Civil and Environmental Research
ISSN 2224-5790 (Paper) ISSN 2225-0514 (Online)
Vol.3, No.12, 2013

An Application of Genetic Algorithms to Time-Cost-Quality Trade-off in Construction Industry

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Abstract

Time, cost and quality are used for measuring project success. So, they are considered the most important objectives in construction projects. Project managers should deliver their project on time with minimum cost and at a certain quality level. To get these conflicting objectives, project managers introduce many possible methods of execution (modes) for each activity in the project. This paper presents an optimization model that supports project managers and decision makers in performing this challenging task and leads to identification of the best solution. Developed model is based on Genetic Algorithms which have many advantages over traditional optimization techniques and considered suitable for more than one objective function. The developed Genetic Algorithms model considers target function, design variables affecting that target, and problem constraints. Through application to two projects, the model feasibility is examined. The results show that the proposed approach can help the practitioners in considering different modes for activities and easily find minimum cost for a certain project time meeting the quality requirements. The model can easily reach the best solution from huge number of solutions in reasonable running time. In addition, the results tell that the present method can be used in generating a group of optimal solutions.

Key words: construction projects; time-cost-quality; trade-off; optimization; Genetic Algorithms

1. Introduction

In few words, optimization is the process of making something better or improving an idea. It consists of trying variations on an initial concept to improve on the idea (Randy & Haupt 2004). Its applicability in many different disciplines makes it hard to give an exact definition. In computing and engineering, the goal is to maximize the performance of a system or application with minimal runtime and resources. A general definition for optimization: It is a search for the best element from a set of elements according to a set of criteria. These criteria are expressed as mathematical functions, the so-called objective functions or fitness functions (Weise 2009).

Optimization algorithms can be divided in two basic classes: deterministic and stochastic algorithms. Deterministic techniques comprise two classes: the calculus-based analytical methods and enumerative methods. The analytical methods have indirect and direct methods. In indirect methods, the local function optima can be determined by solving a system of equations. Direct methods search for a local optimum through "jumping" on the function graph towards the direction specified by the gradient. Both methods are not free from disadvantages. First of all, they have a local scope, because they search for optimum solutions in the neighborhood of a given point. Second, their application depends on the existence of derivatives. Thus, analytical methods have a limited scope of application. Enumerative methods exist in many forms. In a finite search space, the simplest method would consist in calculating the objective function value and reviewing all possible solutions one after another. In spite of its simplicity and similarity to human reasoning, this method has one serious disadvantage - ineffectiveness. Many problems have such a large search space that it is impossible to search all the points within a reasonable time limit. The second main class of optimization algorithms is the random or stochastic techniques which consisted of random space searching and remembering the best solution. They became popular at the moment when scientists became aware of the weaknesses of analytical and enumerative methods (Rutkowski 2008).

In recent years, meta-heuristics, a family of stochastic techniques which are applied to set of objective functions, have become an active research area. They can be defined as higher level frameworks aimed at efficiently and effectively exploring a search space. The initial work in this area was started about half a century ago. Subsequently, a lot of diverse methods have been proposed, and today, this family comprises many well-known techniques such as Evolutionary Algorithms, Tabu Search, Simulated Annealing, Ant Colony Optimization, Particle Swarm Optimization, etc. Among these algorithms, Evolutionary Algorithms are the most widely used meta-heuristics.

In construction industry, a need for the optimization process was discussed in the traditional time-cost trade-off problem by (Kelley & Walker 1959). They assumed a linear relation between time and cost of an activity and offered a mathematical and a heuristic algorithm for solving the problem. Other researchers, such as (Moselhi 1993) tried to solve the time–cost trade-off problem. Elbeltagi *et al*. (2005) presented a solution for time–cost trade-off problem by means of five evolutionary based optimization algorithms. Zheng & Ng (2005) presented stochastic time–cost optimization model which incorporate fuzzy sets theory and non-replaceable front. Kasaeian *et al*. (2007) improved a new multi-objective Genetic Algorithm (GA) to solve the problem. Aladini *et al*. (2011) developed a multi-objective Ant Colony based optimization model for project problem time-cost trade-off. The model locates the near optimum Pareto front with a set of non-dominated solutions.

Recently, contracts considered the quality performance of projects in addition to time and cost. So, many researchers added the quality as an important objective which affects the time and cost. This creates new and pressing need for advanced utilization models that are capable of optimizing the multiple and conflicting objectives of construction time, cost and quality.

Many researchers have investigated the time-cost-quality trade-off in construction projects. El-Rayes & Kandil (2005) presented a multi-objective optimization model for time-cost-quality trade-off. Their model is designed to transform the traditional two-dimensional time-cost trade-off analysis to an advanced three-dimensional time-cost-quality trade-off analysis. Afshar et al. (2007) developed and applied a new meta-heuristic based on multi-Ant Colonies algorithm to solve this problem.

Abd El Razek et al. (2010) presented a general description for time-cost-quality trade-off software. They used the basic concepts of Line of Balance and Critical Path Method in a multi-objective GAs model. Saputra & Ladamay (2011) proposed a method to evaluate probability of a project whether it met its Quality-Cost-Time target under uncertainty. They utilized A Monte Carlo Simulation and Generalized Activity Network. A numerical example is provided to support and validating the proposed method. Shrivastava *et al*. (2012) developed a new meta-heuristic multi-Ant Colonies algorithm for the optimization of the three objectives as a trade-off problem. The model is also applied to two objectives time–cost trade-off problem and the results are compared to those of the existing approaches.

2. Study aims

This study aims to present a new optimization model that supports time-cost-quality trade-off in construction projects. The model is based on developing a computer program using Genetic Algorithms, one of the most popular modern optimization techniques, to find minimum cost for different quality levels at a certain time limit. Thus, the model may provide the project managers with a group of optimal solutions to take their decision easily based on a scientific support tool. The developed model should be applicable for different activities networks shapes taking critical path method in consideration. The model is written in FORTRAN 90 Language program.

3. Genetic Algorithms

The Evolutionary Algorithms optimization techniques, such as GAs, have been developed in the early 1970's and they have a lot of applications since 1980's (Goldberg 1989). GAs have been successfully applied to many branches in civil engineering optimization problems such as bridge water network design (Savic & Walters 1997), tunnel geometric design (Eid & AbdElrehim 2013) and structural optimization (AbdElrehim *et al*. 2009).

GAs have many advantages over traditional optimization techniques (Goldberg 1989). Among other considerations, they do not need further additional information than objective function values or fitness information. This information is used to determine the success or failure of a design in a particular environment. Moreover, its ability to find out the optimum or quasi-optimum solution, even if the optimization function is non-continuous, non-differentiable and with any kind of constraints, gives it a privileged position as a powerful tool in non-conventional optimization problems.

3.1 GA principals and operators

The simplest form of GA involves three types of operators: selection, crossover and mutation. The general form involves other processes: coding, initial population, elitism and termination. The working principals and operators of GAs are discussed on the following.

3.3.1 Coding

It mostly depends upon the number of decision variables for analysis and design to be optimized, and the kind of representation used. The most common schemes are binary and real (floating point or continuous) representation. It is much easier to represent variables with the binary strings form. For example, if *z* is coded as a binary integer of length 4, thus it can take any positions between 1 (0000) and 16 (1111) which means that we have 16 possible positions for z values. By the same way, if *z* is coded as a binary integer of length 5, this means that we have 32 possible positions for z values. These strings represent genes. A group of genes forms a chromosome. Every chromosome consists of specified genes (i.e. any member of any generation has its own values for design variables).

3.3.2 Initial population

GAs do not start from a single point; it starts with a group of chromosomes known as the population (Randy & Haupt 2004). A set of such solutions or individuals forms the population, and the number of them is the size of the population. Initial population is also named as parents. It is responsible for producing the new generation via next operators.

3.3.3 Crossover

Crossover is a genetic operator that combines (mates) two chromosomes (parents) to produce a new chromosome. The idea behind crossover is that the new chromosome may be better than both of the parents if it takes the best characteristics from each of them. Crossover occurs during evolution according to a user-definable crossover probability. Crossover includes many techniques: one-point, two-point, uniform, arithmetic and heuristic crossover (Coley 2001). In the present work, all coded design variables are coded as short binary integers of length 4 or 5. Hence, a simple one-point crossover technique can be used efficiently.

3.3.4 Mutation

Mutation introduces random binary changes in chromosomes. It plays a decidedly secondary role in the operation of GAs. Mutation is needed because, even though reproduction and crossover effectively search and recombine extant notions, occasionally they may become overzealous and lose some potentially useful genetic material. In artificial genetic systems, the mutation operator protects against such an irrecoverable loss. By itself, mutation is a random walk through the string space. When used sparingly with reproduction and crossover, it is an insurance policy against premature loss of important notions (Goldberg 1989). The probability of mutation P_m is a problem dependent. Many researches have used $P_m=1/L$, where L is total chromosome length. Others carry out mutation by visiting each gene's element and replacing the existing value (Coley 2001). Because of its important role, many researches concerned with mutation development. This resulted in variation in mutation types from classical regular mutation to modern adaptive mutation. Any of these types may be applied with any of mutation techniques such as flip bit, boundary, non-uniform, uniform or Gaussian mutation. In the present work a combination of two different mutation techniques (non-uniform and uniform) in adaptive way depends on user definition is used.

3.3.5 Selection

Selection can be considered the main operator in GAs. This operator involves evaluation of produced chromosomes according to fitness equation and the principal “Survival for the Best” and ignores the chromosomes with the lowest fitness value. So, best chromosomes in current generation’s population are selected for inclusion in the next generation’s population. Just like previous operators, selection is applied in different techniques: roulette, tournament, top percent, best and random selection. The current developed algorithm performs extra process with sorting both parents and children generations to select the fittest using the best technique.

3.3.6 Elitism

Elitism is a strategy to guarantee a monotonic improvement in objective function value of the design unless overlapping systems are used. Due to the stochastic nature of the evolution process the valuable information of the best individuals of the population can be lost. Then, this strategy copies some of the best individuals into the next generation without applying any evolutionary operator in order to avoid this situation. The balance between the exploration of the search space and the exploitation of discoveries made within the space is a recurrent theme in GA theory. The more exploitation that is made the faster the progress of the algorithm, but the greater the possibility of the algorithm failing to finally locate the true global optimum. For many applications the search speed can be greatly improved by not losing the best, or elite, member between generations. Ensuring the propagation of the elite member is termed elitism and requires that not only is the elite member selected, but a copy of it does not become disrupted by crossover or mutation (Coley 2001).

3.3.7 Termination

Termination is the process by which the GA decides whether to continue searching or stop the search. Termination is a user specified process. According to its technique, termination may be limited with specified generation number, time or convergence.

4. Shape optimization problem

To define any problem as an optimization problem, three elements should be assigned: the target (the objective function), the design variables affecting that target and problem constraints. The optimization problem addressed herein is to find out the minimum construction cost for a project with a time limit and certain quality requirement. Hence, the objective function can be stated as:

$$\text{find } X \in R_k \quad \text{to minimize } f(X)$$
$$\text{Subject to } g_i(X) \leq 0,\ i = 1, 2, \ldots, n \text{ and}$$
$$X_j^L \leq X \leq X_j^U, \qquad j = 1, 2, \ldots\ldots\ldots, k$$

Where, X is the vector of design variables; f (X) is the objective function; $g_i(X)$ is the performance constraints; and X_j^L and X_j^U refer to the lower and upper bounds on the design variables respectively. The objective function here is construction cost and can be expressed as:

$$\min\ C = \sum_{i=1}^{m} M_i . C_M \tag{1}$$

Where, C is the project overall cost, M is the construction activity number i and C_M is the activity execution cost for a certain mode, which is the design variable.

The performance constraints include concern for the project limited time duration T_{all} and quality level requirement Q_{req} :

$$g = T_{\max} - T_{all} \leq 0 \tag{2}$$
$$g = Q_{req} - Q_{avg} \leq 0 \tag{3}$$

Where, $T_{\max}$ is the expected maximum construction time and Q_{avg} is the quality average for all project activities taking weights in consideration.

5. Numerical examples and model application

Two numerical examples (projects) are presented in order to illustrate the feasibility and performance of the proposed model. The activities network of the first project is shown in Figure (1). This network and relations among activities are taken from Shankar et al., (Shankar *et al*. 2011**)** and four possible construction modes are assumed for each activity, as presented in Table (1), for time, cost and quality. The project consists of eight activities and has nine paths end by one activity. The project has a search space (number of alternative solutions) = $4^{(8)}$ = 65536 solution.

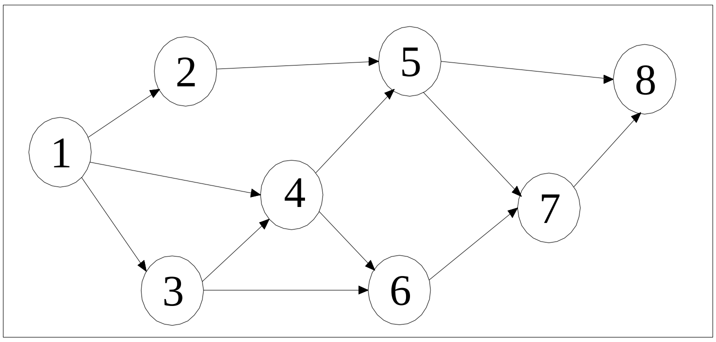

Figure (1): Activities network (Project 1)

Starting the model run, it calculates minimum and maximum possible values for both time and quality and shows them for the user to select the constraints values. For this project, the time limit for execution ranges from 30 to 73 days and the quality ranges from 88.875 to 91.875%. So, the user can choose suitable time and quality and get minimum cost. The model also calculates the Optimum Time Point (OTP) and Optimum Quality Point (OQP). OTP can be defined as the time value at which the minimum cost remains constant even for longer project time. In this project, OTP = 46 days. The model also calculates the OQP which is the quality value at which the minimum cost remains constant even for lower quality levels. The OQP at this project is calculated as 89.25. Table (2) shows model results at minimum quality, while Table (3) shows model results at maximum time.

The activities network of the second project is shown in Figure (2) which introduces the precedence relationships between activities through the network for this project. The number of available modes for each activity along with the time, cost and quality for each mode of construction are given in Table (4). The project contains nine activities with two ends and three paths.

Table 1. Construction modes (Project 1)

Activity	Mode 1			Mode 2			Mode 3			Mode 4		
	duration (days)	cost (L.E.)	quality	duration (days)	cost (L.E.)	quality	duration (days)	cost (L.E.)	quality	duration (days)	cost (L.E.)	quality
A1	10	15000	0.87	9	16500	0.86	8	18000	0.86	11	15000	0.9
A2	7	10000	0.92	6	12000	0.9	5	13500	0.93	8	9500	0.92
A3	8	16000	0.95	7	17000	0.95	9	16000	0.95	11	13000	0.91
A4	7	11000	0.94	6	13000	0.92	8	9500	0.92	10	9000	0.92
A5	13	18000	0.86	11	21000	0.88	9	25000	0.88	15	17000	0.86
A6	15	25000	0.88	12	30000	0.9	18	23000	0.9	20	20000	0.88
A7	6	6000	0.92	5	7000	0.91	7	5500	0.88	8	5000	0.88
A8	8	11000	0.91	9	11000	0.93	11	10500	0.91	13	10000	0.9

Table 2. Minimum cost and corresponding activities modes for different time values (Project 1)

inputs	Results			Activity Mode Results							
Time (days)	Cost (L.E.)	Time (days)	Quality (%)	A1	A2	A3	A4	A5	A6	A7	A8
73	98500	46	89.25	1	4	4	4	4	4	4	4
60	98500	46	89.25	1	4	4	4	4	4	4	4
50	98500	46	89.25	1	4	4	4	4	4	4	4
46	98500	46	89.25	1	4	4	4	4	4	4	4
44	100000	43	89.25	1	1	4	4	1	4	4	4
42	100000	41	89.625	1	1	4	4	4	4	4	2
40	100000	40	89.375	1	1	4	4	4	4	5	1
38	103500	38	89	2	2	4	4	4	4	4	1
36	104000	36	89.625	1	1	4	4	2	4	4	1
34	107500	34	89.25	2	2	4	4	2	4	4	1
32	110500	32	89.625	3	3	4	4	2	4	4	1
31	113000	31	89.625	2	3	4	4	3	4	4	1
30	114500	30	89.625	3	3	4	4	3	4	4	1

Table 3. Minimum cost and corresponding activities modes for different quality levels (Project 1)

inputs	Results			Activity Mode Results							
Quality (%)	Cost (L.E.)	Time (days)	Quality (%)	A1	A2	A3	A4	A5	A6	A7	A8
88.875	98500	46	89.25	1	4	4	4	4	4	4	4
89	98500	46	89.25	1	4	4	4	4	4	4	4
89.25	98500	46	89.25	1	4	4	4	4	4	4	4
89.5	98500	47	89.625	4	4	4	4	4	4	4	4
89.75	99000	45	89.75	4	4	4	4	4	4	4	3
90	99500	47	90.125	4	4	4	4	4	4	1	4
90.25	100000	45	90.25	4	4	4	4	4	4	1	3
90.5	100500	43	90.5	4	4	4	4	4	4	1	2
90.75	103000	45	90.75	4	4	3	4	4	4	1	3
91	103500	43	91	4	4	3	4	4	4	1	2
91.25	105500	42	91.25	4	4	3	1	4	4	1	2
91.5	108500	42	91.5	4	4	3	1	4	3	1	2
91.875	116500	36	91.875	4	3	3	1	2	3	1	2

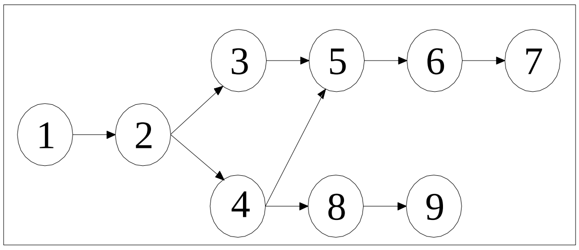

Figure (2): Activities network (Project 2)

Table 4. Construction modes (Project 2)

Activity	Depndency	Mode 1			Mode 2			Mode 3			Mode 4		
		duration (days)	cost (L.E.)	quality	duration (days)	cost (L.E.)	quality	duration (days)	cost (L.E.)	quality	duration (days)	cost (L.E.)	quality
A1	------	10	3000	0.97	9	3500	0.96	8	3500	0.95	6	4500	0.97
A2	A1	7	5000	0.95	9	4000	0.93	11	3500	0.95	5	6500	0.93
A3	A2	8	9000	0.9	7	10000	0.88	6	12000	0.86	4	15000	0.88
A4	A2	6	8000	0.87	6	7000	0.92	6	9000	0.94	5	11000	0.93
A5	A3, A4	7	4000	0.89	8	3500	0.91	10	3000	0.92	6	4500	0.9
A6	A5	5	12500	0.96	6	11500	0.97	7	10000	0.96	8	9500	0.95
A7	A6	6	6000	0.97	5	7000	0.98	4	9000	0.98	7	6000	0.98
A8	A4	7	3200	0.95	6	3600	0.94	7	3000	0.9	8	2800	0.94
A9	A8	6	9500	0.91	5	11000	0.9	7	11000	0.91	7	12000	0.94

For this simple example, the search space includes $4^{(9)}$ = 262144 possible solutions. The previously described nine activities project is solved using the proposed model. The time limit for project execution ranges from 31 to 54 days and the quality ranges from 91.334 to 94.667%. In this project, OTP = 53 days and OQP = 93.667. Table (5) shows model results at minimum quality, while table (6) shows model results at maximum time.

Table 5. Minimum cost and corresponding activities modes for different time values (Project 2)

Inputs	Results			Activity Mode Results								
Time (days)	Cost (L.E.)	Time (days)	Quality (%)	A1	A2	A3	A4	A5	A6	A7	A8	A9
54	53300	53	93.667	1	3	1	2	3	4	1	4	1
53	53300	53	93.667	1	3	1	2	3	4	1	4	1
50	54300	50	93.33	1	3	1	2	2	3	1	4	1
45	55800	45	93.333	3	1	1	2	2	4	1	4	1
40	58800	40	93.444	4	4	1	2	2	3	1	4	1
38	59800	38	93.3333	4	4	1	2	4	3	1	4	1
36	61800	36	93.2222	4	4	2	2	4	3	2	4	1
34	64300	34	93.2222	4	4	2	2	4	1	2	4	1
32	68300	32	93	4	4	3	2	4	1	3	4	1
31	75300	31	93.3333	4	4	4	4	4	1	3	4	1

Table 6. Minimum cost and corresponding activities modes for different quality levels (Project 2)

Inputs	Results			Activity Mode Results								
Quality (%)	Cost (L.E.)	Time (days)	Quality (%)	A1	A2	A3	A4	A5	A6	A7	A8	A9
91.333	53300	53	93.667	1	3	1	2	3	4	1	4	1
91.5	53300	53	93.667	1	3	1	2	3	4	1	4	1
92	53300	54	93.7778	1	3	1	2	3	4	4	4	1
92.5	53300	54	93.7778	1	3	1	2	3	4	4	4	1
93	53800	51	93.4444	1	2	1	2	3	4	1	4	1
93.5	53300	53	93.6667	1	3	1	2	3	4	1	4	1
94	54200	53	94	1	3	1	2	3	3	4	1	1
94.667	60200	52	94.667	1	3	1	3	3	2	4	1	4

6. Computation Procedure and Progression

Processing optimization operators and repeating them through generated population leads to convergence toward global optimum. Difficulty of having optimal or quasi optimal solution increases as convergence rate increases. Figure (3) shows the target function's value progression through 2000 generations for the first project for time limit ≤ 40 days and quality requirement ≥ 90%. Progression is fast in the starting generations and getting slower later. The program reaches the optimal value at generation number 692 and settles after that. Figure (4) shows the progression for the second project through 1000 generations for time limit ≤ 40 days and quality requirement ≥ 92%. The program reaches the optimal value at generation number 136 before settling.

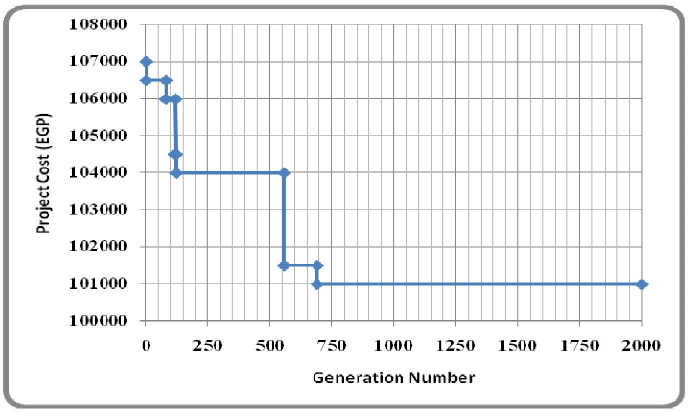

Figure (3): Generations progress for project 1

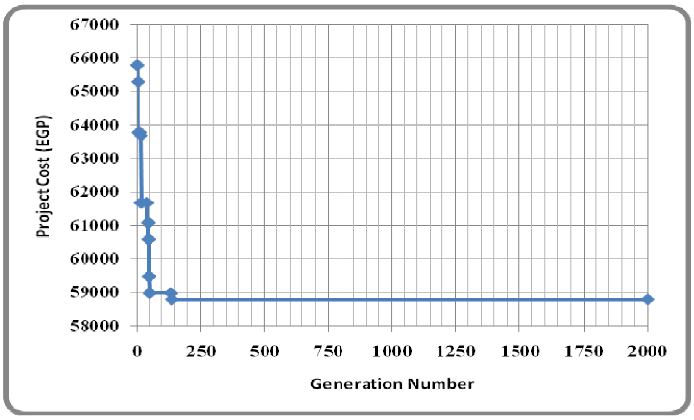

Figure (4): Generations progress for project 2

7. Conclusions

The three interrelated and conflicting objectives of any project are time, cost, and quality and they are the most important factors to be considered in all construction projects. Over the years, many research studies have been conducted to model the time-cost relationship. Recently, contracts consider the quality performance of projects in addition to time and cost. To achieve the project objectives, a number of project activities modes for executions have been considered through designing the project network. Regarding the huge number of alternative solutions, the project managers face a big decision- making problem. In this paper, an optimization model that deals with time-cost-quality trade-off optimization in construction projects is developed. The model is based on a GA to find minimum cost for different quality levels at a certain time limit. The goal of the research is to find the best compromise between multiple and conflicting objectives to help the decision maker to decide an optimal combination of construction methods and choose the modes which achieve his requirements. Details of model formulation are illustrated by two examples projects. The results show that the present method can be used in finding the optimal solution in reasonable running time. The present model provides an attractive alternative for the solution of the construction multi-objective optimization problems. The results include the optimum time and quality points for both projects. The results show the generations progression during model run.

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