METAHEURISTIC ALGORITHMS BASED AUTOMATED EVALUATION METHOD FOR PUBLIC INVESTMENT PROJECTS

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TÜLUĞ FİGEN YILMAZ

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ABSTRACT

METAHEURISTIC ALGORITHMS BASED AUTOMATED EVALUATION METHOD FOR PUBLIC INVESTMENT PROJECTS

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August 2014, 63 pages

The public investment projects are essential to improve the state economy prosperously and to improve life of people. In spite of high need for public investment projects, resources are limited. So, there has been increased requirement on the accountability and efficiency of the public investment projects. To overcome these issues, project performance evaluation systems are needed. Scientific and reasonable performance measurement can be utilized in these systems to evaluate public investment projects. A set of measurement index and the assessment method must be developed to strengthen the measurement of public investment projects performance. In this thesis, a new project evaluation system is introduced. In attribute selection part of this model, Genetic Algorithm and several data mining methods are used. Harmony Search and Genetic Algorithm are used at building evaluation model after attribute selection. The proposed system is applied to evaluation process of 493 World Bank projects. The results are compared with the classical project evaluation technique using the Analytical Hierarchy Process and well known classification methods in the literature. Considering the evaluation results, the proposed work is more successful than these well known methods in the literature.

Keywords: Project Evaluation System, Metaheuristic Computation, Attribute Selection, Classification

ÖZ

KAMU YATIRIM PROJELERİ İÇİN METASEZGİSEL ALGORİTMALAR TABANLI OTOMATİK DEĞERLENDİRME YÖNTEMİ

Yılmaz, Tüluğ Figen
Yüksek Lisans, Bilgisayar Mühendisliği Bölümü
Tez Yöneticisi : Doç. Dr. Pınar Karagöz

Ağustos 2014 , 63 sayfa

Kamu yatırım projeleri başarılı bir şekilde devlet ekonomisini ve insanların yaşamını iyileştirmek için gereklidir. Kamu yatırım projelerine olan ihtiyaç fazla olmasına rağmen kaynaklar kısıtlıdır. Bu nedenle kamu yatırım projelerinin hesap verilebilirliği ve yeterliliğine olan ihtiyaç artmaktadır. Bu sorunları aşmak için proje performans değerlendirme sistemleri gereklidir. Kamu yatırım projelerini değerlendirmek için bu sistemde bilimsel ve akılcı performans ölçümlerden faydalanılabilinir. Kamu yatırım projelerinin performans ölçümünü güçlendirmek için bir grup ölçüm göstergesi ve değerlendirme metodu geliştirilmelidir. Bu tezde yeni bir proje değerlendirme sistemi sunulmaktadır. Bu modelin nitelik seçme bölümünde Genetik Algoritma ve çeşitli veri madenciliği metotları kullanılmıştır. Nitelik seçildikten sonra değerlendirme modeli oluşturulurken Harmoni Arama ve Genetik Algoritma kullanılmıştır. Sunulan sistem 493 Dünya Bankası projesinin değerlendirme işlemine uygulanmıştır. Sonuçlar klasik proje değerlendirme tekniği olan Analitik Hiyerarşi Süreci ve literatürdeki çok bilinen sınıflandırma metotlarıyla karşılaştırılmıştır. Değerlendirme sonuçlarına göre sunulan çalışma literatürdeki çok bilinen bu metotlardan daha başarılıdır.

Anahtar Kelimeler: Proje Değerlendirme Sistemi, Metasezgisel Hesaplama, Nitelik Seçme, Sınıflandırma

To my husband and my baby

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LIST OF ABBREVIATIONS

AHP	Analytic Hierarchy Process
FCE	Fuzzy Comprehensive Evaluation
6-D	6-Dimension
DEA	Data Envelopment Analysis
GA	Genetic Algorithm
HS	Harmony Search
GAMIC	Genetic Algorithm for Multicriteria Inventory Classification
CI	Consistency Index
ELM	Extreme Learning Machine
RBF	Radial Basis Function
BIRCH	Balanced Iterative Reducing and Clustering using Hierarchies
HM	Harmony Memory
HMCR	Harmony Memory Considering Rate
WEKA	Waikato Environment for Knowledge Analysis
ARFF	Attribute-Relation File Format
CFS	Correlation-based Feature Selection

CHAPTER 1

INTRODUCTION

1.1 Motivation

Public investment is capital expenditure from government resources on

- physical infrastructure
  - roads, government buildings, etc.
- soft infrastructure
  - human capital development, innovation support, research and development, etc.

with a productive use that extends beyond a year [29].

The public investment projects are essential to improve the state economy prosperously and to improve life of people [38]. The main purpose of public investment projects is remedying regional market failure, offering necessary public services and facilities for regional economic development, serving social masses, work for the welfare of the people, and farthest meeting demands of majority of people. The fact that public investment can bidirectional regulate the total demand, enhance economy supply level and accelerate long term economic development is proved by the public investment practice of the developed countries [46].

In spite of high need for public investment projects, resources are limited. So, there has been increased requirement on the accountability and efficiency of the public investment projects. To provide for the efficient and effective use of public resources allocated for public investments and to overcome these issues, project performance evaluation systems are needed. Scientific and reasonable performance measurement can be utilized in these systems to evaluate public investment projects. A set of measurement index and the assessment method must be developed to strengthen the measurement of public investment projects performance [38].

Project evaluation system can be separated into three parts:

- Selecting performance evaluation indexes
- Finding the weight of evaluation indexes
- Building complete evaluation model

The first phase of project evaluation system is to determine performance evaluation indexes. That means which attributes are used to evaluate a project. After that, weights of these indexes are determined and assessment methods are applied to carry on evaluation result.

All of the studies we saw in project evaluation topic used classical approaches mentioned in Section 2.1. The problem with these approaches is that while the results of some methods have certain subjectivity, the results of other methods are not practical or method does not measure absolute efficiency.

In this thesis, firstly projects data is collected. Then, performance evaluation indexes are determined. In this part, Genetic Algorithm and several data mining methods are used. In determination of weights of these indexes, we utilize Harmony Search (HS) and Genetic Algorithm (GA). After the weights of indexes are obtained, the weighted scores of the projects are calculated. Then, according to these scores and the values of cut-off points, projects are evaluated.

1.2 Contributions

The main contributions of this study can be explained as follows:

- A new project evaluation framework is introduced. To confirm our work, a project dataset is collected. We construct our dataset from World Bank projects data [8].
- Different attribute selection methods are combined. Additionally, a GA based attribute selection method is developed.
- GA and HS based project evaluation model is presented.
- Our project evaluation system and the similar ones in the literature are compared and the results are discussed. Experimental results indicate that the results of proposed work is more accurate.

1.3 Thesis Organization

This thesis is organized as follows:

- Chapter 2 includes a review on the related studies existing in literature.
- In Chapter 3, theoretical background information of the methods used in this study is given.
- In Chapter 4, the proposed work is described in detail.
- In Chapter 5, experimental results of the proposed algorithms are given.
- In Chapter 6, conclusion and future work are discussed.

CHAPTER 2

LITERATURE SURVEY

The aim of this study is to contribute to the evaluation of public investment projects. There are various methods that are used for evaluation process. Information about studies based on these methods is given in three parts. In Section 2.1, studies using classical approaches are summarized. In Section 2.2, metaheuristic computation approaches related to the topic are mentioned. Studies based on data mining approaches are discussed in Section 2.3.

2.1 Studies using Classical Approaches

Two of the methods widely used are Fuzzy Mathematics and Analytic Hierarchy Process (AHP) on the subject of evaluation. The AHP is a multi-criteria decision-making approach, can solve complex decision problems and was introduced by Saaty [36]. General structure of AHP is in Figure 2.1. Fuzzy Comprehensive Evaluation (FCE) method is a synthetical assessment method that applies fuzzy mathematical principles to evaluate things and phenomenon affected by variety of factors [26]. The process of fuzzy comprehensive evaluation is in Figure 2.2.

Zhen-hua et al. [47][46] studied on evaluation of benefits of the Land Fund investment projects in Shenzhen using FCE. In this study, weights of indexes are confirmed according to actual expenditure of the Land Fund and AHP. In scoring the index part, the mark method after the index is compared with appointed standards, is used. And finally, the evaluation is made according to Fuzzy Comprehensive Evaluation Model.

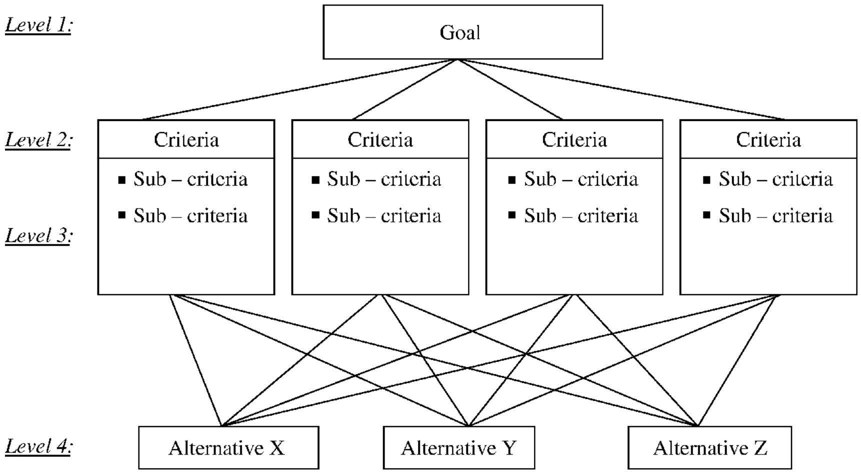


Figure 2.1: General Structure of AHP [13]

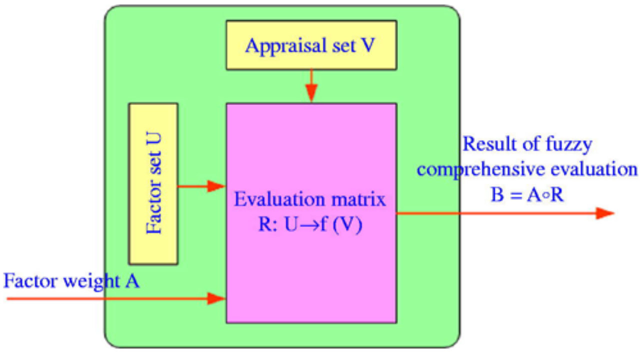


Figure 2.2: The Process of Fuzzy Comprehensive Evaluation [43]

Kai et al. [22] established a method for evaluation index system of 6-Dimension (6-D) force sensor performance. The general evaluation index system of 6-D force sensor is established with AHP. In addition, evaluation index weights are calculated with AHP and fuzzy assessment method is applied.

Yang et al. [41] studied on comprehensive benefit evaluation of planning projects of the Land Consolidation by applying AHP and FCE. Weights of indexes are found using AHP and projects evaluation is carried out according to FCE.

The problem with these approaches is that the result has certain subjectivity and evaluation must be done more objectively and efficiently.

Kim et al. [23] presented a performance and monitoring evaluation system model for the national R&D program. This study presents three methods which are selfweighting method, Data Envelopment Analysis (DEA)-based evaluation method and AHP-based evaluation method, using that model. DEA-based evaluation excludes the subjective views, however DEA does not measure absolute efficiency. Additionally, the results of another methods are not practical or objective.

Yun-na and Ying-ying [45] proposed a method for evaluation of construction agents' work for government investment projects based on the variable weight synthesizing theory and AHP. According to design of the method, while changing weights, the method has achieved both effects of incentive and penalty. So, the assessment of the construction agents' work is more reasonable.

2.2 Metaheuristic Computation Approaches

Mostly used metaheuristic computation approaches in evaluation and similar topics are Genetic Algorithm (GA) and Harmony Search (HS) algorithm. GA is a tool for solving search and optimization problems. GAs are based on the principle of genetics and evolution [34]. HS algorithm is a relatively new population-based metaheuristic optimization algorithm. It imitates the music improvisation process where musicians improvise their instruments' pitch by searching for a perfect state of harmony [11]. Detailed information about these algorithms is in Chapter 3.

Guvenir and Erel [15][16] studied on the problem of multicriteria inventory classification. To optimize a set of parameters that represent the weights of criteria along with some cut-off points, the method Genetic Algorithm for Multicriteria Inventory Classification (GAMIC) uses GA, is proposed. After the weights of criteria are obtained, the weighted scores of the items in the inventory are calculated. Then, according to these scores and the values of cut-off points, items are classified. To evaluate this method, results of classical AHP technique and GAMIC on sample inventory classification tasks are compared. As a result, the classification made by GAMIC is much closer to the desired classification than the one made by the AHP technique. The main advantage of this technique to classical methods is enhance reliability because classical methods are based on subjective views. We are inspired by this technique in our study. GAMIC is used for classification, however we adopt some innovation of

GAMIC to a part of our study based on project evaluation.

Another study [44][35] use AHP and modified GA approach to evaluate education. The hierarchical structure of the evaluation model is built according to AHP. Judgments of five experts are computed according to that model and these judgment matrices generate GA initial population. GA is repeated until Consistency Index (CI) in the model is lower than 0.1. At that point, weights of the evaluation indices are found.

Landa-Torres et al. [25] presented a hybrid algorithm for evaluating the internationalization success of a company based on past data. This algorithm is composed of HS and Extreme Learning Machine (ELM) algorithms. While HS is responsible for forming feature groups, ELM is used for obtaining the objective function for every such groups. Ensemble structure of the hybrid HS-ELM is given in Figure 2.3. We are inspired by this methodology in feature selection part of our study, however, we use different encoding procedure and algorithm.

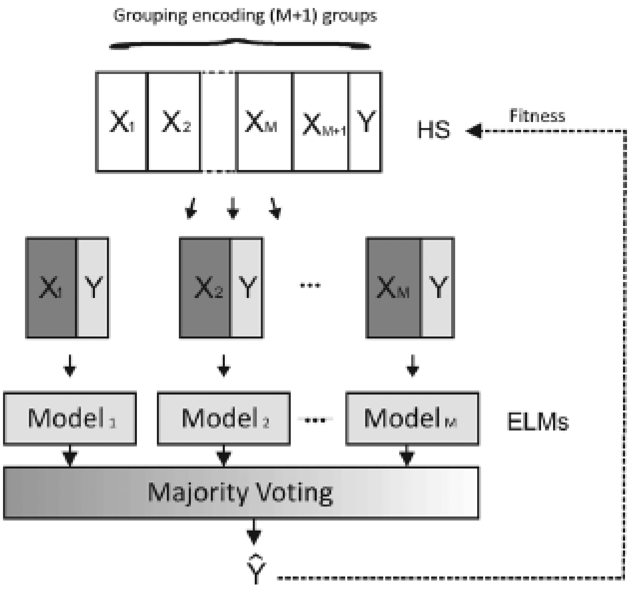


Figure 2.3: Ensemble Structure of the Hybrid HS-ELM Approach [25]

Ai-ling et al. [10] made a research on evaluation of engineering projects in the bid system. According to their design, the problem is encoded using GA structure. AHP is used in construction and calculation of fitness function. According to AHP assessment, weight values of bidders is obtained.

Guan et al. [14] studied on machining scheme selection of digital manufacturing. Hybrid AHP and GA is applied to make the optimal selection of machining scheme that is a multi-objective decision-making problem. Although the problem is multi-objective, by using weights which are computed by AHP, the problem is transformed into single objective optimization problem. Since Guan obtained set of weights, the algorithm ends up with a set of solutions.

2.3 Studies Based on Data Mining Approaches

Data mining techniques allow a high level extraction of knowledge from raw data [32]. Classification is a data mining function that assigns items in a collection to target categories or classes. The goal of classification is to accurately predict the target class for each case in the data [7]. So, the classification task can be used to evaluate items.

Ramesh et al. [32] made an investigation to evaluate performance of a student and to find what are the factors that influence the performance of the students using data mining functions. Firstly, attribute selection is used to find which subset of attributes works for prediction. While taking into consideration selected attributes, classification techniques are applied to predict the performance of the students.

Yadav et al. [39][40] used the classification task of data mining to evaluate student's performance. Many approaches can be applicable for data classification. In this study, decision tree classifiers are studied.

Shana and Venkatachalam [33] built a prediction model to predict course result of students by analyzing key performance indicators. In first part, feature selection techniques are applied to identify the key performance indicators that affect the result of the student in the course. Then, to predict the result, various decision tree classification algorithms are used.

Huping and Chunhua [21] studied to mine a set of general local government performance evaluation indicators out of the massive data. In this study, data mining is used to design evaluating indicators and to find the weights of this indicators. Firstly, Radial Basis Function (RBF) neural network is used as soft clustering data mining technique. Then, hard clustering is done by Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH) algorithm to mine the local government performance indicators.

All of the studies we saw in project evaluation topic used classical approaches mentioned in Section 2.1. In this thesis, classification, metaheuristic computation and data mining approaches based project evaluation methods are proposed.

CHAPTER 3

BACKGROUND

3.1 Genetic Algorithms

Genetic Algorithm (GA) is proposed as a heuristic method based on "Survival of the fittest" by John Holland. GA makes use of the principle of natural evolution and is a useful tool for search and optimization problems [34].

In GA procedure, firstly a representation of potential solutions to the problem and a measure for evaluating quality of each candidate solution is defined. The goal is to find a solution or a set of solutions that perform best with respect to the specified measure [30].

Before steps of GA, definitions of main GA terms are as follows [28]:

Fitness Function: Fitness function assigns a score (fitness) to each chromosome (candidate solution) in the current population to evaluate how well that chromosome solves the problem.

Selection: This operator selects chromosomes in the population for reproduction. The fitter the chromosome, the more times it is likely to be selected to reproduce.

Crossover: A locus (position in chromosome) is randomly chosen and the subsequences before and after that locus are exchanged between two chromosomes to create two offspring. For instance, the strings 10000100 and 11111111 could be crossed over after the third locus in each to produce the two offsprings 10011111 and 11100100.

Mutation: Some of the bits in a chromosome are randomly flipped in this operator. For instance, the string 00000100 might be mutated in its second locus to yield 01000100. Mutation can occur at each bit position in a string with some probability, which is usually a very small value.

GA process is as follows [34]:

1. Start

   Genetic population of n chromosomes is randomly generated (candidate solutions for the problem).

2. Fitness

   The fitness of each chromosome in the population is calculated.

3. New population

   A new population is created by repeating following steps until the "New population" is complete.

   - selection

     Two parent chromosomes from a population is selected according to their fitness (the better fitness, the bigger chance to get selected).

   - crossover

     With a crossover probability p_c, the parents are crossed over to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.

   - mutation

     With a mutation probability p_m, new offspring at each locus (position in chromosome) is mutated.

   - accepting

     New offspring in the new population is placed.

4. Replace

   New generated population is used for a further sum of the algorithm.

5. Test

   If the end condition is satisfied, stop, and return the best solution in current population.

6. Loop

   Go to step2 for fitness evaluation.

The flowchart of the GA process is given in Figure 3.1.

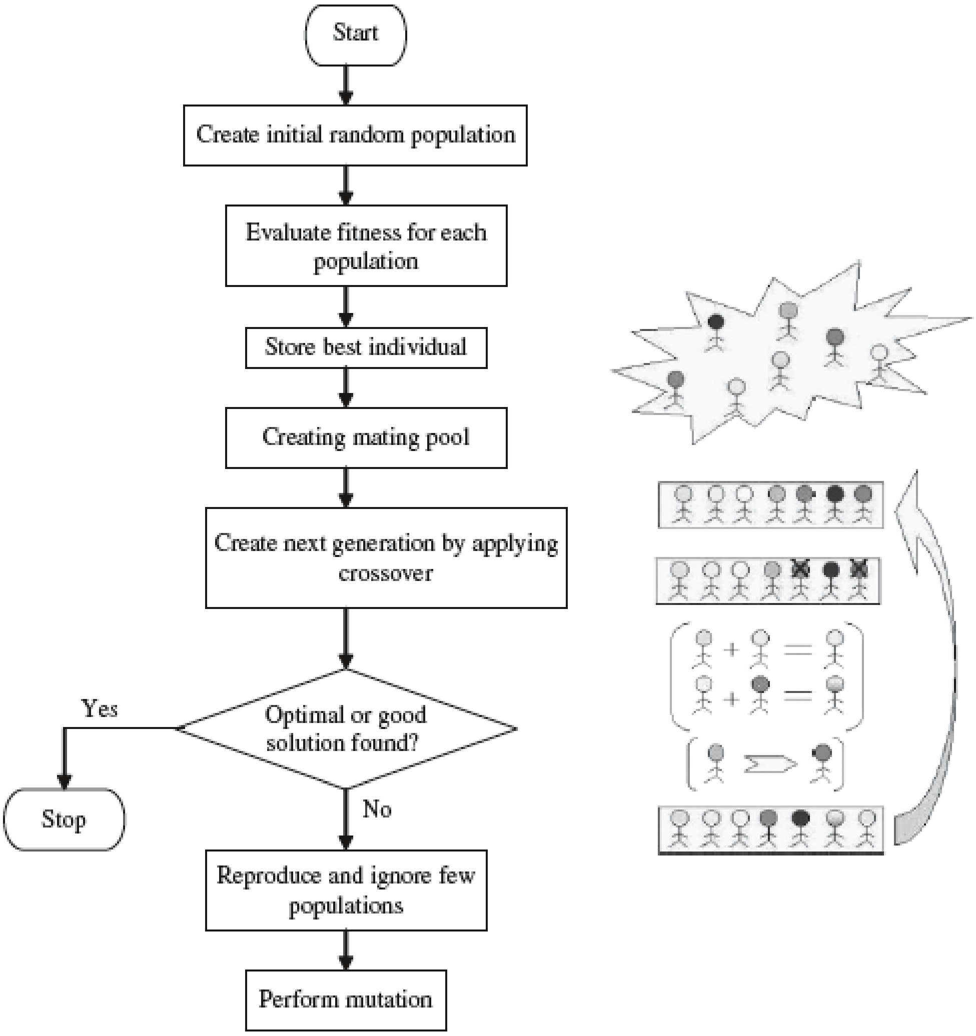


Figure 3.1: Flowchart of the GA[34]

3.2 Harmony Search

Harmony search (HS) is metaheuristic algorithm and is applied to many optimization problems. HS is a music-based algorithm and the goal in music to find for a perfect state of harmony is similar to search the optimality in an optimization process. So, the aim of both process is to find the best or optimum [42].

The process in HS can be summarized as follows [27]:

1. Initialization of the Harmony Memory (HM-a set of solutions)
2. Improvisation of a new harmony
3. Inclusion of the newly generated harmony in the HM provided that its fitness improves the worst fitness value in the previous HM
4. Returning to step 2 until a termination criteria (e.g.maximum number of iterations or fitness stall) is satisfied.

The flow diagram of the HS algorithm is given in Figure 3.2.

Step 2 - Improvisation of a new harmony process is one of three choices [42]:

- Playing any famous tune exactly from memory - Usage of HM

  By using HM, good harmonies are taken into account as elements of new solution vector. To effectively adjust usage of HM, $r_{accept} \in$ [0.7,0.95] called Harmony Memory Considering (or accepting) Rate (HMCR), is adopted. This process is similar to the choice of the best-fit individuals in GA.

- Playing something similar to the aforementioned tune - Pitch adjusting

  Existing pitch is adjusted slightly to obtain new one. In this step, the degree of adjustment is controlled by pitch adjusting rate($r_{pa} \in$ [0.1,0.5]) This process is analogous to the mutation operator in GA.

- Composing new or random notes - Randomization

  To increase the diversity of the solution, randomization is done in HS.

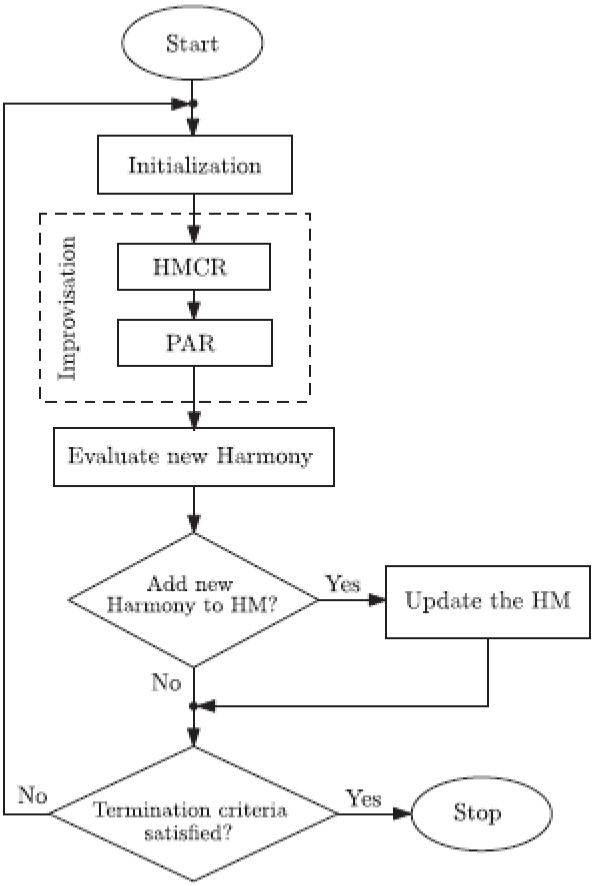


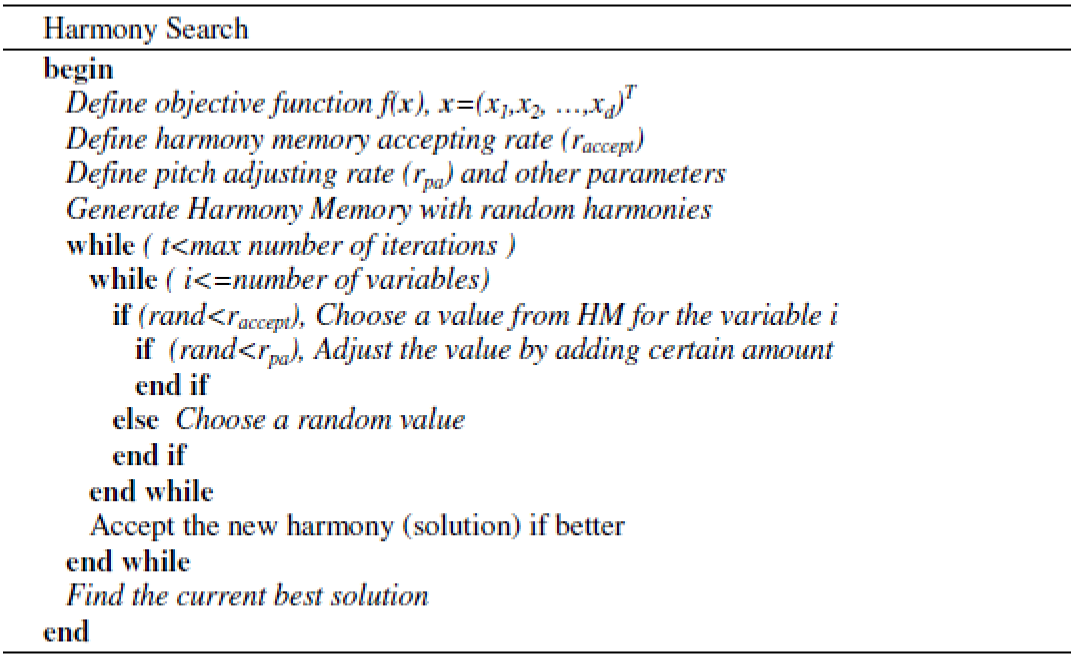
Figure 3.2: Flowchart of the HS Algorithm [27]

Pseudo code of HS including these three components is given Figure 3.3.

Improvisation operators in HS balance diversification and intensification. While pitch adjustment and randomization control diversification, retainment of good local solutions guaranteed by both memory consideration and pitch adjustment [42].

3.3 WEKA

The Waikato Environment for Knowledge Analysis (WEKA) project provides machine learning algorithms and data preprocessing tools. The project is an open source software and has user friendly graphical user interfaces. Various algorithms are provided by WEKA for regression, classification, clustering, association rule mining and attribute selection [17]. A screenshot of WEKA is given in Figure 3.4.



```
Harmony Search
begin
  Define objective function $f(x)$, $x=(x_1,x_2, \ldots,x_d)^T$
  Define harmony memory accepting rate ($r_{accept}$)
  Define pitch adjusting rate ($r_{pa}$) and other parameters
  Generate Harmony Memory with random harmonies
  while ( $t<$max number of iterations )
    while ( $i<=$number of variables)
      if ($rand<r_{accept}$), Choose a value from HM for the variable $i$
        if ($rand<r_{pa}$), Adjust the value by adding certain amount
        end if
      else Choose a random value
      end if
    end while
    Accept the new harmony (solution) if better
  end while
  Find the current best solution
end
```

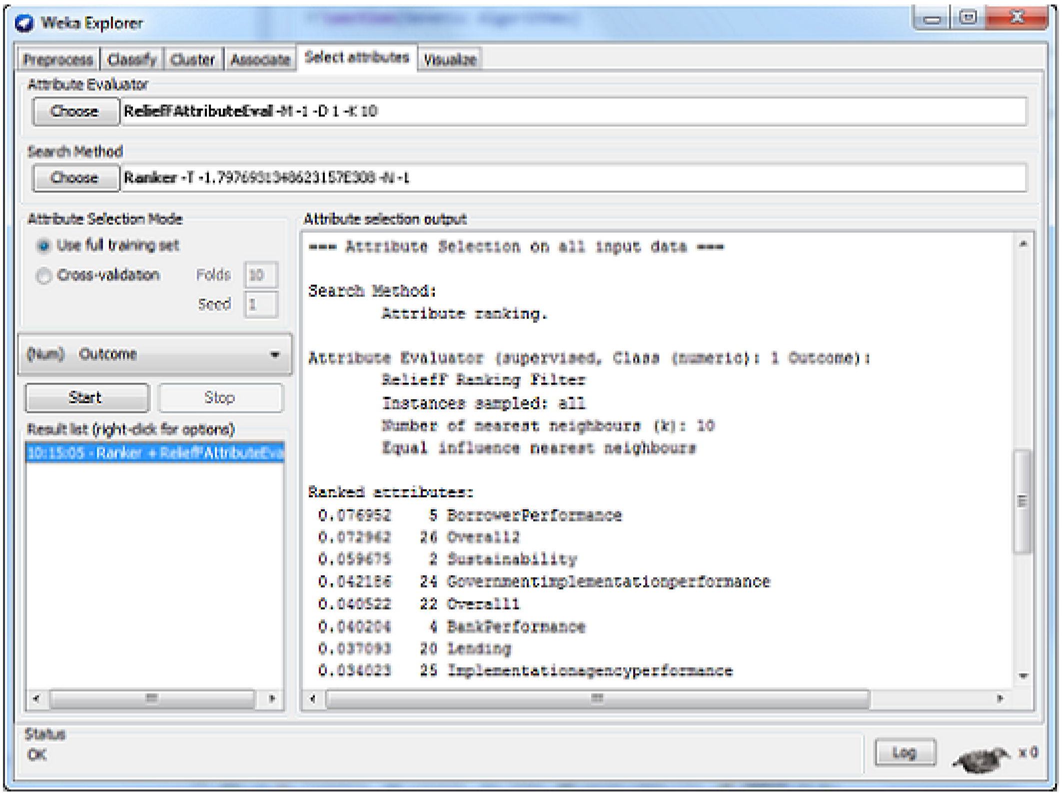
Figure 3.3: Pseudo Code of HS Algorithm [42]

Supported file formats by WEKA are WEKA's own ARFF format, CSV, LibSVM's format, and C4.5's format [17]. In this thesis, our data is converted to WEKA's own Attribute-Relation File Format (ARFF). Relations and their attributes, together with all the instances of the relation compose ARFF files. They are stored as plain text. Relations refer to the concept to be learned and they are simply a single word or string. Each attribute has a name, a data type and a value range. The instances of the relation are provided in comma-separated form. Missing or unknown values are specified by the '?' character [20]. An example ARFF file is given in Figure 3.5.

3.3.1 Attribute Selection

While some attributes in the data are the most predictive ones, another attributes can be irrelevant in data mining. To identify these predictive attributes in the dataset, WEKA's Explorer has a dedicated panel for attribute selection, "Select attributes". "Select attributes" panel has a wide variety of algorithms and evaluation criteria. Different search methods with different evaluation criteria can be combined here [17].

In this thesis, we used attribute selection feature of WEKA to identify relevant at-



Attribute Evaluator: ReliefFAttributeEval -M -1 -D 1 -K 10

Search Method: Ranker -T -1.7976931348623157E308 -N -1

Attribute Selection Mode: ● Use full training set ○ Cross-validation Folds 10 Seed 1

(Num) Outcome

Result list (right-click for options): 10:15:05 - Ranker + ReliefFAttributeEva

Attribute selection output:

```
=== Attribute Selection on all input data ===

Search Method:
        Attribute ranking.

Attribute Evaluator (supervised, Class (numeric): 1 Outcome):
        ReliefF Ranking Filter
        Instances sampled: all
        Number of nearest neighbours (k): 10
        Equal influence nearest neighbours

Ranked attributes:
 0.076952    5 BorrowerPerformance
 0.072962   26 Overall2
 0.059675    2 Sustainability
 0.042186   24 Governmentimplementationperformance
 0.040522   22 Overall1
 0.040204    4 BankPerformance
 0.037093   20 Lending
 0.034023   25 Implementationagencyperformance
```

Status: OK

Figure 3.4: A screenshot of WEKA

tributes that contribute towards classification. Used attribute evaluators and search methods are given in the following subsections:

ReliefFAttributeEval Attribute Evaluator

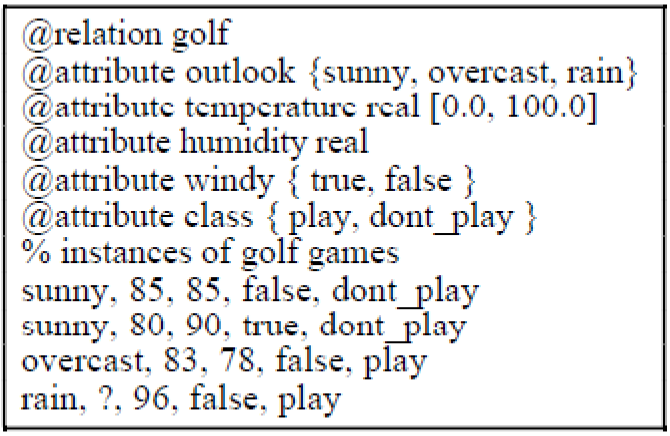
The worth of an attribute is evaluated by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different class. Discrete and continuous class data can be operated [5].

Relief algorithm is based on completely statistical analysis, uses few heuristic. The algorithm is fairly noise tolerant and is less often fooled [24].

CfsSubsetEval Attribute Evaluator

The worth of a subset of attributes is evaluated by considering the individual predictive ability of each feature along with the degree of redundancy between them [2].

Correlation-based Feature Selection (CFS) heuristic algorithm evaluates the worth of a subset of features by taking into account the usefulness of individual features for



```
@relation golf
@attribute outlook {sunny, overcast, rain}
@attribute temperature real [0.0, 100.0]
@attribute humidity real
@attribute windy { true, false }
@attribute class { play, dont_play }
% instances of golf games
sunny, 85, 85, false, dont_play
sunny, 80, 90, true, dont_play
overcast, 83, 78, false, play
rain, ?, 96, false, play
```

Figure 3.5: Example ARFF File [20]

predicting the class label along with the level of intercorrelation among them [18].

Ranker Search Method

Attributes are ranked according to their individual evaluations [4].

GreedyStepwise Search Method

Through the space of attribute subsets, a greedy forward or backward search is performed [3].

BestFirst Search Method

The space of attribute subsets is searched by greedy hillclimbing augmented with a backtracking facility [1].

3.4 Weighted Sum Method

Weighted Sum Method is one of the most commonly used multi-objective optimization approach. Weighted sum method helps in structuring a problem. Its methodology is simple and the method provides transparency to the evaluation process. Weighted sum method has been used to support the evaluation of a large number of problems.

Incomparable attributes are made comparable by weighted sum method. Weighted sum method prioritises these attributes by assigning weights and reduces the amount of information by aggregating the weighted standardized scores. So, alternatives are ranked.

The process of weighted sum method is as follows [37]:

1. Alternatives are defined.
2. Attributes which are relevant indicators for the decision are selected and defined.
3. Scores are assigned to each attribute for all alternatives.
4. Scores are standardized in order to make the attribute comparable with each other.
5. Weight of attributes are found to assign priorities to them.
6. Alternatives are ranked according to a total score for each alternative that is calculated by multiplying the standardized scores with its appropriate weight, followed by summing the weighted scores of all attributes.

The total score for each alternative a_j, ws(a_j) is calculated according to this formula:

$$ws(a_j) = \sum_{i=1}^{N} w_i * v_i(s_{ij}) \tag{3.1}$$

The notions and abbreviations are summarized in Table 3.1.

Table 3.1: Notions and Abbreviations

Meaning	Abbreviation
Number of attributes	N
Value function for attribute c_i	v_i
Score from alternative a_j for attribute c_i	s_{ij}
Weight for attribute c_i	w_i

Value Function and Standardization Method:

Value function is used to standardize the attribute scores.

The scores of the various attributes must be transformed to comparable units. The scores of these attributes can be compared or combined, if the scales of the attributes are the same. Standardization or normalization is the making the scores of the attributes comparable.

The effect scores s_{ij} are transformed to the interval [0, 1] according to their relative position on the interval between the lowest and highest score. This transformation equation is given in Formula 3.2.

$$v_i(s_{ij}) = \frac{s_{ij} - min_i}{max_i - min_i} \tag{3.2}$$

Here, max_i and min_i stands for the maximum and minimum scores of attribute i among all alternatives.

Suitable weighting method is chosen to estimate the relative importance of the attributes.

CHAPTER 4

PROPOSED METHODS

In this chapter, the general architecture for proposed project evaluation method and the developed methods are described.

The shown in Figure 4.1, main phases of our system are:

- data gathering
- attribute selection
- finding the weights of selected attributes
- evaluation

In implementation of system, Java is chosen as a programming language and eclipse is used as a development environment. WEKA tool is used in one part of attribute selection.

In Section 4.1, data gathering process is explained. Suitable data for our analysis is collected in this process. In Section 4.2, information about attribute selection and finding the weights of selected attributes are given. Different approaches are tried in attribute selection part, such as GA and combinations of several data mining methods. In finding the weights of selected attributes, different approaches are developed, such as GA, HS and hybrid GA-HS algorithms. In Section 4.3, last step of this system that is evaluation is described. According to weighted scores of the projects and the values of cut-off points, evaluation is done.

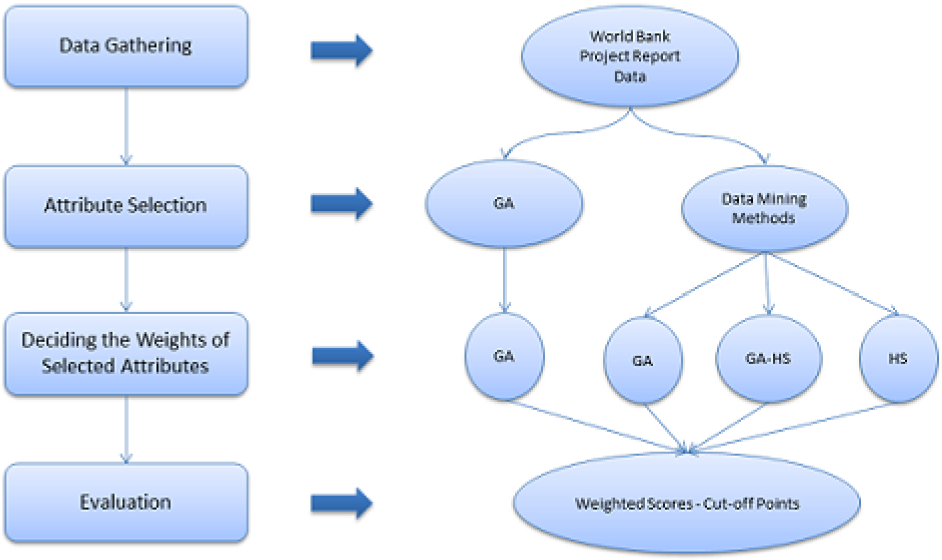


Figure 4.1: Overview of the System

4.1 Data Gathering

We construct our dataset from World Bank projects data [8]. Project outcome information and performance ratings for various attributes of projects from completion reports are collected manually. On the total, data of the 493 projects are collected. Project outcome information has four class labels such as High Satisfactory (HS), Satisfactory (S), Unsatisfactory (U), Highly Unsatisfactory (HU). This data includes performance ratings for 25 attributes of projects.

Most of the attributes of the project data are ordinal values such as HS, S, U, HU. As the first step, we converted these ratings into numeric values in [0,1] interval. For example HS, S, U, US values are mapped to 1.00,0.70,0.30,0.00, respectively. Conversion process for the other attributes are performed in similar manner and mapped numeric values for the ordinal attributes can be seen in Table 4.1.

As the next preprocessing step, project IDs are removed from data. Afterwards, we

Table 4.1: Possible Values for Attribute Rating - Converted Numeric Values

Possible Values for Attribute Rating	**Converted Numeric Values**
HS, S, U, HU	1.00, 0.70 ,0.30, 0.00
HL, L, UN, HUN	1.00, 0.70, 0.30, 0.00
H, S, SU, M, N	1.00, 0.75, 0.50, 0.25, 0.00
YES, NO	1, 0
H, SU, M, N, NA	1.00, 0.75, 0.50, 0.25, 0.00

handled the missing values in the data. We used two file formats for processing: Arff file format for processing with WEKA tool, and txt file format for processing with our own implementation of the system. Different procedures are applied to missing values in two formats. While missing values are changed to "0" value in txt file format, missing values are replaced by "?" character in Arff file format.

Arff file format is used in:

- Attribute selection feature of WEKA tool for one part of attribute selection of proposed work
- Classification feature of WEKA tool for calculation of similar methods in the literature, so comparison of our work and these methods is done.

In implementation of our system, data used in:

- Attribute selection of proposed work
- Finding the weights of selected attributes and evaluation of proposed work
- Calculation of common method in the literature, so comparison of our work and this method is done.

4.2 Attribute Selection and Finding the Weights of Selected Attributes

4.2.1 Metaheuristic-based Methods for Finding Attribute Weights

4.2.1.1 Data mining based Attribute Selection

For attribute selection, in addition to proposing a GA-based method, conventional techniques are elaborated as well.

In our attribute selection phase, different approaches are tried. In this work, attribute selection feature of WEKA tool is used. In this process, attributes are ranked by searching through all possible combinations of attributes in the data, and the best predictive subset of attributes is found. In WEKA, in order to select attributes, an attribute evaluator and a search method must be specified. Attribute evaluator specifies method to evaluate the worth of attributes and search method determines what kind of search is performed [32].

In this thesis, combinations of ReliefFAttributeEval attribute evaluator and Ranker search method; CfsSubsetEval attribute evaluator and GreedyStepwise search method; CfsSubsetEval attribute evaluator and BestFirst search method are used. 7 attributes are selected from 25 attributes according to the intersection set of these combinations.

4.2.1.2 Finding the Attribute Weights

Next step is that the weights of selected attributes are found. We use 3 different methods to find the weights of attributes such as GA, HS and hybrid GA-HS algorithms.

Finding the Weights of Selected Attributes Based on GA Our problem is to find weights of selected attributes and cut-off values. According to this problem, our chromosome structure is composed of 7 attributes weights and 3 cut-off values. Because project outcome information in our dataset has four class labels, chromosome structure has 3 cut-off values which separate groups. General structure of a chromosome for *k* attributes can be seen in Figure 4.2.

Figure 4.2: General Structure of a Chromosome

$$\sum_{i=1}^{k} w_i = 1 \tag{4.1}$$

As shown in formula 4.1, total weights of attributes equal to 1 and here w_i is the weight of the i^{th} attribute. $0 \leq w_i, cp_1, cp_2, cp_3 \leq 1$ and $cp_1 < cp_2 < cp_3$

GA operators applied are as follow:

Fitness Function:

How well the chromosome evaluates the training set correctly is used as the fitness value of the chromosome. In fitness calculation, we consider the similarity between class label prediction to the real class label under linear ordering.

The fitness of chromosome c is:

$$fitness(c) = \frac{1}{n_t} \sum_{p=1}^{n_t} a_p \tag{4.2}$$

Here, n_t is the number of training set and

$$a_p = \begin{pmatrix} 1, & \text{if evaluation(c, p) = realValue(p)} \\ 0.4, & \text{if | evaluation(c, p) - realValue(p) | = 1} \\ 0.1, & \text{if | evaluation(c, p) - realValue(p) | = 2} \\ 0, & \text{otherwise} \end{pmatrix} \tag{4.3}$$

Here, realValue(p) is actual outcome of project p and evaluation(c, p) is evaluated outcome of project p for given chromosome c. The similarity between the predicted class label and real label is considered. As an example of this condition, if realValue(p) is

HS and evaluation(c, p) is S, then a_p is 0.4. Or if realValue(p) is S and evaluation(c, p) is HU, then a_p is 0.1.

The evaluation formula of a project p for given chromosome c is:

$$evaluation(c,p) = \left(\begin{array}{ll} \text{HS}, & \text{if } cp_3 \leq \text{ws(c, p)} \\ \text{S}, & \text{if } cp_2 \leq \text{ws(c, p)} < cp_3 \\ \text{U}, & \text{if } cp_1 \leq \text{ws(c, p)} < cp_2 \\ \text{HU}, & \text{otherwise} \end{array} \right) \tag{4.4}$$

ws(c, p) is weighted sum of project p for given chromosome c. The formula for weighted sum is as follows:

$$ws(c,p) = \sum_{i=1}^{k} w_i \frac{p_i - min_i}{max_i - min_i} \tag{4.5}$$

Here, p_i is the rating value of the project p for the attribute i. max_i and min_i stands for the maximum and minimum rating values of attribute i among all projects in dataset.

Crossover:

Uniform crossover is applied to randomly selected pairs of chromosomes with probability p_c. To protect problem specifications, crossover operation is applied under control. Crossover operation applied to chromosomes is given in Figure 4.3. In this operation, c is the constant and $0 \leq c < 0.5$. This operation preserves the problem specifications such as sum of attributes weights in one chromosome is 1 and greater than relation of cut-off points in one chromosome is maintained.

Mutation:

In mutation operator, attribute values in genes are set to 0 or 1 with equal probability. This operator is applied to chromosomes with probability p_m. After mutation operator is applied, chromosome is normalized to preserve the specification that sum of attributes weights in one chromosome is 1.

Elitism that fittest chromosome always survive to the next generation is employed in implementation. The proposed GA-based attribute weight determination algorithm is

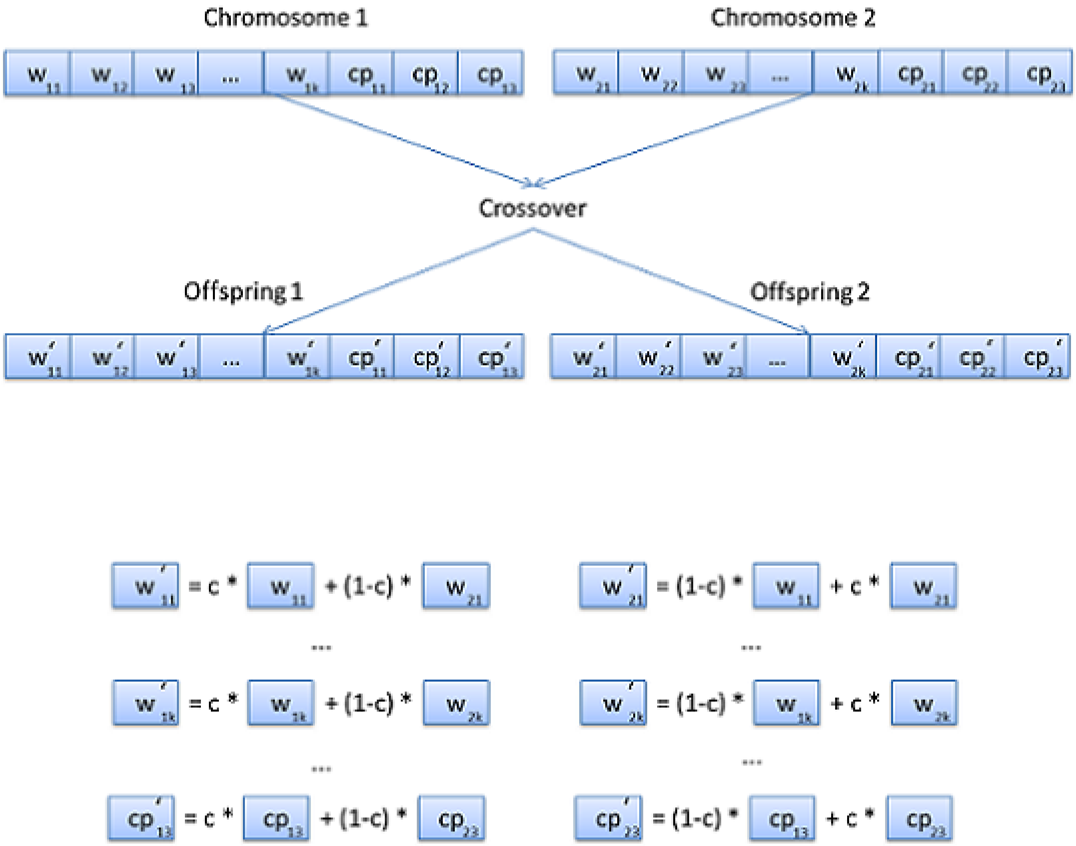


Figure 4.3: Crossover Operation

given in Algorithm 1.

Finding the Weights of Selected Attributes Based on HS Our harmony structure is composed of 7 attributes weights and 3 cut-off values. Since project outcome information in our dataset has four class labels, chromosome structure has 3 cut-off values which separate groups. General structure of a harmony for *k* attributes can be seen in Figure 4.4.

Figure 4.4: General Structure of a Harmony

Algorithm 1 Genetic Algorithm used in Implementation

```
function GENETIC-ALGORITHM
    Define Fitness Function
    Define Crossover Probability $p_c$
    Define Mutation Probability $p_m$
    Define populationDimension
    $P \leftarrow InitPopulationRandomly()$
    repeat
        ComputeFitnessOfPopulation()
        for $i = 0 \rightarrow populationDimension$ do
            $c_1, c_2 \leftarrow getFittestChromosome() - Elitism$
            $p_1, p_2 \leftarrow$ getParentChromosomesGivingHighlyFitIndividualsAGreaterChanceOfBeingSelected()
            if $getRandom() < p_c$ then
                $c_3, c_4 \leftarrow doUniformCrossover(p_1, p_2)$
            else
                $c_3, c_4 \leftarrow p_1, p_2$
            end if
        end for
        for $i = 0 \rightarrow populationDimension$ do
            if $c_i$ is not BestFittestChromosome then
                if $c_i$ is WorstFittestChromosome or $getRandom() < p_m$ then
                    doMutation($c_i$)
                end if
            end if
        end for
    until max number of generations is reached
end function
```

$$\sum_{i=1}^{k} w_i = 1 \tag{4.6}$$

As shown in formula 4.6, total weights of attributes equal to 1 and here w_i is the weight of the i^{th} attribute. $0 \leq w_i, cp_1, cp_2, cp_3 \leq 1$ and $cp_1 < cp_2 < cp_3$

HS operators applied are as follow:

Fitness Function:

How well the harmony evaluates the training data set is considered as the fitness value of the harmony. In fitness calculation, we consider the similarity between class label prediction to the real class label under linear ordering.

The fitness of harmony h is:

$$fitness(h) = \frac{1}{n_t} \sum_{p=1}^{n_t} a_p \tag{4.7}$$

Here, n_t is the number of training set and

$$a_p = \begin{pmatrix} 1, & \text{if evaluation(h, p) = realValue(p)} \\ 0.4, & \text{if | evaluation(h, p) - realValue(p) | = 1} \\ 0.1, & \text{if | evaluation(h, p) - realValue(p) | = 2} \\ 0, & \text{otherwise} \end{pmatrix} \tag{4.8}$$

Here, realValue(p) is actual outcome of project p and evaluation(h, p) is evaluated outcome of project p for given harmony h. The similarity between the predicted class label and real label is considered. As an example of this condition, if realValue(p) is HS and evaluation(h, p) is S, then a_p is 0.4. Or if realValue(p) is S and evaluation(h, p) is HU, then a_p is 0.1.

The evaluation formula of a project p for given harmony h is:

$$evaluation(h,p) = \begin{pmatrix} \text{HS}, & \text{if } cp_3 \leq \text{ws(h, p)} \\ \text{S}, & \text{if } cp_2 \leq \text{ws(h, p)} < cp_3 \\ \text{U}, & \text{if } cp_1 \leq \text{ws(h, p)} < cp_2 \\ \text{HU}, & \text{otherwise} \end{pmatrix} \tag{4.9}$$

ws(h, p) is weighted sum of project p for given harmony h. The formula for weighted sum is as follows:

$$ws(h,p) = \sum_{i=1}^{k} w_i \frac{p_i - min_i}{max_i - min_i} \tag{4.10}$$

Here, p_i is the rating value of the project p for the attribute i. max_i and min_i stands for the maximum and minimum rating values of attribute i among all projects in dataset.

Pitch Adjustment:

In pitch adjustment, attribute values in harmony are set to 0 or 1 with equal probability. The degree of adjustment is controlled by pitch adjusting rate r_{pa}. After pitch adjustment is applied, harmony is normalized to preserve the specification that sum of attributes weights in one harmony is 1.

The algorithm used in our implementation can be seen in Algorithm 2.

Finding the Weights of Selected Attributes Based on Hybrid GA-HS In this part, the results of algorithm based on GA explained in Section "Finding the Weights of Selected Attributes Based on GA" is given as a input to the algorithm based on HS explained in Section "Finding the Weights of Selected Attributes Based on HS". After algorithm terminate, pitch adjustment is again applied to best harmony in HM until decided iteration count is reached.

First Phase of the Algorithm:

In the first phase of the algorithm, the algorithm based on GA explained in Section "Finding the Weights of Selected Attributes Based on GA" is applied.

Our problem is to find weights of selected attributes and cut-off values. According

Algorithm 2 Harmony Search Algorithm used in Implementation

```
function HARMONY-SEARCH-ALGORITHM
    Define Fitness Function
    Define Harmony Memory Considering Rate HMCR
    Define Pitch Adjusting Rate $r_{pa}$
    Define iterationCount
    $HM \leftarrow InitHarmonyMemoryRandomly()$
    for $i = 0 \rightarrow iterationCount$ do
        ComputeFitnessOfHarmonyMemory()
        if $getRandom() < HMCR$ then
            $h_m \leftarrow getRandomHarmony(HM)$
            if $getRandom() < r_{pa}$ then
                $h_m \leftarrow doPitchAdjustment(h_m)$
            end if
        else
            $h_m \leftarrow generateNewHarmony()$
        end if
        if $fitness(h_m) > fitness(worstFittestHarmony)$ then
            accept $h_m$
        end if
    end for
end function
```

to this problem, our chromosome structure is composed of 7 attributes weights and 3 cut-off values. Because project outcome information in our dataset has four class labels, chromosome structure has 3 cut-off values which separate groups. General structure of a chromosome for *k* attributes can be seen in Figure 4.5.

Figure 4.5: General Structure of a Chromosome

$$\sum_{i=1}^{k} w_i = 1 \tag{4.11}$$

As shown in formula 4.11, total weights of attributes equal to 1 and here w_i is the weight of the i^{th} attribute. $0 \leq w_i, cp_1, cp_2, cp_3 \leq 1$ and $cp_1 < cp_2 < cp_3$

GA operators applied are as follow:

Fitness Function:

How well the chromosome evaluates the training set correctly is used as the fitness value of the chromosome. In fitness calculation, we consider the similarity between class label prediction to the real class label under linear ordering.

The fitness of chromosome c is:

$$fitness(c) = \frac{1}{n_t} \sum_{p=1}^{n_t} a_p \tag{4.12}$$

Here, n_t is the number of training set and

$$a_p = \left(\begin{array}{ll} 1, & \text{if evaluation(c, p) = realValue(p)} \\ 0.4, & \text{if | evaluation(c, p) - realValue(p) | = 1} \\ 0.1, & \text{if | evaluation(c, p) - realValue(p) | = 2} \\ 0, & \text{otherwise} \end{array} \right) \tag{4.13}$$

Here, realValue(p) is actual outcome of project p and evaluation(c, p) is evaluated outcome of project p for given chromosome c. The similarity between the predicted class label and real label is considered. As an example of this condition, if realValue(p) is HS and evaluation(c, p) is S, then a_p is 0.4. Or if realValue(p) is S and evaluation(c, p) is HU, then a_p is 0.1.

The evaluation formula of a project p for given chromosome c is:

$$evaluation(c,p) = \left(\begin{array}{ll} \text{HS}, & \text{if } cp_3 \leq \text{ws(c, p)} \\ \text{S}, & \text{if } cp_2 \leq \text{ws(c, p)} < cp_3 \\ \text{U}, & \text{if } cp_1 \leq \text{ws(c, p)} < cp_2 \\ \text{HU}, & \text{otherwise} \end{array} \right) \tag{4.14}$$

ws(c, p) is weighted sum of project p for given chromosome c. The formula for weighted sum is as follows:

$$ws(c,p) = \sum_{i=1}^{k} w_i \frac{p_i - min_i}{max_i - min_i} \tag{4.15}$$

Here, p_i is the rating value of the project p for the attribute i. max_i and min_i stands for the maximum and minimum rating values of attribute i among all projects in dataset.

Crossover:

Uniform crossover is applied to randomly selected pairs of chromosomes with probability p_c. To protect problem specifications, crossover operation is applied under control. Crossover operation applied to chromosomes is given in Figure 4.6. In this operation, c is the constant and $0 \leq c < 0.5$. This operation preserves the problem specifications such as sum of attributes weights in one chromosome is 1 and greater than relation of cut-off points in one chromosome is maintained.

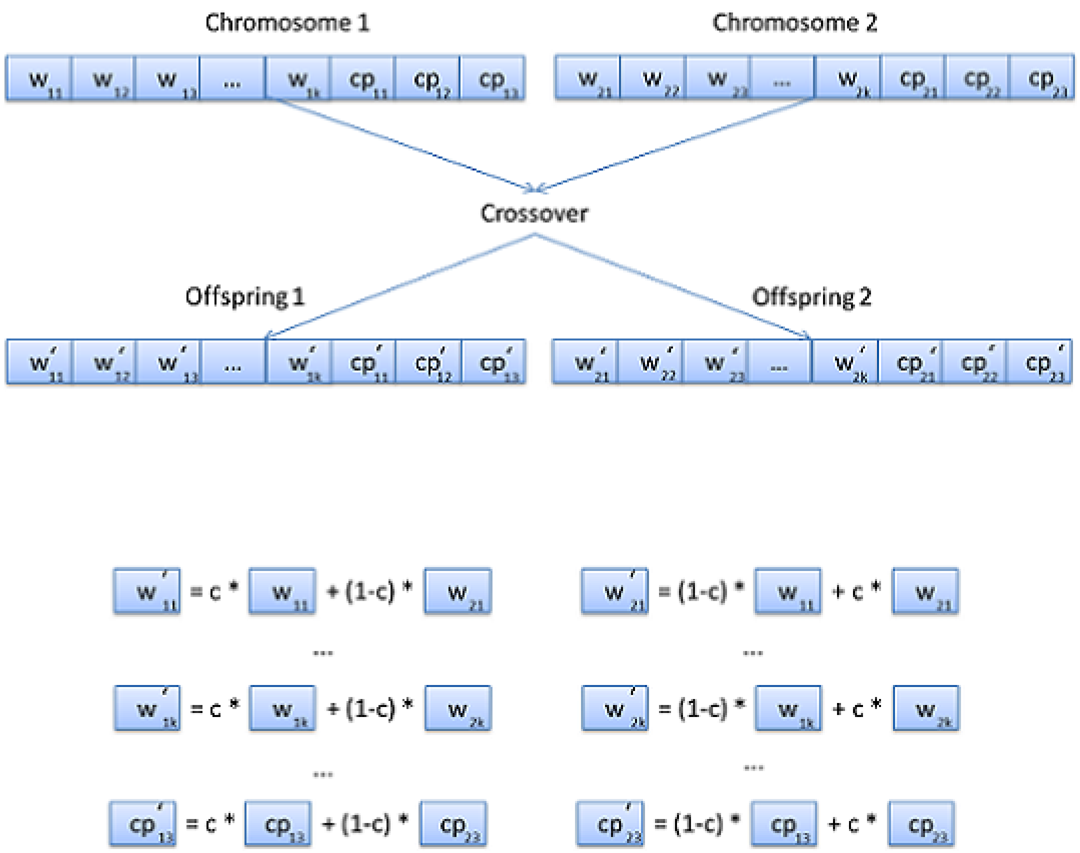


Figure 4.6: Crossover Operation

Mutation:

In mutation operator, attribute values in genes are set to 0 or 1 with equal probability. This operator is applied to chromosomes with probability p_m. After mutation operator is applied, chromosome is normalized to preserve the specification that sum of attributes weights in one chromosome is 1.

Elitism that fittest chromosome always survive to the next generation is employed in implementation.

Second Phase of the Algorithm:

In the second phase of the algorithm, the results of algorithm explained in first phase is given as a input to the algorithm based on HS explained in Section "Finding the Weights of Selected Attributes Based on HS". So, initial HM is composed of the results of algorithm explained in first phase.

Our harmony structure is composed of 7 attributes weights and 3 cut-off values. Since project outcome information in our dataset has four class labels, chromosome structure has 3 cut-off values which separate groups. General structure of a harmony for k attributes can be seen in Figure 4.7.

Figure 4.7: General Structure of a Harmony

$$\sum_{i=1}^{k} w_i = 1 \tag{4.16}$$

As shown in formula 4.16, total weights of attributes equal to 1 and here w_i is the weight of the i^{th} attribute. $0 \leq w_i, cp_1, cp_2, cp_3 \leq 1$ and $cp_1 < cp_2 < cp_3$

HS operators applied are as follow:

Fitness Function:

How well the harmony evaluates the training data set is considered as the fitness value of the harmony. In fitness calculation, we consider the similarity between class label prediction to the real class label under linear ordering.

The fitness of harmony h is:

$$fitness(h) = \frac{1}{n_t} \sum_{p=1}^{n_t} a_p \tag{4.17}$$

Here, n_t is the number of training set and

$$a_p = \begin{pmatrix} 1, & \text{if evaluation(h, p) = realValue(p)} \\ 0.4, & \text{if | evaluation(h, p) - realValue(p) | = 1} \\ 0.1, & \text{if | evaluation(h, p) - realValue(p) | = 2} \\ 0, & \text{otherwise} \end{pmatrix} \tag{4.18}$$

Here, realValue(p) is actual outcome of project p and evaluation(h, p) is evaluated outcome of project p for given harmony h. The similarity between the predicted class label and real label is considered. As an example of this condition, if realValue(p) is HS and evaluation(h, p) is S, then a_p is 0.4. Or if realValue(p) is S and evaluation(h, p) is HU, then a_p is 0.1.

The evaluation formula of a project p for given harmony h is:

$$evaluation(h,p) = \begin{pmatrix} \text{HS}, & \text{if } cp_3 \leq \text{ws(h, p)} \\ \text{S}, & \text{if } cp_2 \leq \text{ws(h, p)} < cp_3 \\ \text{U}, & \text{if } cp_1 \leq \text{ws(h, p)} < cp_2 \\ \text{HU}, & \text{otherwise} \end{pmatrix} \tag{4.19}$$

ws(h, p) is weighted sum of project p for given harmony h. The formula for weighted sum is as follows:

$$ws(h,p) = \sum_{i=1}^{k} w_i \frac{p_i - min_i}{max_i - min_i} \tag{4.20}$$

Here, p_i is the rating value of the project p for the attribute i. max_i and min_i stands for the maximum and minimum rating values of attribute i among all projects in dataset.

Pitch Adjustment:

In pitch adjustment, attribute values in harmony are set to 0 or 1 with equal probability. The degree of adjustment is controlled by pitch adjusting rate r_{pa}. After pitch adjustment is applied, harmony is normalized to preserve the specification that sum of attributes weights in one harmony is 1.

Last Phase of the Algorithm:

Pitch adjustment is again applied to best harmony in HM until decided iteration count is reached.

The proposed hybrid attribute weight determination is given in Algorithm 3.

4.2.2 Attribute Selection and Finding the Weights of Selected Attributes by using GA Approach

Since our dataset involves many attributes, dimensionality reduction is required in order to have more relevant attributes for evaluation. Irrelevant attributes are removed from the dataset by Attribute Selection. After attribute selection, next step is that the weights of selected attributes are found. In this approach, GA is used to select attributes and find the weights of selected attributes.

The problem that we model in GA is to select attributes, find weights of selected attributes and cut-off values. According to this problem, our chromosome structure is composed of *k* attributes, *k* attributes weights and 3 cut-off values. Since project outcome information in our dataset has four class labels (HS, S, U, HU), chromosome structure has 3 cut-off values which separate groups. General structure of a chromosome for *k* attributes can be seen in Figure 4.8.

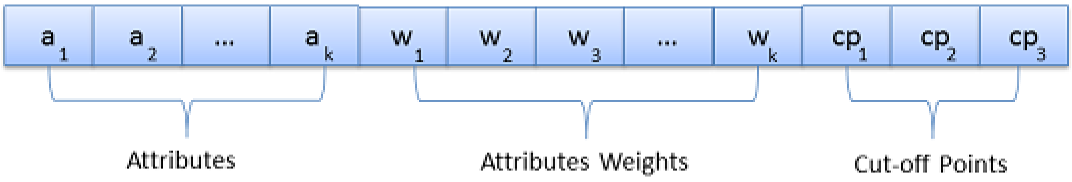


Figure 4.8: General Structure of a Chromosome

First *k* items in the chromosome stand for whether attributes are to be selected. The value of gene can be 0 or 1. $a_i = 1$ means that attribute i is considered in calculation of evaluation, so the attribute i is relevant for evaluation. $a_i = 0$ means that attribute is not considered in calculation of evaluation, so the attribute is irrelevant for evaluation.

Algorithm 3 Hybrid GA-HS Algorithm used in Implementation

```
function HYBRID-GA-HS-ALGORITHM
    Define Fitness Function
    Define Harmony Memory Considering Rate HMCR
    Define Pitch Adjusting Rate $r_{pa}$
    Define iterationCount
    $HM \leftarrow GENETIC-ALGORITHM()$
    for $i = 0 \rightarrow iterationCount$ do
        ComputeFitnessOfHarmonyMemory()
        if $getRandom() < HMCR$ then
            $h_m \leftarrow getRandomHarmony(HM)$
            if $getRandom() < r_{pa}$ then
                $h_m \leftarrow doPitchAdjustment(h_m)$
            end if
        else
            $h_m \leftarrow generateNewHarmony()$
        end if
        if $fitness(h_m) > fitness(worstFittestHarmony)$ then
            accept $h_m$
        end if
    end for
    repeat
        $h_f \leftarrow getFittestHarmony()$
        $h_p \leftarrow doPitchAdjustment(h_f)$
        if $fitness(h_p) > fitness(bestFittestHarmony)$ then
            $bestFittestHarmony \leftarrow h_p$
        end if
    until iterationCount2 reached
end function
```

$$\sum_{i=1}^{k} w_i = 1 \tag{4.21}$$

As shown in Formula 4.21, total weights of attributes equal to 1 and here w_i is the weight of the i^{th} attribute. $0 \le w_i, cp_1, cp_2, cp_3 \le 1$ and $cp_1 < cp_2 < cp_3$

GA operators applied are as follow:

Fitness Function:

How well the chromosome evaluates the training data set is considered as the fitness value of the chromosome. In fitness calculation, we consider the similarity between class label prediction to the real class label under linear ordering.

The fitness of chromosome c is:

$$fitness(c) = \frac{1}{n_t} \sum_{p=1}^{n_t} t_p \tag{4.22}$$

Here, n_t is the number of training set and

$$t_p = \begin{pmatrix} 1, & \text{if evaluation(c, p) = realValue(p)} \\ 0.4, & \text{if | evaluation(c, p) - realValue(p) | = 1} \\ 0.1, & \text{if | evaluation(c, p) - realValue(p) | = 2} \\ 0, & \text{otherwise} \end{pmatrix} \tag{4.23}$$

Here, realValue(p) is actual outcome of project p and evaluation(c, p) is evaluated outcome of project p for given chromosome c. The similarity between the predicted class label and real label is considered. As an example of this condition, if realValue(p) is HS and evaluation(c, p) is S, then t_p is 0.4. Or if realValue(p) is S and evaluation(c, p) is HU, then t_p is 0.1.

The evaluation formula of a project p for given chromosome c is:

$$evaluation(c,p) = \begin{pmatrix} \text{HS}, & \text{if } cp_3 \leq \text{ws(c, p)} \\ \text{S}, & \text{if } cp_2 \leq \text{ws(c, p)} < cp_3 \\ \text{U}, & \text{if } cp_1 \leq \text{ws(c, p)} < cp_2 \\ \text{HU}, & \text{otherwise} \end{pmatrix} \tag{4.24}$$

ws(c, p) is weighted sum of project p for given chromosome c. The formula for weighted sum is as follows:

$$ws(c,p) = \sum_{i=1}^{k} a_i * w_i \frac{p_i - min_i}{max_i - min_i} \tag{4.25}$$

Here, p_i is the rating value of the project p for the attribute i. max_i and min_i stands for the maximum and minimum rating values of attribute i among all projects in dataset. Used weight values are normalized to have that total weight of attributes equals to 1. It can be seen in Formula 4.26

$$\sum_{i=1}^{k} w_i * a_i = 1 \tag{4.26}$$

Crossover:

Uniform and two point crossover are applied to randomly selected pairs of chromosomes with probability p_c. To protect problem specifications, crossover operation is applied under control. Crossover operation applied to chromosomes is given in Figure 4.9. In this operation, c is the constant and $0 \leq c < 0.5$. This operation preserves the problem specifications such as sum of attributes weights in one chromosome is 1 and greater than relation of cut-off points in one chromosome is maintained.

Mutation:

In mutation operator, attribute values in genes are set to 0 or 1 with equal probability. This operator is applied to chromosomes with probability p_m. After mutation operator is applied, chromosome is normalized to preserve the specification that sum of attributes weights in one chromosome is 1.

Elitism that fittest chromosome always survive to the next generation is employed

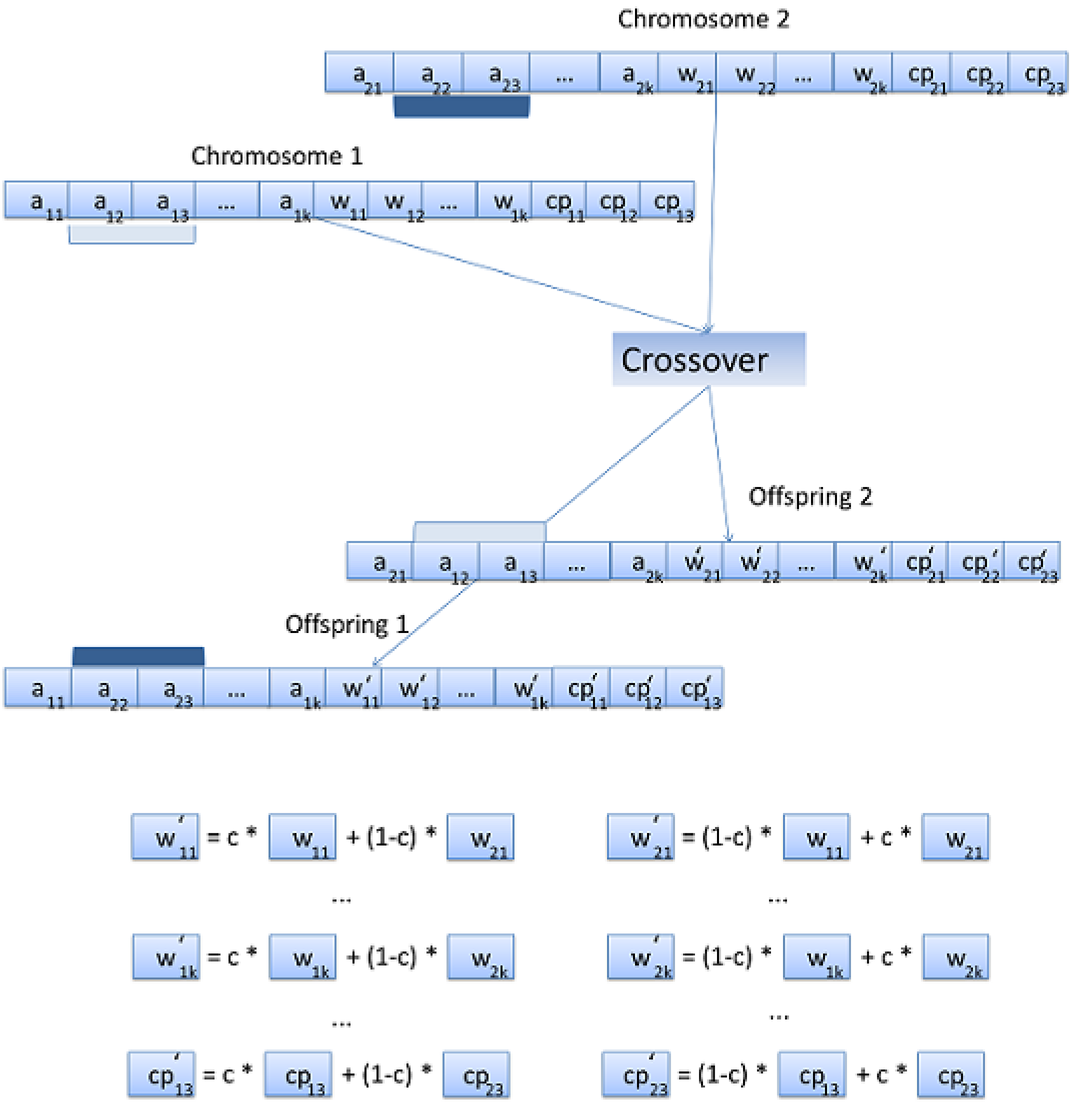


Figure 4.9: Crossover Operation

in implementation. The proposed GA-based attribute selection algorithm is given in Algorithm 4.

4.3 Evaluation

Projects are evaluated by using the selected attributes, attribute weights and cut-off values learned by the algorithms explained in previous section. Firstly, weighted sum value for given project p is calculated according to Formula 4.27.

$$ws_{eval}(p) = \sum_{i=1}^{k} a_i * w_i \frac{p_i - min_i}{max_i - min_i} \tag{4.27}$$

The best harmony or the best chromosome is used in calculation of weighted sum value for given project p. The harmony and the chromosome have the information about the selected attributes, attribute weights and cut-off values learned by the algorithms explained in previous section. Detailed information about parameters in formula is given Section 4.2. If used harmony or chromosome is output of the algorithms in Section 4.2.1.2, a_i is always 1 in Formula 4.27. If used chromosome is output of the algorithm in Section 4.2.2, information about a_i is in that chromosome for Formula 4.27.

After weighted sum value for given project p is calculated, project p is evaluated according to Formula 4.28. In this formula, information about used cut-off values is in the best harmony or the best chromosome.

$$evaluation_{eval}(p) = \begin{pmatrix} \text{HS}, & \text{if } cp_3 \leq ws_{eval}(p) \\ \text{S}, & \text{if } cp_2 \leq ws_{eval}(p) < cp_3 \\ \text{U}, & \text{if } cp_1 \leq ws_{eval}(p) < cp_2 \\ \text{HU}, & \text{otherwise} \end{pmatrix} \tag{4.28}$$

Algorithm 4 Genetic Algorithm used in Implementation

```
function GENETIC-ALGORITHM
    Define Fitness Function
    Define Crossover Probability $p_c$
    Define Mutation Probability $p_m$
    Define populationDimension
    $P \leftarrow InitPopulationRandomly()$
    repeat
        ComputeFitnessOfPopulation()
        for $i = 0 \rightarrow populationDimension$ do
            $c_1, c_2 \leftarrow getFittestChromosome() - Elitism$
            $p_1, p_2 \leftarrow$ getParentChromosomesGivingHighlyFitIndividualsAGreaterChanceOfBeingSelected()
            if $getRandom() < p_c$ then
                $c_3, c_4 \leftarrow doUniformCrossoverToOnePart(p_1, p_2)$
                $c_3, c_4 \leftarrow doTwoPointCrossoverToTheOtherPart(p_1, p_2)$
            else
                $c_3, c_4 \leftarrow p_1, p_2$
            end if
        end for
        for $i = 0 \rightarrow populationDimension$ do
            if $c_i$ is not BestFittestChromosome then
                if $c_i$ is WorstFittestChromosome or $getRandom() < p_m$ then
                    doMutation($c_i$)
                end if
            end if
        end for
    until max number of generations is reached
end function
```

CHAPTER 5

EXPERIMENTAL RESULTS

In this chapter, details of the experimental settings and experiment results are presented for the study described in Chapter 4. In addition, we compare these results with the methods in the literature.

Experiments are carried out on the project dataset collected from World Bank projects data. Dataset contains 493 samples in total. Our aim is to find the project outcome information of a project according to evaluation result. In evaluation process, 25 attributes of projects are used. Project outcome information consists of four class labels such as Highly Satisfactory (HS), Satisfactory (S), Unsatisfactory (U), Highly Unsatisfactory (HU).

At first, dimensionality reduction in attributes is done. Relevant attributes are selected from 25 attributes. Then, the weights of selected attributes are found. Different approaches are tried in attribute selection and finding the weights of selected attributes part. In attribute selection part, GA and combinations of several data mining methods are used. In finding the weights of selected attributes, GA, HS and hybrid GA-HS algorithms are used. Finally, evaluation is done according to weighted scores of the projects and the values of cut-off points. The details of the experimental results are given in the following sections.

5.1 Experiments of the Work Based on Several Data Mining Methods, HS and GA Approach

In attribute selection part, attribute selection feature of WEKA tool is used. Combinations of ReliefFAttributeEval attribute evaluator and Ranker search method; CfsSubsetEval attribute evaluator and GreedyStepwise search method; CfsSubsetEval attribute evaluator and BestFirst search method are used. 7 attributes are selected from 25 attributes according to the intersection set of these combinations. Selected attributes and their explanations are given in Table 5.1 [31][9].

5.1.1 Experimental Results of Metaheuristic Algorithm-based Methods

In finding the weights of selected attributes, 3 different methods used such as GA, HS and hybrid GA-HS algorithms explained in Section 4.2.1.

Used GA parameters are given in Table 5.2. While deciding the GA parameters, we refer to study [19], [15] and [16].

Used HS algorithm parameters are given in Table 5.3. While deciding the HS algorithm parameters, we refer to study [42] and [6].

Dataset is separated into two parts: training data 66% of all data and test data 34% of all data. Training data is composed of 325 projects information and test data is composed of 168 projects information. Two different training and test data is constructed by different combinations of projects: Data 1 and Data 2.

Using selected 7 attributes, true estimate percentage of GA, HS and hybrid GA-HS algorithm results for Data 1 and Data 2 are given in Table 5.4. Average for 3 algorithms is given in Table 5.5. As presented in these tables, GA is more successful than HS and hybrid GA-HS algorithms in two data although there is slight difference.

In addition, we repeat the experiment of the method based on GA on Data 1 to find only attribute weights by using constant cut-off points (0.25,0.50,0.75). In this experiment, our chromosome structure consists of attribute weights. According to this experiment, the average accuracy of 20 runs for this technique is 89.1667%. In the

Table 5.1: Selected Attributes and Explanations

Selected Attribute	**Attribute Explanation**
Sustainability	The risk, at the time of evaluation, that development outcomes (or expected outcomes) will not be maintained (or realized).
Borrower Performance	The extent to which the borrower (including the government and implementing agency or agencies) ensured quality of preparation and implementation, and complied with covenants and agreements, toward the achievement of development outcomes.
Poverty Reduction	Evaluating the extent to which project benefits reached the target group, providing information on the operation's positive or negative effect on poverty, and examining possible leakage of benefits in comparison with the operation's objectives.
Quality at Entry - ICR	The rating by Implementation Completion Report's Quality at Entry Assessment for the operation.
Project at Risk at Any Time - QAG	Shows whether the operation was flagged as a potential problem project at any time during implementation by Quality Assurance Group.
Physical	Construction and renovations which are carried out
Public Sector Management	The extent to which public sector management systems are strengthen within the executive branch, including the management of public finances and public employment.

Table 5.2: GA Parameters

GA Parameter Name	**Value**
Population Count	100
Crossover Probability	70%
Mutation Probability	0.1%
Maximum Generation Count	1000
Crossover Type	Uniform Crossover
Random Selection Chance	25%

Table 5.3: HS Algorithm Parameters

HS Algorithm Parameter Name	**Value**
HMCR - Harmony Memory Considering Rate	0.9
r_{pa} - Pitch Adjusting Rate	0.3
Harmony Memory Size	30

previous experiment, attribute weights and cut-off points are calculated by using GA. Accuracy of the previous experiment (90.8333%) on Data 1 is higher than accuracy of this experiment since GA generates optimal cut-off values.

5.1.2 Experimental Results of Metaheuristic Algorithm-based Methods without Attribute Selection

To show that attribute selection increase accuracy, we repeat this experiment with 25 attributes without dimensionality reduction in attributes for Data 1. The result of this experiment is given in Table 5.6. The result of the experiment with attribute selection is more accurate than the experiment without attribute selection.

5.1.3 Experimental Results of Methods in Literature

We compare our methods with the methods in the literature. Firstly we implement AHP method that is commonly used in evaluation process in literature. In this exper-

Table 5.4: GA, HS and Hybrid GA-HS Algorithm True Estimate Percentage Results

	DATA 1			**DATA 2**		
	Methods			**Methods**		
	GA	**HS**	**GA+HS**	**GA**	**HS**	**GA+HS**
1. Run	91.0714	91.0714	90.4762	88.6905	89.8810	89.8810
2. Run	90.4762	91.0714	88.6905	88.6905	91.0714	88.0952
3. Run	91.0714	89.8810	90.4762	89.2857	89.8810	88.0952
4. Run	90.4762	92.2619	90.4762	88.0952	88.0952	89.2857
5. Run	91.0714	89.8810	91.6667	89.2857	88.6905	88.0952
6. Run	91.6667	89.2857	91.6667	88.0952	81.5476	89.2857
7. Run	92.2619	92.8571	89.2857	89.8810	89.8810	88.6905
8. Run	90.4762	91.0714	90.4762	87.5000	90.4762	88.6905
9. Run	90.4762	86.3095	90.4762	89.8810	86.9048	87.5000
10. Run	89.8810	89.2857	89.2857	89.2857	88.0952	90.4762
11. Run	91.6667	88.6905	88.0952	88.6905	88.0952	86.3095
12. Run	91.6667	91.6667	91.6667	88.0952	88.0952	86.9048
13. Run	91.0714	91.0714	89.8810	89.2857	88.6905	89.2857
14. Run	91.6667	89.8810	90.4762	87.5000	88.0952	86.3095
15. Run	90.4762	91.0714	90.4762	88.6905	88.0952	89.8810
16. Run	91.6667	91.6667	90.4762	91.0714	88.0952	89.2857
17. Run	91.0714	90.4762	90.4762	88.6905	89.8810	87.5000
18. Run	88.6905	91.6667	91.0714	89.8810	90.4762	89.8810
19. Run	91.6667	91.6667	89.2857	90.4762	89.2857	89.8810
20. Run	88.0952	89.8810	90.4762	89.8810	90.4762	87.5000
Average	**90.8333**	**90.5357**	**90.2679**	**89.0476**	**88.6905**	**88.5417**

Table 5.5: Average GA, HS and Hybrid GA-HS Algorithm True Estimate Percentage Results

	Methods		
	GA	**HS**	**GA-HS**
Average	89.9405	89.6131	89.4048

Table 5.6: GA, HS and Hybrid GA-HS Algorithm True Estimate Percentage Results without Attribute Selection

	DATA 1		
	Methods		
	GA	**HS**	**GA+HS**
1. Run	91.0714%	88.0952%	90.4762%
2. Run	89.2857%	89.2857%	90.4762%
3. Run	91.6667%	91.6667%	91.0714%
4. Run	90.4762%	90.4762%	91.0714%
5. Run	88.6905%	90.4762%	89.2857%
6. Run	91.0714%	86.9048%	90.4762%
7. Run	91.6667%	91.0714%	92.2619%
8. Run	90.4762%	90.4762%	90.4762%
9. Run	88.6905%	88.6905%	90.4762%
10. Run	88.0952%	90.4762%	91.0714%
11. Run	89.2857%	89.8810%	89.8810%
12. Run	91.0714%	91.6667%	91.0714%
13. Run	89.8810%	85.7143%	90.4762%
14. Run	90.4762%	92.2619%	90.4762%
15. Run	91.0714%	91.6667%	91.0714%
16. Run	89.8810%	89.8810%	91.6667%
17. Run	90.4762%	89.8810%	92.2619%
18. Run	89.8810%	90.4762%	90.4762%
19. Run	90.4762%	91.0714%	91.0714%
20. Run	92.2619%	89.8810%	89.8810%
Average	**90.2976%**	**90.0000%**	**90.7738%**

iment, we consult to two project evaluation experts because expert opinion is necessary in AHP method. According to expert opinion, weights of selected 7 attributes are found. 493 projects are evaluated according to these weights and weighted sum method. 254 projects are estimated correctly and true estimate percentage of this technique is 51.5%.

Secondly, we repeat the experiments on WEKA's classification feature. We performed experiments under 10 Folds Cross Validation and Percentage Split (66%). Data which is arranged in the same order as the Data 1 is given to WEKA. Experiments are repeated for several classifiers that are mostly used ones in literature. These classifiers are SMO, NaiveBayes, NaiveBayesSimple, RBFNetwork, SimpleLogistic, MultilayerPerceptron, lazy-IB1, MultiClassClassifier, DecisionTable, BFTree, ZeroR, OneR, Ibk, RandomForest, REPTree and SimpleCart. The result of the experiment is given in Table 5.7. Results of our proposed work that are GA, HS and Hybrid GA-HS Algorithm are more accurate than results of experiment done in WEKA. While result of the GA is 90.8333%, all results of experiment done in WEKA is below 90%.

5.2 Experimental Comparison for GA-based and Classification based Project Evaluation

GA approach explained in Section 4.2.2 is used to select attributes and find the weights of selected attributes. Used GA parameters are given in Table 5.8. While deciding the GA parameters, we refer to study [19], [15] and [16].

Dataset is separated into two parts: training data 66% of all data and test data 34% of all data. Training data is composed of 325 projects information and test data is composed of 168 projects information. Two different training and test data is constructed by different combinations of projects: Data 1 and Data 2.

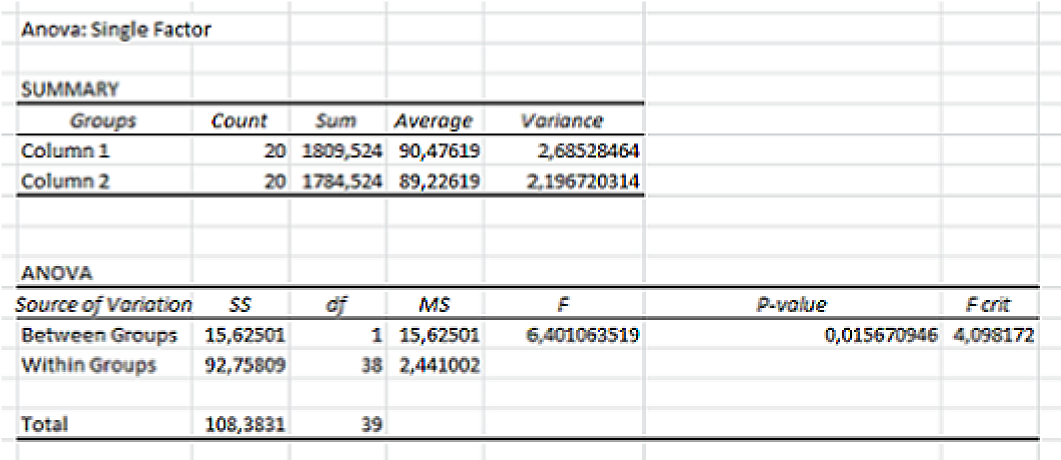
To compare proposed work with methods in literature, classification feature of WEKA is used. Most successful classifiers in previous section and our work are compared. To ensure using same training and test set in our implementation and WEKA, we use WEKA's "Supplied test set" test option. So, in our implementation and WEKA, training and test set are the same.

Table 5.7: WEKA Classification Result

Classifier	**Percentage Split 66%**	**10 Folds Cross Validation**	**Average**
SMO	86.9048%	89.4523%	88.1786%
NaiveBayes	88.6905%	89.0467%	88.8686%
NaiveBayesSimple	88.6905%	89.0467%	88.8686%
RBFNetwork	77.3810%	81.7444%	79.5627%
SimpleLogistic	88.0952%	89.2495%	88.6724%
MultilayerPerceptron	82.1429%	86.6126%	84.3778%
lazy-IB1	85.1190%	84.7870%	84.9530%
MultiClassClassifier	82.7381%	88.4381%	85.5881%
DecisionTable	82.1429%	88.6410%	85.3920%
BFTree	84.5238%	86.6126%	85.5682%
ZeroR	75.5952%	78.9047%	77.2500%
OneR	89.2857%	88.4381%	88.8619%
Ibk	83.3333%	87.6268%	85.4801%
RandomForest	88.0952%	89.4523%	88.7738%
REPTree	89.2857%	88.4381%	88.8619%
SimpleCart	89.2857%	88.0325%	88.6591%

Table 5.8: GA Parameters

GA Parameter Name	**Value**
Population Count	100
Crossover Probability	70%
Mutation Probability	0.1%
Maximum Generation Count	1000
Crossover Type	Uniform Crossover
Random Selection Chance	25%



Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Column 1	20	1809,524	90,47619	2,68528464
Column 2	20	1784,524	89,22619	2,196720314

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	15,62501	1	15,62501	6,401063519	0,015670946	4,098172
Within Groups	92,75809	38	2,441002			
Total	108,3831	39				

Figure 5.1: Analysis of GA & SMO Results

Because GA include ramdomness, at each run of our work, we have different size and combination of attributes in attribute selection. An example set of selected attributes for one run and their explanations are given in Table 5.9 [31][9]. To able to do exact comparison, while testing in WEKA, we prepare data files includes different attributes according to GA attribute selection of our implementation. Results of our proposed work based on GA and WEKA classifiers that are SMO, REPTree and OneR are given in Table 5.10. Results of our proposed technique are more accurate than results of these methods that are most successful according to experiment in previous section.

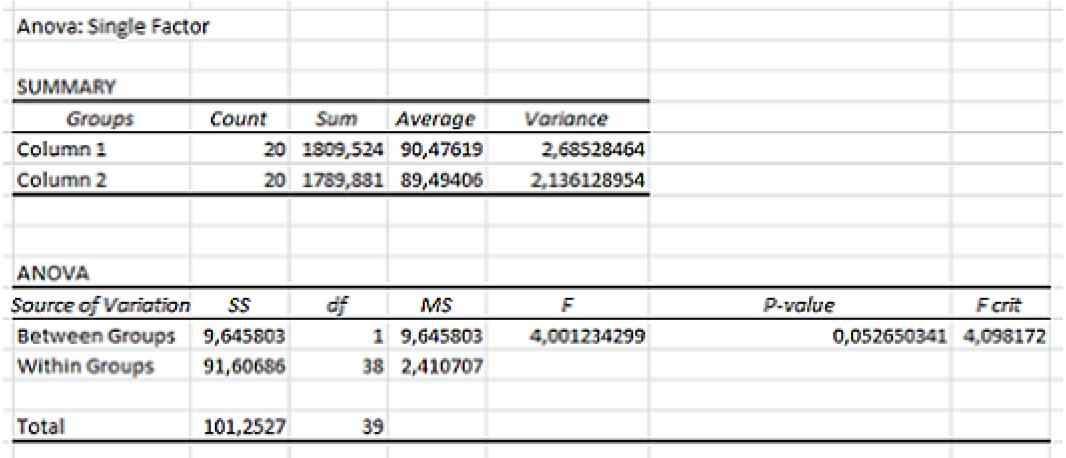
To analyze these results, we apply one-way analysis of variance (ANOVA) to data in Table 5.10. ANOVA is statistical technique for testing the null hypothesis that two or more population means are equal [12]. Results of tests are given in Figure 5.1, 5.2 and 5.3. In the results, if F > F crit, the null hypothesis is rejected. In Figure 5.1, F > F crit. Therefore, we reject the null hypothesis and the means of the two populations (GA & SMO Results) are not all equal. In Figure 5.2, F < F crit, so null hypothesis is retained. In Figure 5.3, F > F crit, null hypothesis is rejected and the means of the two populations (GA & OneR Results) are not all equal.

Table 5.9: An Example Set of Selected Attributes for One Run and Explanations

Selected Attribute	**Attribute Explanation**
Sustainability	The risk, at the time of evaluation, that development outcomes (or expected outcomes) will not be maintained (or realized).
Borrower Performance	The extent to which the borrower (including the government and implementing agency or agencies) ensured quality of preparation and implementation, and complied with covenants and agreements, toward the achievement of development outcomes.
Quality at Entry - ICR	The rating by Implementation Completion Report's Quality at Entry Assessment for the operation.
Public Sector Management	The extent to which public sector management systems are strengthen within the executive branch, including the management of public finances and public employment.
Government Implementation Performance	The extent to which the the government ensured quality of implementation
Implementation Agency Performance	The extent to which the implementing agency or agencies ensured quality of implementation

Table 5.10: Results of our proposed work based on GA and most successful WEKA classifiers

		GA	**SMO**	**REPTree**	**OneR**
DATA 1	**1. Run**	91.6667%	88.0952%	90.4762%	91.0714%
	2. Run	91.0714%	88.6905%	91.0714%	91.0714%
	3. Run	92.2619%	92.2619%	90.4762%	91.6667%
	4. Run	92.8571%	89.8810%	92.2619%	91.0714%
	5. Run	91.6667%	92.2619%	88.6905%	91.0714%
	6. Run	89.8810%	90.4762%	88.0952%	91.0714%
	7. Run	88.6905%	88.0952%	90.4762%	91.0714%
	8. Run	90.4762%	87.5000%	90.4762%	91.0714%
	9. Run	91.0714%	91.0714%	89.8810%	91.0714%
	10. Run	91.6667%	88.0952%	89.8810%	91.0714%
DATA 2	**1. Run**	91.0714%	89.8810%	86.3095%	87.5000%
	2. Run	88.6905%	89.2857%	87.5000%	87.5000%
	3. Run	89.8810%	89.2857%	90.4762%	87.5000%
	4. Run	87.5000%	88.0952%	89.2857%	87.5000%
	5. Run	92.2619%	88.6905%	89.8810%	87.5000%
	6. Run	90.4762%	88.0952%	89.8810%	87.5000%
	7. Run	88.6905%	86.9048%	89.8810%	87.5000%
	8. Run	86.9048%	88.6905%	89.8810%	87.5000%
	9. Run	91.6667%	90.4762%	87.5000%	87.5000%
	10. Run	91.0714%	88.6905%	87.5000%	87.5000%
	Average	**90.4762%**	**89.2262%**	**89.4941%**	**89.3155%**



Anova: Single Factor

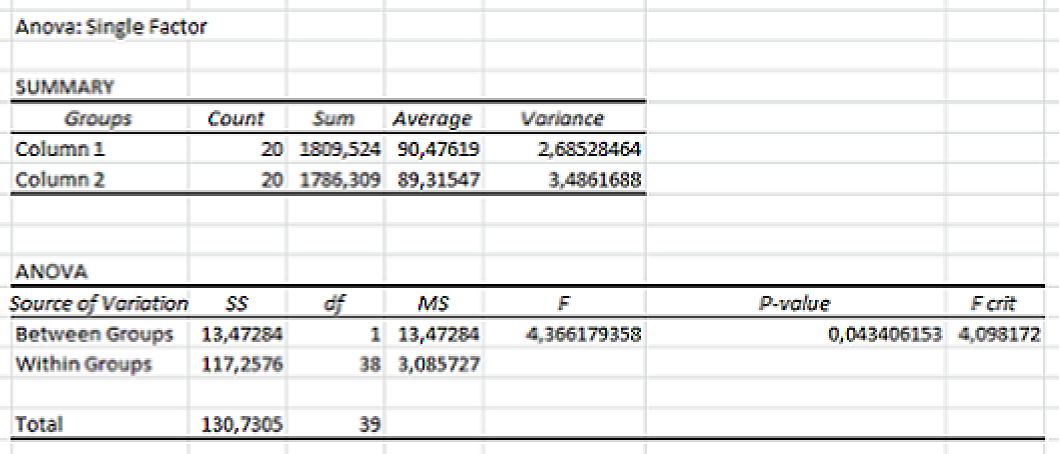
SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	20	1809,524	90,47619	2,68528464
Column 2	20	1789,881	89,49406	2,136128954

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	9,645803	1	9,645803	4,001234299	0,052650341	4,098172
Within Groups	91,60686	38	2,410707			
Total	101,2527	39				

Figure 5.2: Analysis of GA & REPTree Results



Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Column 1	20	1809,524	90,47619	2,68528464
Column 2	20	1786,309	89,31547	3,4861688

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	13,47284	1	13,47284	4,366179358	0,043406153	4,098172
Within Groups	117,2576	38	3,085727			
Total	130,7305	39				

Figure 5.3: Analysis of GA & OneR Results

CHAPTER 6

CONCLUSION AND FUTURE WORK

Public investment projects are essential for welfare of people. In spite of high need for public investment projects, resources are limited. To provide for the efficient and effective use of public resources allocated for public investments, project performance evaluation systems are needed.

In this thesis, we focused on project evaluation system and it is shown that using metaheuristic algorithms and data mining methods for evaluation of projects is feasible and gives promising results. Several methods were applied to get the best results and experimental results were evaluated. Considering the evaluation results, the proposed work performs better than some other well known works in the literature.

All of the studies we saw in project evaluation topic used classical approaches mentioned in Section 2.1. In this thesis, classification, metaheuristic computation and data mining approaches based project evaluation methods were proposed.

Since we did not find suitable dataset on this subject for project evaluation, we generated a new dataset. We constructed our dataset from World Bank projects data [8]. Project outcome information and performance ratings for various attributes of projects from completion reports were collected manually. 493 projects data were collected. This data included performance ratings for 25 attributes of projects.

Then, related attributes were selected and the weights of selected attributes were found. In this part, we applied two different approaches that are based on GA and based on several data mining methods, HS and GA. In the work based on GA, GA was used for attribute selection and finding the weights of selected attributes. In the work based on several data mining methods, HS and GA; several data mining methods were used for attribute selection and HS and GA were used for finding the weights of selected attributes.

Finally, projects were evaluated using the selected attributes, attribute weights and cut-off values learned by the algorithms from previous phase. According to weighted scores of the projects and the values of cut-off points, evaluation was done.

Performance evaluation indexes were determined according to GA and several data mining methods. From the experimental results, it can be said that attribute selection helps to increase the success of evaluation.

Experiments with two proposed approaches and methods in literature showed that proposed approaches are more successful than methods in literature and the work based on GA is the best one among the others. Generated dataset evaluation was 90.476% of accuracy by using the approach based on GA. We had 89.941%, 89.613% and 89.405% of accuracies by using the approach based on data mining methods+GA, data mining methods+HS and data mining methods+GA-HS respectively. Since GA and HS include randomness, we had different results at each run. For this reason, we got the average of results.

This study can be used for evaluation in other topics. To be able to strengthen our inference and to analyse more comprehensively, our dataset may be expanded with some additional project information as a future work.

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