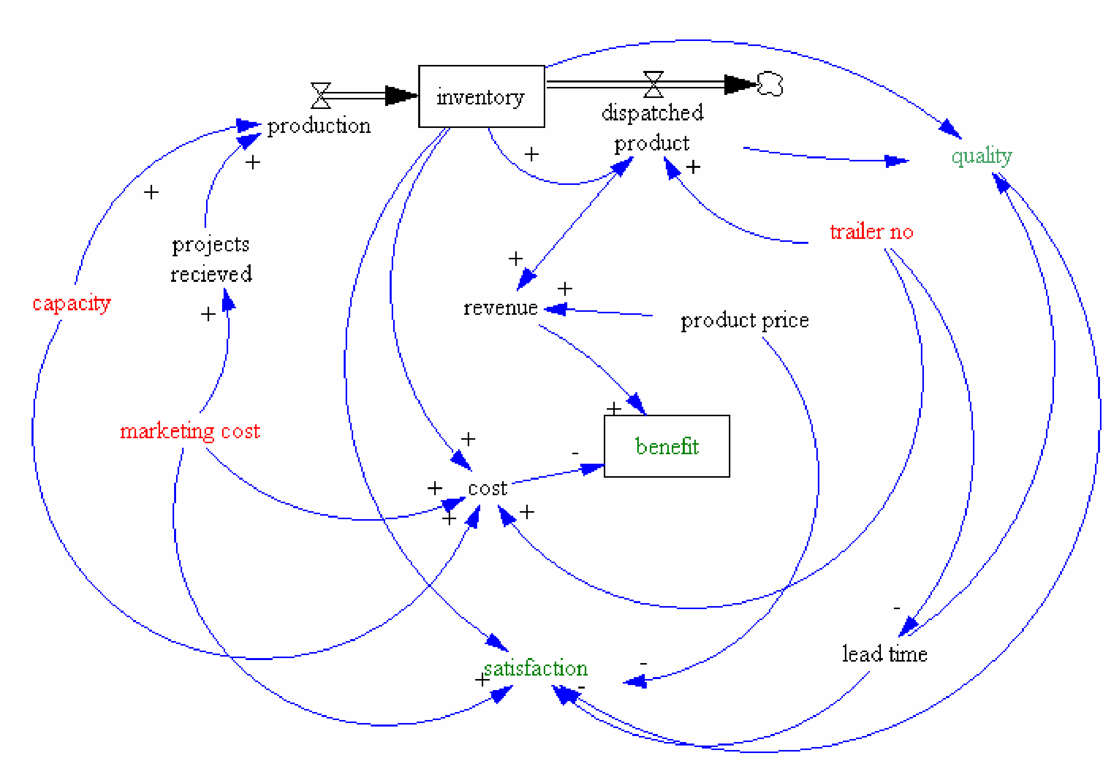

Figure 3: Production and Inventory Model

The problem facing the management is how to decide on a number of decision variables to maximize multiple objectives i.e. company profits, the satisfaction of its customers, as well as the quality of the products produced.

5-1 Controllable Input Variables

The controllable input variables, i.e. the decision variables under the jurisdiction of the management, within allowable ranges are namely, (1) production capacity, (2) marketing budget and (3) the number of trailers deployed.

5-2 Output Variables

Following are the output variables. The desired direction of optimization for all three variables is maximization. This would not cause any loss of generality, as any minimization situation, if present, could be treated as maximization by negation

(1) Product Quality: Management would like to maximize it to eliminate costs of defects to enhance customers satisfaction.

(2) Benefit: Management wouldnaturally like to maximize the company's profit.

(3) Customers Satisfaction: Management would like to maximize customers satisfaction to achieve a better market position.

The output variables, nevertheless, have to compete for the resources input to the system. The problem is clearly a multi-criteria decision problem, with some decision variables to be traded off.

5-3 Using The Hybrid SD/GA/TOPSIS Optimization model

We deployed *Vensim* and *MsExcel* to implement the described model, and followed the steps as set in Section 4. System Dynamics module was modeled in *Vensim.* The genetic algorithm and the TOPSIS modules were both modeled in *MsExcel.*

Step 1- Figure 3 shows the SD model in *Vensim*.

Step 2- The list of decision variables and the allowable range of each variable was set for the GA module.

Allowable ranges were set as follows:

1- Production Capacity: 1 to 511 units per day
2- Marketing Budget: 1 to 511 (in 100 Dollars)
3- Number of Trailers deployed: 1 to 511 trailers

Step 3- The list of output variables, each considered as a criteria for ranking, were set for the TOPSIS module.

Step 4- GA module was invoked. The input variables were coded first to form the population of chromosome strings using the binary coding scheme (Figure 4). The module parameters i.e. population size, cross-over probability and scheme, mutation probability and scheme, selection/replacement scheme and the stopping rule were all set as follows:

Population Size: 50
Cross-over Probability: 90%
Cross-over Scheme: Single Point
Mutation Probability: 5%
Mutation Scheme; Single Point
Selection/replacement Scheme: Roulette Wheel

input variables in binary order			input variables concatenated to form chromosomes
0001001001	0011110001	0010111111	000100100100111100010010111111
0111100011	0101011010	0001110101	011110001101010110100001110101
0001001001	0011110001	0010110001	000100100100111100010010110001
0011110011	0111011010	0001011101	001111001101110110100001011101
0001010010	0001000101	0100101101	000101001000010001010100101101
0101110000	0010011101	0100010001	010111000000100111010100010001
…	…	…	…

Figure 4: Forming the initial population

Step 5- System Dynamics was subsequently invoked. Inputs to the System Dynamics module were formed by decoding the respective portion of the chromosomes pertaining to each variable (Figure 4). For each member of the GA population a separate System Dynamics simulation was run. The outputs were recorded.

Step 6- TOPSIS was then invoked. Each set of the outputs was ranked using the TOPSIS module. The direction of optimization for each criteriawas taken form Section 5-2 above.

TOPSIS: **best** solution and the distance of each alternative from the best				TOPSIS: **worst** solution and distance of each alternative from the worst			
ideal of output 1	**ideal of output 2**	**ideal of output 3**	**distance to ideal**	**nadir of output 1**	**nadir of output 2**	**nadir of output 3**	**distance to nadir**
-0.00291	**0.05287**	**0.04831**		**-0.07186**	**-0.12071**	**-0.08071**	
			0.102542242				0.075790234
			0.111769372				0.082644313
			0.09891414				0.073238073
			0.054292595				0.053282141
			…				…

Figure 5: TOPSIS ranking of the population

Step7- It was checked to see if near optimum solution was found. This could be the time when all population members yield more or less the same output results. Else:

Step 8- Using GA operators a new population was formed (Figure 6).

chromosomes after cross-over and mutation (new generation)	new input in **binary** order		
	number of trailers	**marketing budget**	**capacity**
01111011010110101001001001010 0	0111101101	0110101001	0010010100
000100111001000001110111111101	0001001110	0100000111	0111111101
001000110000001010110111000100	0010001100	0000101011	0111000100
011101000000001010100111101110	0111010000	0000101010	0111101110
000110000000101101100110111111	0001100000	0010110110	0110111111
…	…	…	…

Figure 6: A new population formed

Step 9- Step 5 onward was repeated

We tried to link the three modules of GA(*Excel*), SD(*Vensim*) and TOPSIS(*Excel*), together. While it was possible to import data from *MsExcel* into *Vensim* we found it difficult to export data from *Vensim* into *MsExcel,* because of special *Vensim* file extension. Hence while the GA /SD route of the procedure worked automatically, we had to do the SD/TOPSIS part manually. We continued the genetic algorithm for six iterations. To see if the model is converging and if the TOPSIS ranking is effective, a seemingly novel test of convergence was contrived. The ten top members (20%)of the sixth generation as ranked by TOPSIS were added to each of the previous generations, and each set of now 60 chromosomes were subjected to TOPSIS ranking again. The result is given in Figure 7. As it can be clearly seen the procedures shows good sign of convergence. The higher the TOPSIS ranking in the final generation the higher seems the rank when tested with earlier generations.

10 top chromosomes in 6th iteration	rank in iteration 1	rank in iteration 2	rank in iteration 3	rank in iteration 4	rank in iteration 5
1	6	6	2	2	2
2	7	7	3	4	4
3	9	9	4	7	7
4	11	11	5	8	9
5	13	12	6	9	10
6	16	17	11	11	11
7	21	21	18	18	17
8	22	23	19	19	19
9	24	25	21	21	20
10	27	29	29	26	22
	ranked in comparison with 60 chromosomes				

Figure7: The top 10 chromosomes in the 6th generation tested with the previous

6- Summary and Conclusion

This paper presents an idea to combine Genetic Algorithm optimization heuristic and TOPSIS multi-criteria decision making method with System Dynamics simulation to render it an optimization capability in a multi-criteria setting. The model presented in this paper consists of three modules, i.e. a Genetic Algorithm module, a System Dynamics module, and a TOPSIS module. The GA module is the agent searching for the best set of input controllable variables. Each set of input variables, coded and linked together as a string, forms a member of the GA population. System Dynamics module runs simulation for every member of the GA population. TOPSIS module acts as the multi-variable fitness function to the GA module, ranking the result of each simulation run. Fitter population is constructed after each iteration of the model. The procedure continues till a near optimum solution is reached. That is when all members of the GA population give almost the same result when run through the SD module.

The paper used a hypothetical production and inventory case to demonstrate the model.

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