Comparison of Selection Methods of Genetic Algorithms for Automated Component-Selection of Design Synthesis with Model-Based Systems Engineering

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Abstract

One of the important tasks of design synthesis with the Model-Based Systems Engineering (MBSE) is the component-selection. A trade study analysis is commonly used to perform this task, but when it is used for a complex system such as a hybrid car, the analysis will be error-prone, time and cost-consuming. A Genetic Algorithm (GA) is an evolutionary searching technique that can be optimized and used to solve the selection problems. This paper compares between the GA's Elitism and the Roulette-Wheel selection methods when performing a trade study analysis for physical components-selection based on the Systems Modeling Language (SysML) logical architecture model of a hybrid car consisting of an engine, an electric motor, and a battery; and selects the optimum method for automating the MBSE-based trade study analysis. The results indicate that the Elitism selector has a better comparative performance than the Roulette-Wheel selector.

Keywords: Model-Based System Engineering (MBSE), Systems Modeling Language (SysML), Genetic Algorithms (GA), Evolutionary Algorithms, Elitism, Roulette-Wheel, trade study, design synthesis.

1. Introduction

Systems complexity today has increased dramatically. The complexity is driven by the number of components including software and the dependencies between those components. The Model-Based Systems Engineering (MBSE) has a promising approach to manage system complexity. The Systems Modeling Language or SysML [1] was developed to facilitate MBSE. SysML provides systems engineers with a high-level abstraction and visual representation of 4 main design concerns, requirements, system structure and behavior, and parameters. In MBSE, design synthesis is a process that includes the generation of physical architecture specifications that satisfy the logical design and desired functional specifications [2].

Trade study is one of the tasks in design synthesis that can help the system engineers select the right design and components. The system engineers usually need to design several possible alternative architectures of a system and manually analyze them to find the best design. However, with today's system complexity such as autonomous vehicle and its increasing number of components, their dependency and integration, the traditional method may be insufficient because searching through many possibilities based on the specific requirements is often time and cost consuming [3] and error-prone [4]. Therefore, optimizing the searching method is necessary to overcome this problem [3].

The Genetic Algorithms (GAs) [5] have been applied successfully to solve many engineering problems, e.g. electromagnetic system design, aircraft control system and its aerodynamics [6] [7]. Some research studies have shown the potentials of using GAs in system engineering and thus some scholars think that GAs and design synthesis can complement each other [8]. In his book, Engineering Design Synthesis [9], Chakrabarti also presents a survey and detailed investigation of the application of design synthesis such as generating a pattern of solutions with design synthesis. However, a Genetic Algorithm is not a silver bullet that can solve every problem in searching and optimization processes. Before using a GA, there are many selection methods that need to be pre-considered because selection is one of the most urgent operations in the processes [10]. Thus, to improve and optimize the GA usage, a pre-comparison study might be necessary to discover the most suitable selection method for a particular context of a case study. The previous studies [10] [11] [12] show that the Elitism and Roulette-Wheel selectors are the most commonly used selection techniques. In most of the cases, Elitism shows a better performance than the other techniques based on a pre-defined context of the case studies.

This paper proposes a comparison study of both common GA selectors, Elitism and Roulette-Wheel. The primary contribution of this paper is to help the systems engineers to select the most suitable GA selector and in addition, assist them using the best fitness solution based on the fitness value pre-defined by the domain experts.

2. Literature Review

2.1. Overview of Genetic Algorithms

The Genetic Algorithm (GA) is inspired by Charles Darwin's Theory of Evolution [10], which illustrates the natural biological systems evolution and its natural selection [3]. Computer scientists have adopted this approach as a metaheuristic searching algorithms to solve optimization problems [11]. The searching method of GAs is mainly based on randomization with natural selection [12] Darwin's theory of evolution by natural selection means that the fittest individual will survive. The GA process starts with a sample set of potential solutions (initial population) [12] represented by chromosomes to produce a new population or the next generation. The process continues with two parent chromosomes within the population mate by sharing their genetic information [13]. The mating process of these two chromosomes to form the next generation is known as crossover. This crossover results in the offspring receiving a part of the genes from one parent chromosome and a part of the genes from the other parent. However, gene mutation may occur when copying of the parent's genetic information, which causes the genes of the new offspring to be slightly different from their parent chromosomes [13].

2.2. Selection Methods

Selection is also known as reproduction [13]. It is applied to a population to find the best chromosomes to be the parents [14]. From the population, the parent chromosomes are chosen to perform crossover and produce the potential offspring [13]. *Elitism* is one of the selection methods that copies the best chromosome of the previous population to the new one [14]. In addition, the chance of the current fittest chromosome to lose the best chromosome is high when producing a new population by performing crossover and mutation [14]. *Roulette-Wheel*, which is also known as the fitness proportional selector [15], is commonly used for selecting potentially useful solutions for recombination. Its method is very similar to how a roulette wheel rotates in a roulette game. The chance of an offspring to be selected is proportional to its fitness to the other competitors' fitness [13]. For example, (Figure 1), the Roulette-Wheel simulates 8 offspring and each fitness value marked around the wheel. The 5th offspring has the highest fitness value than the others; therefore, the chance of the 5th offspring to be selected is higher than that of the other offspring [13].

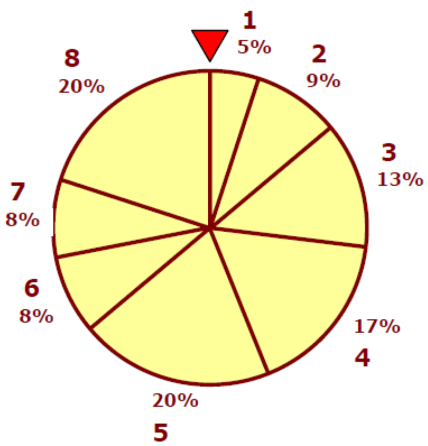

Figure 1 Roulette-Wheel Selector

2.3. Example of Application

This paper proposes a solution for the component-selection problem in the instance level of a hybrid car model. Figure 2 shows an example of a hybrid car model structure in a Block Definition Diagram. The hybrid car consists of an engine, an electric motor, and a battery. Since the main objective of this preliminary research is to show how the proposed technique can be applied to the design synthesis problem, only the simplified partial conceptual level hybrid car system design and a set of simplified formulas for calculating the solution with basic parameters, such as total horsepower, total cost, and total weight, are considered. Any complex system and formula can be used instead of the simplified version for future work, depending on the type of domain and industry. Only three important parameters, i.e., *totalHP*, *totalCost*, and *totalWeight* are considered in this research. These parameters are used to evaluate the system design's fitness using a fitness function. The details will be elaborated in the methodology section.

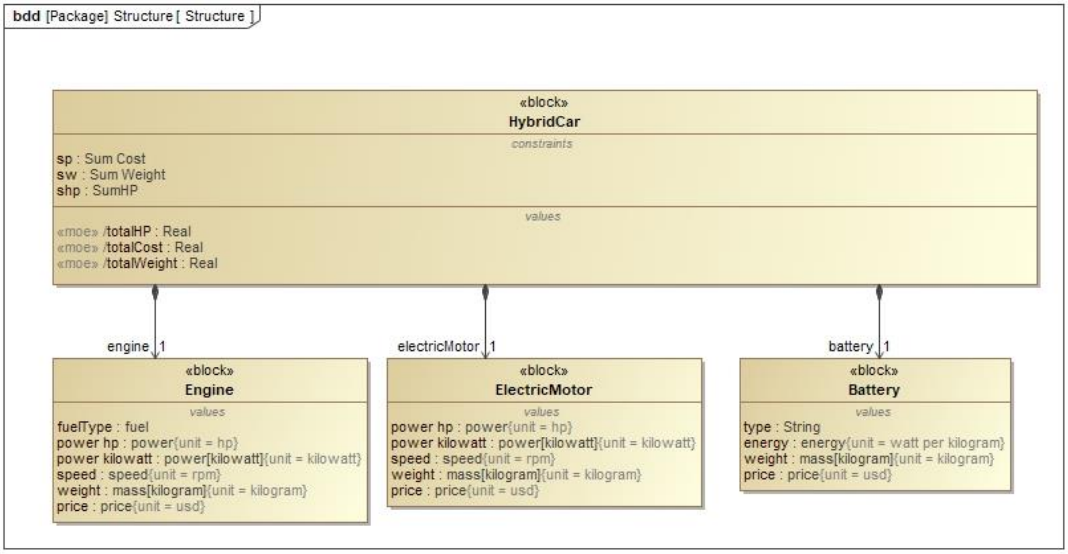

Figure 2 Example of a Hybrid Car Structure

3. Selection Methods of Genetic Algorithms in Design Synthesis

In Genetic Algorithms, evaluation involves measuring the fitness of a candidate solution. The analogy comes from Darwin's theory of evolution "The strongest species that survives" [13]. To do this, a fitness value is needed to define the quality of each gene in a population in order to perform a selection process [16]. A kind of measurement to derive the quality is called a fitness function [3] [16]. The purpose is to evaluate how close an individual is to an optimal solution [14]. According to the design, the model requirement parameters and the measures of effectiveness (MoE) are used to identify the best optimized value or the Fitness Value. Figure 3 shows that the evolutionary trade-off also needs a model of fitness function to perform the natural selection of GAs. It depicts the additional model for a hybrid car and its components. The GA parameters provide the code and the gene value for each battery, engine, and electric motor required by GA to do the evaluation. The Trade Study Analysis block includes the Fitness Function to analyze the Hybrid Car System Model. The Fitness Function block represents the model of the fitness value formula and includes the parameters required by GA.

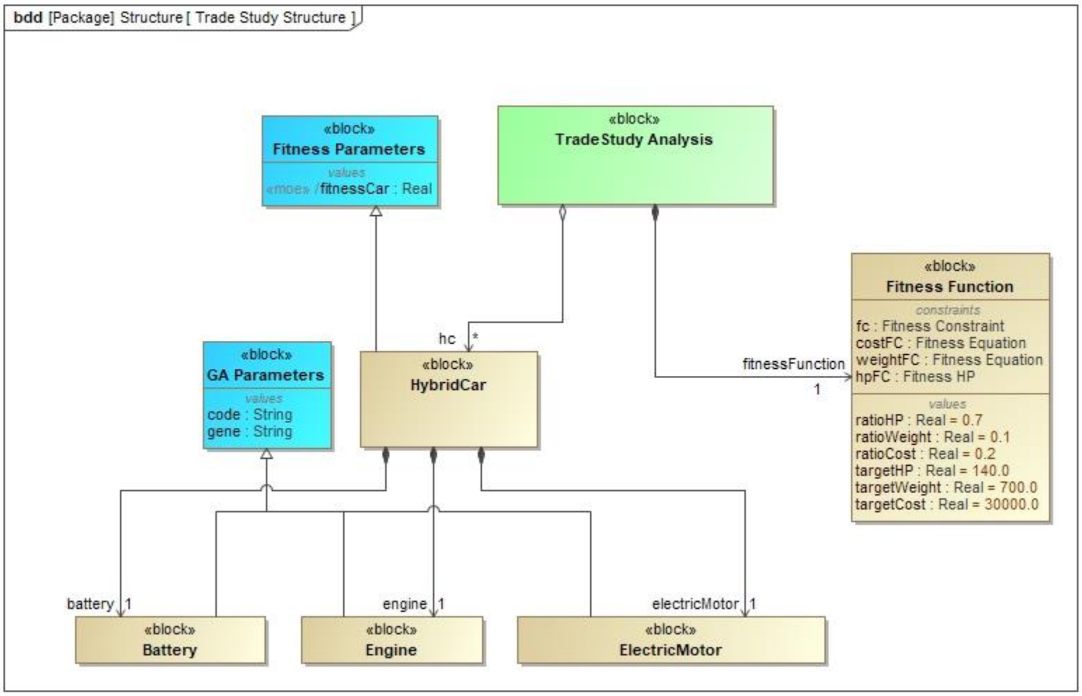

Figure 3 Trade Study Structure model with GA's parameter and Fitness Function

Table 1 shows the stakeholders' needs and the design parameters considered in the trade-off study: Performance, Cost, and Weight. The weighted ratio is used to define the weighted fitness function to evaluate the chromosomes.

Table 1 Requirements Example

Requirements	Value	Weight Ratio
Target HP	140 hp	0.7
Maximum Cost	US$30,000	0.2
Maximum Weight	700 kg	0.1

Before measuring the fitness value, it is necessary to calculate the gained horsepower (hp), cost, and weight of the potential solution in the selection process. The following shows the examples of a hybrid car's performance calculation:

$$totalHP = hpEngine + hpElectricMotor \quad (1)$$

$$totalCost=enginePrice+electricMotorPrice+batteryPrice \quad (2)$$

$$totalWeight=engineWeight+electricMotorWeight+batteryWeight \quad (3)$$

Whereas:

- totalHP is the total power of a solution in horsepower;
- totalCost is the total cost of a solution;
- totalWeight is the total mass of a solution.

In this GA, the authors use a Weighted Fitness Function to evaluate the solutions. The example of Weighted GA's Fitness Function is as follows:

$$fitness=w1 \cdot fitnessHP+w2 \cdot fitnessCost+w3 \cdot fitnessWeight \quad (4)$$

Whereas:

- fitnessHP is the fitness value of the performance of a solution;
- fitnessCost is the fitness value of the cost of solution;
- fitnessWeight is the fitness value of the mass of a solution;
- w1, w2 and w3 are real positive weights, indicating the contribution of each fitness value to the overall fitness function whereas *w1* + *w2* + *w3* = *1.*

$fitnessHP= MAX_{BOUND}-\frac{\lvert targetHP-totalHP \rvert}{targetHP}$
If $(totalCost \leqslant maxCost)$ $fitnessCost=\frac{\lvert maxCost-totalCost \rvert}{maxCost}$ Else $fitnessCost= MIN_{BOUND}$
If $(totalWeight \leqslant maxWeight)$ $fitnessWeight=\frac{\lvert maxWeight-totalWeight \rvert}{maxWeight}$ Else $fitnessWeight= MIN_{BOUND}$

Whereas:

- MINbound is the lowest bound of fitness value, 0.00;
- MAXbound is the highest bound of fitness value, 1.00;
- targetHP is the target performance of a solution in horsepower;
- maxCost is the maximum cost of a solution;
- maxWeight is the maximum mass of a solution.

The following are the Java code samples related to the fitness function evaluation.

```
public double evaluate(IChromosome a_subject) {
        HybridCar hybCar = HybridCar.getHybridCarByChromosome(m_comLib,
a_subject);
        double fitness = GAParameters.FITNESS_MIN_BOUND; // fitness scale is 0 to 1
        /* 1. Calculate fitness for the greatest HP */
        double hpDiff = Math.abs(m_req.getTARGET_HP() - hybCar.getTotalHp());
        fitness += m_req.getRATIO_HP() * (GAParameters.FITNESS_MAX_BOUND -
        (hpDiff / m_req.getTARGET_HP()));
        /* End */

        /* 2. Calculate fitness for the cheapest cost */
        double costDiff = Math.abs(m_req.getMAX_COST() - hybCar.getTotalCost());
        if (hybCar.getTotalCost() <= m_req.getMAX_COST()) {
                fitness += m_req.getRATIO_COST() * (costDiff / m_req.getMAX_COST());
        } else {
                fitness = GAParameters.FITNESS_MIN_BOUND;
        }
        /* End */

        /* 3. Calculate fitness for the lightest weight */
        double weightDiff = Math.abs(m_req.getMAX_WEIGHT() -
hybCar.getTotalWeight());
        if (hybCar.getTotalWeight() <= m_req.getMAX_WEIGHT()) {
```

```
            fitness += m_req.getRATIO_WEIGHT() * (weightDiff /
        m_req.getMAX_WEIGHT());
        } else {
            fitness = GAParameters.FITNESS_MIN_BOUND;
        }
        /* End */
}
```

Before using GAs, it is important to define the ratio of the algorithm parameters and its target data encoding representation. There are several key operations in designing GAs to solve an optimization problem such as the representation and encoding technique, the initial population (how the first generation is generated), the selection method (how to select parent individuals to be involved in reproduction), the crossover operator (how to produce an offspring from two parent chromosomes), and the mutation operator (how to mutate offspring) [14]. Table 2 shows the GAs' parameters and their ratio.

Table 2 The Genetic Algorithms' Parameters

Operators	Method	Rate
Population Size	n/a	10
Number of Evolutions	n/a	20
Selection	Elitism	0.9
	Roulette-Wheel	n/a
Crossover	One-Point	0.35
Mutation	Custom String Gene Mutation	12

In the initial prototype, the initial population is randomly generated by a random number generator to simulate the nature of evolutions [8]. However, if the systems engineers already had some potential designs from the previous experiences, they can use them as the initial population. The number of chromosomes in the initial population depends on the population size which is specified by the engineers.

Crossover is also known as recombination [16]. It is like simulating the “biological mating” of two parent chromosomes by swapping and mixing their genes [15] so that the parents can pass their genetic information to their offspring. The default configuration of the initial prototype is a one-point crossover. The one-point crossover locates a crossover point and then clones the everything behind this point from the first parent chromosome and then the rest after the crossover point from the second parent chromosome [16] [17]. The crossover point is chosen randomly with a probability rate of 0.35 of the specified population size.

Mutation is the random changes of the gene values in the chromosomes of a potential solution [15]. The changes are mainly caused by errors in copying genes from the parent chromosomes [17]. After the crossover helps the parent chromosomes to produce their successors, the mutation is applied to each successor. By applying mutation, it can help retain the diversity of the individuals in the whole population [15] [16]. The default configuration of the initial prototype is a custom mutation for the string-typed gene at a rate of 12. It means that the mutation is applied to 1 in 12 genes in the whole population. It is often necessary to develop a custom type of mutation in value encoding [16]. The mutation is simply done by performing a change at the mutation point with another permitted string value. A set of the permitted string value is called permitted alphabet [15]. The rate is dictated by the size of the chromosome multiplied by the size of the population divided by the rate. Therefore, the probability of mutation rate is 1/12. The mutation point is random.

4. The Implementation of the Example

This paper used Cameo Systems Modeler (CSM), a modeling tool developed by No Magic, Inc., together with an open source library JGAP to perform the trade study to test the GA with SysML. With its open API and its SysML implementation, which is the most Object Management Group (OMG) standard-compliant, CSM allows us to access the model information and test the GA. The architecture of the GA plugin for Cameo Systems Modeler is shown in Figure 4.

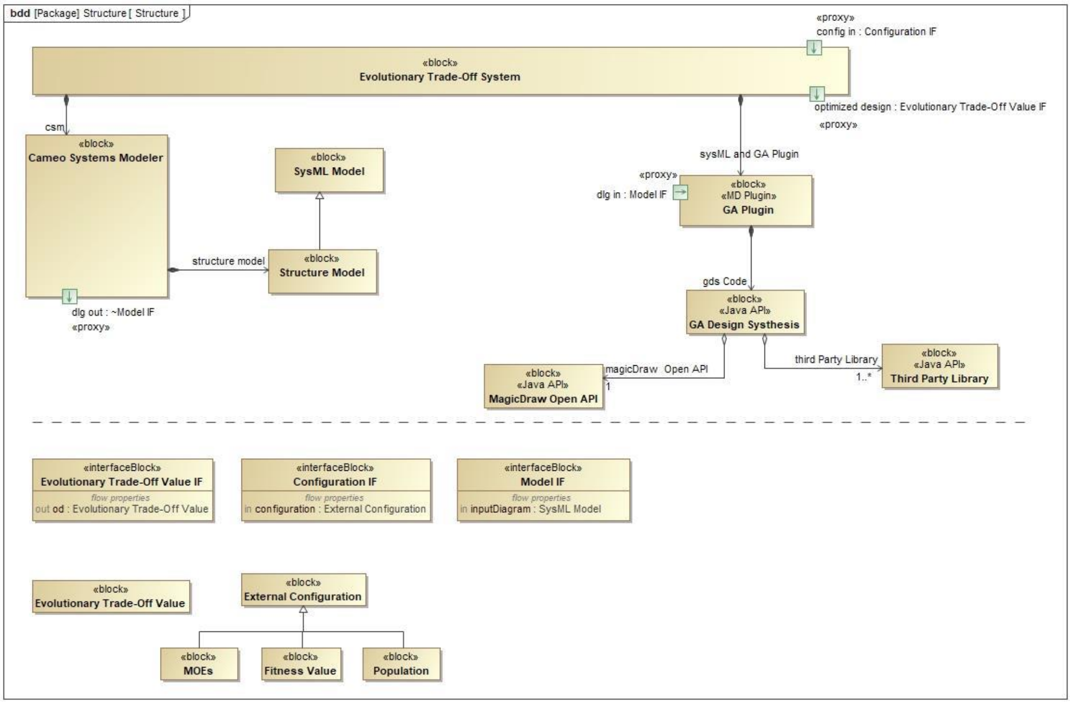

Figure 4 GA Plugin for Cameo Systems Modeler Architecture

5. Results of Evaluation

The initial prototype involves 20 alternative components: 10 engines, 5 electric motors, and 5 batteries. Therefore, the total permutation of possible solutions is 250 for the trade study. The experiments performed two selection methods to simulate the evolutionary trade study based on the desired requirements (i.e., target power = 140 hp; maximum cost = US$ 30,000; and maximum weight = 700 kg). The parameters used in this experiment are: Population Size = 10, Number of Evolution = 20, Crossover Rate = 0.35, Mutation Rate = 12, and Selection Rate is 90 percent with the Elitism approach.

The results (see Appendix) show that the Elitism selector is more suitable to use in this case study context than the Roulette-Wheel selector. The reason is that based on 100 experiments for each selector, the Elitism selector discovers a better solution with the closest fitness value (i.e., Engine A – Electric Motor D – Battery C with the fitness value = 0.802 out of 1.0) more frequently than the other one. The most optimized component configuration selected is the one made use of Elitism as the selection method (Figure 5) to keep the best alternative from the previous solution as the potential alternative for the next one.

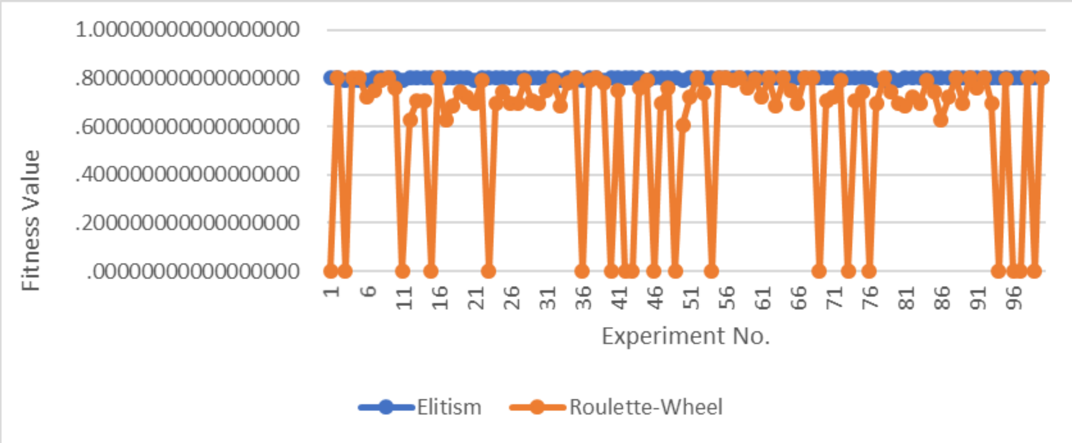

Figure 5 Comparison Result between the Elitism and Roulette-Wheel Selectors on Fitness Value

6. Conclusions and Future Works

This paper demonstrated the genetic algorithm (GA) usage in the initial prototype to perform the evolutionary trade study in design synthesis by using the SysML model to specify the system structure and its requirements. By comparing both the Elitism and Roulette-Wheel selectors we found that Elitism has a better mutation performance and fitness value when used with the controlled system structure and requirements modeled in SysML as its constraint.

A single synthesis method cannot always solve every kind of problem [8]. Therefore, GA used in this paper should be reconfigured and optimized depending on the problem. GA can perform well in an initial prototype, but the prototype will always be much simpler than a real system because the real system requires much more specifications and detail, such as the interfaces between each components, parameters and items that need to flow through each connector, dimension of each component and part, etc. to control the mutation and ensure the selected components can be assembled. Also, the right fitness value and function requires different knowledge of each domain to optimize GA and make it perform accurately. For future research, the experimental results can be measured quantitatively using some statistical technique, such as correlative coefficient [16] and regression.

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Appendix

#	Name	engine : Engine	electricMotor : ElectricMotor	battery : Battery	totalHP : Real	totalCost : Real	totalWeight : Real	fitnessCar : Real
1	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
2	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
3	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
4	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
5	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
6	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
7	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
8	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
9	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
10	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
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13	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
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16	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
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19	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
20	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
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24	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
25	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
26	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
27	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
28	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
29	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
30	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
31	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
32	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
33	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
34	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
35	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
36	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
37	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
38	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
39	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
40	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
41	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
42	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
43	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
44	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
45	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
46	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
47	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
48	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
49	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
50	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523

Figure A1 Experimental Results of the Elitism Selector Part 1

#	Name	engine : Engine	electricMotor : ElectricMotor	battery : Battery	totalHP : Real	totalCost : Real	totalWeight : Real	fitnessCar : Real
51	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
52	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
53	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
54	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
55	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
56	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
57	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
58	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
59	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
60	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
61	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
62	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
63	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
64	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
65	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
66	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
67	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
68	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
69	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
70	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
71	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
72	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
73	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
74	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
75	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
76	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
77	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
78	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
79	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
80	HybridCar_BCC	Engine B : 2 Logical Model::S	Electric Motor C : 2 Logical M	Battery C : 2 Logical Model::	137.0	14600.0	674.0	0.7913809523809523
81	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
82	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
83	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
84	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
85	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
86	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
87	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
88	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
89	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
90	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
91	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
92	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
93	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
94	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
95	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
96	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
97	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
98	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
99	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905
100	HybridCar_ADC	Engine A : 2 Logical Model::S	Electric Motor D : 2 Logical M	Battery C : 2 Logical Model::	138.0	15400.0	594.0	0.8024761904761905

Figure A2 Experimental Results of the Elitism Selector Part 2

#	Name	engine : Engine	electricMotor : ElectricMotor	battery : Battery	totalHP : Real	totalCost : Real	totalWeight : Real	fitnessCar : Real
1	HybridCar_FEB	Engine F : 2 Logical Mo	Electric Motor E : 2 Log	Battery B : 2 Logical Mo	148.0	17700.0	992.0	0.0
2	HybridCar_ADB	Engine A : 2 Logical Mo	Electric Motor D : 2 Log	Battery B : 2 Logical Mo	138.0	15200.0	605.0	0.8022380952380952
3	HybridCar_JBE	Engine J : 2 Logical Mo	Electric Motor B : 2 Log	Battery E : 2 Logical Mo	144.0	20500.0	1112.0	0.0
4	HybridCar_ADA	Engine A : 2 Logical Mo	Electric Motor D : 2 Log	Battery A : 2 Logical Mo	138.0	15000.0	620.0	0.8014285714285714
5	HybridCar_ADC	Engine A : 2 Logical Mo	Electric Motor D : 2 Log	Battery C : 2 Logical Mo	138.0	15400.0	594.0	0.8024761904761905
6	HybridCar_ACE	Engine A : 2 Logical Mo	Electric Motor C : 2 Log	Battery E : 2 Logical Mo	125.0	16000.0	656.0	0.7246190476190477
7	HybridCar_BDB	Engine B : 2 Logical Mo	Electric Motor D : 2 Log	Battery B : 2 Logical Mo	150.0	15400.0	700.0	0.7473333333333334
8	HybridCar_BCC	Engine B : 2 Logical Mo	Electric Motor C : 2 Log	Battery C : 2 Logical Mo	137.0	14600.0	674.0	0.7913809523809523
9	HybridCar_ADC	Engine A : 2 Logical Mo	Electric Motor D : 2 Log	Battery C : 2 Logical Mo	138.0	15400.0	594.0	0.8024761904761905
10	HybridCar_AEC	Engine A : 2 Logical Mo	Electric Motor E : 2 Log	Battery C : 2 Logical Mo	148.0	16400.0	614.0	0.7629523809523808
11	HybridCar_JBB	Engine J : 2 Logical Mo	Electric Motor B : 2 Log	Battery B : 2 Logical Mo	144.0	18700.0	1046.0	0.0
12	HybridCar_AAB	Engine A : 2 Logical Mo	Electric Motor A : 2 Log	Battery B : 2 Logical Mo	98.0	12200.0	555.0	0.6293809523809523
13	HybridCar_CBC	Engine C : 2 Logical Mo	Electric Motor B : 2 Log	Battery C : 2 Logical Mo	120.0	13900.0	690.0	0.7087619047619048
14	HybridCar_CBC	Engine C : 2 Logical Mo	Electric Motor B : 2 Log	Battery C : 2 Logical Mo	120.0	13900.0	690.0	0.7087619047619048
15	HybridCar_JBE	Engine J : 2 Logical Mo	Electric Motor B : 2 Log	Battery E : 2 Logical Mo	144.0	20500.0	1112.0	0.0
16	HybridCar_ADA	Engine A : 2 Logical Mo	Electric Motor D : 2 Log	Battery A : 2 Logical Mo	138.0	15000.0	620.0	0.8014285714285714
17	HybridCar_AAA	Engine A : 2 Logical Mo	Electric Motor A : 2 Log	Battery A : 2 Logical Mo	98.0	12000.0	570.0	0.6285714285714284
18	HybridCar_BBC	Engine B : 2 Logical Mo	Electric Motor B : 2 Log	Battery C : 2 Logical Mo	114.0	13600.0	650.0	0.6864761904761905
19	HybridCar_ACA	Engine A : 2 Logical Mo	Electric Motor C : 2 Log	Battery A : 2 Logical Mo	125.0	14000.0	605.0	0.7452380952380953
20	HybridCar_ACE	Engine A : 2 Logical Mo	Electric Motor C : 2 Log	Battery E : 2 Logical Mo	125.0	16000.0	656.0	0.7246190476190477
21	HybridCar_CAB	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery B : 2 Logical Mo	116.0	12700.0	690.0	0.6967619047619048
22	HybridCar_BCB	Engine B : 2 Logical Mo	Electric Motor C : 2 Log	Battery B : 2 Logical Mo	137.0	14400.0	685.0	0.791142857142857
23	HybridCar_HEE	Engine H : 2 Logical Mo	Electric Motor E : 2 Log	Battery E : 2 Logical Mo	166.0	22000.0	1136.0	0.0
24	HybridCar_CAC	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery C : 2 Logical Mo	116.0	12900.0	679.0	0.697
25	HybridCar_ACC	Engine A : 2 Logical Mo	Electric Motor C : 2 Log	Battery C : 2 Logical Mo	125.0	14400.0	579.0	0.7462857142857142
26	HybridCar_CAB	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery B : 2 Logical Mo	116.0	12700.0	690.0	0.6967619047619048
27	HybridCar_CAC	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery C : 2 Logical Mo	116.0	12900.0	679.0	0.697
28	HybridCar_BCB	Engine B : 2 Logical Mo	Electric Motor C : 2 Log	Battery B : 2 Logical Mo	137.0	14400.0	685.0	0.791142857142857
29	HybridCar_CBC	Engine C : 2 Logical Mo	Electric Motor B : 2 Log	Battery C : 2 Logical Mo	120.0	13900.0	690.0	0.7087619047619048
30	HybridCar_CAB	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery B : 2 Logical Mo	116.0	12700.0	690.0	0.6967619047619048
31	HybridCar_BDC	Engine B : 2 Logical Mo	Electric Motor D : 2 Log	Battery C : 2 Logical Mo	150.0	15600.0	689.0	0.7475714285714286
32	HybridCar_BCB	Engine B : 2 Logical Mo	Electric Motor C : 2 Log	Battery B : 2 Logical Mo	137.0	14400.0	685.0	0.791142857142857
33	HybridCar_BBC	Engine B : 2 Logical Mo	Electric Motor B : 2 Log	Battery C : 2 Logical Mo	114.0	13600.0	650.0	0.6864761904761905
34	HybridCar_ADE	Engine A : 2 Logical Mo	Electric Motor D : 2 Log	Battery E : 2 Logical Mo	138.0	17000.0	671.0	0.7808095238095237
35	HybridCar_ADC	Engine A : 2 Logical Mo	Electric Motor D : 2 Log	Battery C : 2 Logical Mo	138.0	15400.0	594.0	0.8024761904761905
36	HybridCar_DCE	Engine D : 2 Logical Mo	Electric Motor C : 2 Log	Battery E : 2 Logical Mo	165.0	17000.0	916.0	0.0
37	HybridCar_BCC	Engine B : 2 Logical Mo	Electric Motor C : 2 Log	Battery C : 2 Logical Mo	137.0	14600.0	674.0	0.7913809523809523
38	HybridCar_ADA	Engine A : 2 Logical Mo	Electric Motor D : 2 Log	Battery A : 2 Logical Mo	138.0	15000.0	620.0	0.8014285714285714
39	HybridCar_ADE	Engine A : 2 Logical Mo	Electric Motor D : 2 Log	Battery E : 2 Logical Mo	138.0	17000.0	671.0	0.7808095238095237
40	HybridCar_HBC	Engine H : 2 Logical Mo	Electric Motor B : 2 Log	Battery C : 2 Logical Mo	120.0	17400.0	1000.0	0.0
41	HybridCar_BDB	Engine B : 2 Logical Mo	Electric Motor D : 2 Log	Battery B : 2 Logical Mo	150.0	15400.0	700.0	0.7473333333333334
42	HybridCar_HAE	Engine H : 2 Logical Mo	Electric Motor A : 2 Log	Battery E : 2 Logical Mo	116.0	18000.0	1066.0	0.0
43	HybridCar_HED	Engine H : 2 Logical Mo	Electric Motor E : 2 Log	Battery D : 2 Logical Mo	166.0	20500.0	1070.0	0.0
44	HybridCar_AEC	Engine A : 2 Logical Mo	Electric Motor E : 2 Log	Battery C : 2 Logical Mo	148.0	16400.0	614.0	0.7629523809523808
45	HybridCar_BCC	Engine B : 2 Logical Mo	Electric Motor C : 2 Log	Battery C : 2 Logical Mo	137.0	14600.0	674.0	0.7913809523809523
46	HybridCar_DCE	Engine D : 2 Logical Mo	Electric Motor C : 2 Log	Battery E : 2 Logical Mo	165.0	17000.0	916.0	0.0
47	HybridCar_CAC	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery C : 2 Logical Mo	116.0	12900.0	679.0	0.697
48	HybridCar_AEB	Engine A : 2 Logical Mo	Electric Motor E : 2 Log	Battery B : 2 Logical Mo	148.0	16200.0	625.0	0.7627142857142856
49	HybridCar_DCE	Engine D : 2 Logical Mo	Electric Motor C : 2 Log	Battery E : 2 Logical Mo	165.0	17000.0	916.0	0.0
50	HybridCar_AAE	Engine A : 2 Logical Mo	Electric Motor A : 2 Log	Battery E : 2 Logical Mo	98.0	14000.0	621.0	0.6079523809523808

Figure A3 Experimental Results of the Roulette-Wheel Selector Part 1

#	Name	engine : Engine	electricMotor : ElectricMotor	battery : Battery	totalHP : Real	totalCost : Real	totalWeight : Real	fitnessCar : Real
51	HybridCar_ACE	Engine A : 2 Logical Mc	Electric Motor C : 2 Log	Battery E : 2 Logical Mo	125.0	16000.0	656.0	0.7246190476190477
52	HybridCar_ADC	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery C : 2 Logical Mc	138.0	15400.0	594.0	0.8024761904761905
53	HybridCar_AEE	Engine A : 2 Logical Mc	Electric Motor E : 2 Log	Battery E : 2 Logical Mo	148.0	18000.0	691.0	0.7412857142857143
54	HybridCar_JBE	Engine J : 2 Logical Mo	Electric Motor B : 2 Log	Battery E : 2 Logical Mo	144.0	20500.0	1112.0	0.0
55	HybridCar_ADC	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery C : 2 Logical Mc	138.0	15400.0	594.0	0.8024761904761905
56	HybridCar_ADC	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery C : 2 Logical Mc	138.0	15400.0	594.0	0.8024761904761905
57	HybridCar_BCB	Engine B : 2 Logical Mo	Electric Motor C : 2 Log	Battery B : 2 Logical Mo	137.0	14400.0	685.0	0.791142857142857
58	HybridCar_ADC	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery C : 2 Logical Mc	138.0	15400.0	594.0	0.8024761904761905
59	HybridCar_AEC	Engine A : 2 Logical Mc	Electric Motor E : 2 Log	Battery C : 2 Logical Mc	148.0	16400.0	614.0	0.7629523809523808
60	HybridCar_ADD	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery D : 2 Logical Mc	138.0	15500.0	605.0	0.8002380952380952
61	HybridCar_ACE	Engine A : 2 Logical Mc	Electric Motor C : 2 Log	Battery E : 2 Logical Mo	125.0	16000.0	656.0	0.7246190476190477
62	HybridCar_ADB	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery B : 2 Logical Mo	138.0	15200.0	605.0	0.8022380952380952
63	HybridCar_BBC	Engine B : 2 Logical Mo	Electric Motor B : 2 Log	Battery C : 2 Logical Mc	114.0	13600.0	650.0	0.6864761904761905
64	HybridCar_ADC	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery C : 2 Logical Mc	138.0	15400.0	594.0	0.8024761904761905
65	HybridCar_BDC	Engine B : 2 Logical Mo	Electric Motor D : 2 Log	Battery C : 2 Logical Mc	150.0	15600.0	689.0	0.7475714285714286
66	HybridCar_CAC	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery C : 2 Logical Mc	116.0	12900.0	679.0	0.697
67	HybridCar_ADB	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery B : 2 Logical Mo	138.0	15200.0	605.0	0.8022380952380952
68	HybridCar_ADA	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery A : 2 Logical Mc	138.0	15000.0	620.0	0.8014285714285714
69	HybridCar_EAB	Engine E : 2 Logical Mo	Electric Motor A : 2 Log	Battery B : 2 Logical Mo	140.0	14700.0	855.0	0.0
70	HybridCar_CBC	Engine C : 2 Logical Mo	Electric Motor B : 2 Log	Battery C : 2 Logical Mc	120.0	13900.0	690.0	0.7087619047619048
71	HybridCar_ACE	Engine A : 2 Logical Mc	Electric Motor C : 2 Log	Battery E : 2 Logical Mo	125.0	16000.0	656.0	0.7246190476190477
72	HybridCar_BCA	Engine B : 2 Logical Mo	Electric Motor C : 2 Log	Battery A : 2 Logical Mc	137.0	14200.0	700.0	0.7903333333333333
73	HybridCar_CBE	Engine C : 2 Logical Mo	Electric Motor B : 2 Log	Battery E : 2 Logical Mo	120.0	15500.0	767.0	0.0
74	HybridCar_CBC	Engine C : 2 Logical Mo	Electric Motor B : 2 Log	Battery C : 2 Logical Mc	120.0	13900.0	690.0	0.7087619047619048
75	HybridCar_BDD	Engine B : 2 Logical Mo	Electric Motor D : 2 Log	Battery D : 2 Logical Mc	150.0	15700.0	700.0	0.7453333333333334
76	HybridCar_EDE	Engine E : 2 Logical Mo	Electric Motor D : 2 Log	Battery E : 2 Logical Mo	180.0	19500.0	971.0	0.0
77	HybridCar_CAD	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery D : 2 Logical Mc	116.0	13000.0	690.0	0.6947619047619048
78	HybridCar_ADA	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery A : 2 Logical Mc	138.0	15000.0	620.0	0.8014285714285714
79	HybridCar_ACB	Engine A : 2 Logical Mc	Electric Motor C : 2 Log	Battery B : 2 Logical Mo	125.0	14200.0	590.0	0.746047619047619
80	HybridCar_CAB	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery B : 2 Logical Mo	116.0	12700.0	690.0	0.6967619047619048
81	HybridCar_BBC	Engine B : 2 Logical Mo	Electric Motor B : 2 Log	Battery C : 2 Logical Mc	114.0	13600.0	650.0	0.6864761904761905
82	HybridCar_ACE	Engine A : 2 Logical Mc	Electric Motor C : 2 Log	Battery E : 2 Logical Mo	125.0	16000.0	656.0	0.7246190476190477
83	HybridCar_CAC	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery C : 2 Logical Mc	116.0	12900.0	679.0	0.697
84	HybridCar_BCA	Engine B : 2 Logical Mo	Electric Motor C : 2 Log	Battery A : 2 Logical Mc	137.0	14200.0	700.0	0.7903333333333333
85	HybridCar_ACA	Engine A : 2 Logical Mc	Electric Motor C : 2 Log	Battery A : 2 Logical Mc	125.0	14000.0	605.0	0.7452380952380953
86	HybridCar_AAB	Engine A : 2 Logical Mc	Electric Motor A : 2 Log	Battery B : 2 Logical Mo	98.0	12200.0	555.0	0.6293809523809523
87	HybridCar_ACE	Engine A : 2 Logical Mc	Electric Motor C : 2 Log	Battery E : 2 Logical Mo	125.0	16000.0	656.0	0.7246190476190477
88	HybridCar_ADB	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery B : 2 Logical Mo	138.0	15200.0	605.0	0.8022380952380952
89	HybridCar_CAC	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery C : 2 Logical Mc	116.0	12900.0	679.0	0.697
90	HybridCar_ADC	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery C : 2 Logical Mc	138.0	15400.0	594.0	0.8024761904761905
91	HybridCar_AEA	Engine A : 2 Logical Mc	Electric Motor E : 2 Log	Battery A : 2 Logical Mc	148.0	16000.0	640.0	0.7619047619047619
92	HybridCar_ADA	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery A : 2 Logical Mc	138.0	15000.0	620.0	0.8014285714285714
93	HybridCar_CAB	Engine C : 2 Logical Mo	Electric Motor A : 2 Log	Battery B : 2 Logical Mo	116.0	12700.0	690.0	0.6967619047619048
94	HybridCar_HED	Engine H : 2 Logical Mc	Electric Motor E : 2 Log	Battery D : 2 Logical Mc	166.0	20500.0	1070.0	0.0
95	HybridCar_ADD	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery D : 2 Logical Mc	138.0	15500.0	605.0	0.8002380952380952
96	HybridCar_HBC	Engine H : 2 Logical Mc	Electric Motor B : 2 Log	Battery C : 2 Logical Mc	120.0	17400.0	1000.0	0.0
97	HybridCar_JBE	Engine J : 2 Logical Mo	Electric Motor B : 2 Log	Battery E : 2 Logical Mo	144.0	20500.0	1112.0	0.0
98	HybridCar_ADB	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery B : 2 Logical Mo	138.0	15200.0	605.0	0.8022380952380952
99	HybridCar_JBE	Engine J : 2 Logical Mo	Electric Motor B : 2 Log	Battery E : 2 Logical Mo	144.0	20500.0	1112.0	0.0
100	HybridCar_ADB	Engine A : 2 Logical Mc	Electric Motor D : 2 Log	Battery B : 2 Logical Mo	138.0	15200.0	605.0	0.8022380952380952

Figure A4 Experimental Results of the Roulette-Wheel Selector Part 2

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Ho Kit Robert Ong started as a Borland C++Builder 6 product certified trainer and consultant for Borland Together and CaliberRM. He joined No Magic, Inc. a standards-driven software provider of model-driven enterprise solutions based on the Object Management Group (OMG) standards as a Senior Analyst and was promoted as a Director of Product Development, assuring client requirements were delivered by improving features and capabilities of the tools to meet the needs. Having been in the position for years, he challenged himself to take on new responsibilities as a Director of Business Development. With his 16+ years of experience in working with clients in a fast-moving environment, Robert accumulates strengths in the MBSE/MBRE, project management, requirements engineering, IT solutions finding, domain, and business process analysis, business process re-engineering, and Enterprise Architecture.

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