DOKUZ EYLÜL UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

COMBINING SYSTEMS DYNAMICS MODELLING WITH DYNAMIC MULTI CRITERIA DECISION MAKING

by

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İZMİR

COMBINING SYSTEMS DYNAMICS MODELLING WITH DYNAMIC MULTI CRITERIA DECISION MAKING

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M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"COMBINING SYSTEMS DYNAMICS MODELLING WITH DYNAMIC MULTI CRITERIA DECISION MAKING"** completed by **DİLEK YEŞİLKAYA** under supervision of **PROF. DR. ADİL BAYKASOĞLU** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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COMBINING SYSTEMS DYNAMICS MODELLING WITH DYNAMIC MULTI CRITERIA DECISION MAKING

ABSTRACT

Since time factor is ignored in multi criteria decision making (MCDM) methods, recently it has been criticized by many researchers in decision making area. Under the heading of dynamic multi criteria decision making (DMCDM), new methods have been developed to overcome this deficiency of MCDM methods. DMCDM models are an approach that considers the temporal performance of alternatives in different time periods, and so helps to specify the most suitable alternative in decision making process. However, with the methods of DMCDM which have been developed in the literature so far, it has been solely aimed to determine the most suitable alternative by considering the past and present performance data of the alternatives. Few of the proposed methods are related to predicting the future performance of alternatives. Yet, the decisions taken are for the future. For this reason, making decisions by predicting the future performance of alternatives will provide much more accurate choices. In this thesis, the system dynamics (SD) approach modeling changes in the behavior of alternatives over time is proposed. According to the proposed method, performance changes depending on the behavior of alternatives have been analyzed using SD simulation software STELLA. As a result of multiple runs of the simulation program, different raking values for the available alternatives have been obtained. The obtained alternative ratings have been aggregated by the borda count method, and thus a single raking value for all available alternatives has been formed. In addition the scenario of changing the weights of evaluation criteria is discussed in this method. With the change in weight of criteria, the order of alternatives has also changed. An example of long term supplier selection is presented to show the practicability of the proposed method.

Keywords: Dynamic multi criteria decision making, system dynamics, borda count method, supplier selection

DİNAMİK ÇOK KRİTERLİ KARAR VERME İLE SİSTEM DİNAMİKLERİ MODELİNİN ENTEGRASYONU

ÖZ

Çok kriterli karar verme (ÇKKV) yöntemlerinde zaman faktörü göz ardı edildiği için son zamanlarda karar verme alanında bir çok araştırmacı tarafından eleştirilmiştir. Çok kriterli karar verme yöntemlerinin bu eksikliğini gidermek için dinamik çok kriterli karar verme (DÇKKV) başlığı altında yeni yöntemler geliştirilmiştir. DÇKKV modelleri, karar verme sürecinde alternatiflerin farklı zaman periyotlarındaki geçici performanslarını dikkate alan ve böylece en uygun alternatifin belirlenmesine yardımcı olan bir yaklaşımdır. Ancak literatürde şu ana kadar geliştirilen DÇKKV yöntemleri ile sadece alternatiflerin geçmiş ve şuan ki performans verilerine bakılarak en uygun alternatifin belirlenmesi amaçlanmıştır. Önerilen yöntemlerden çok azı alternatiflerin gelecek performansını tahminleme üzerine yapılmıştır. Oysaki alınan kararlar geleceğe yöneliktir. Bu sebeple alternatiflerin gelecekteki performanslarını tahminleyerek karar vermek çok daha doğru seçimler yapılmasını sağlayacaktır. Bunun için bu tez çalışmasında alternatiflerin zaman içerisindeki davranışlarının değişimlerini modelleyen sistem dinamiği (SD) yaklaşımı önerilmektedir. Önerilen yönteme göre, alternatiflerin davranışlarına bağlı performans değişimleri SD simülasyon yazılımı STELLA kullanılarak analiz edilmiştir. Simülasyon programının çoklu çalıştırılması sonucu mevcut alternatifler için farklı sıralama değerleri elde edilmiştir. Elde edilen alternatif sıralamaları borda sayım yöntemi ile birleştirilmiş ve böylece mevcut tüm alternatifler için tek bir sıralama değeri oluşturulmuştur. Bu yöntemde ayrıca değerlendirme kriterlerinin ağırlıklarının değişimi senaryosu ele alınmıştır. Kriterlerin ağırlıklarının değişmesiyle alternatiflerin sıralaması da değişim göstermiştir. Önerilen yöntemin uygulanabilirliğini göstermek amacıyla uzun dönemli bir tedarikçi seçimi örneği sunulmuştur.

Anahtar kelimeler: Dinamik çok kriterli karar verme, sistem dinamiği, borda sayım yöntemi, tedarikçi seçimi

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CHAPTER ONE
INTRODUCTION

People make decisions in their both personal and professional lives, which makes decision making as a problem that mankind encounters in every period of their lives. In the simplest way, we are confronted with the decision making situation in almost every area, from deciding what to eat in a restaurant to investment decisions which are more strategic for businesses. Namely, decision making is an essential part of our life. Although the concept of decision making is defined in different ways by different researchers, we can generally define it as follows: Decision making is the selection of the most appropriate option among the available options by taking into consideration the determined criteria to accomplish certain purpose (Özbek, 2017). The important thing in decision making is to achieve the intended results.

People in the decision making process make a choice based on their knowledge and experience. However, knowledge and experience may not be sufficient in some complex and strategic decision problems. For this reason, scientific methods like multi criteria decision making (MCDM) models are used as a scientific approach for solving decision problems. MCDM, which is an important branch of operations research, proposes many methods related to the solution of decision making problems. These methods allow us to assess a set of alternatives in terms of multiple qualitative and quantitative criteria which usually conflicting each other.

Although there exists a vast amount of study about MCDM models to solve various decision making problems, some authors have pointed out missing aspects of the methods so far developed. Traditional MCDM techniques make some assumptions to simplify decision making process. Accordingly, the performances of the alternatives to be preferred and the decision criteria determined by the decision makers are assumed to be constant. In other words, evaluating decision options and making decisions are considered as a fixed moment of time period. In the process of evaluating decision options, the time dimension is neglected. However, in the face of changing events, our preferences change over time. In order to overcome this

deficiency of classical MCDM models, dynamic multi criteria decision making (DMCDM) methods are proposed in the literature. The temporary performances of alternatives are considered in these proposed methods.

Many proposed methods for the solution of DMCDM problems focus on evaluating the past and present data of alternatives together and determining the most suitable alternative. Few studies in the literature take into account predicting future performances of alternatives in decision process. It is very difficult to evaluate the past and present status of decision options and predict their future. Therefore, it is necessary that such decision problems should be considered from a holistic perspective. In other words, not only the performance of the alternatives, but also the factors affecting this performance should be considered. Thus it should be investigated how their behavior changes.

The purpose of this thesis is to analyze the behavioral changes of alternatives in decision problems over time and to predict future performances of alternatives. Thus, the best alternative for the future will be specified. In this study, system dynamics modeling approach is proposed to solve DMCDM problems. System dynamics is an approach that takes into account the feedback loops arising in a system that deals with the dynamic behavior of systems. In this aspect, it can be considered as an appropriate approach for evaluating the performance of alternatives.

This thesis comprises of six chapters and the rest of the thesis is as follows:

Chapter two is covered under three separate headings. Firstly, brief information about MCDM problems is given and in the second part some shortcomings of these methods are mentioned and dynamic multi criteria decision making problems are explained. Finally, some basic information about system dynamics approach is provided.

In chapter three, the proposed methods in the literature for the solution of DMCDM problems are explained. In addition, system dynamics and MCDM methods used together in literature are mentioned.

In chapter four, a new method is proposed for the solution of DMCDM problems. The steps of the method are explained individually.

In chapter five, an example of supplier selection problem is presented so as to demonstrate applicability of the new proposed method.

Chapter six summarizes and concludes the thesis.

CHAPTER TWO
BACKGROUND

This chapter provides basic information about multi criteria decision making, dynamic multi criteria decision making, and system dynamics modeling. The first subsection gives general knowledge about multi criteria decision making problems, in the second subsection, dynamic multi criteria decision making problems are mentioned. Finally, an overview of system dynamics is presented.

2.1 Multi Criteria Decision Making

Multi criteria decision making which is a sub discipline of operations research is the best known branch of decision making (Triantaphyllou, Shu, Sanchez, & Ray, 1998). Today, it is applied making decision problems in many areas. It allows evaluating a set of alternatives with respect to multiple qualitative and quantitative criteria which may be in conflict with each other and determining the most suitable alternative among other alternatives.

Although there are numerous methods to solve MCDM problems, they have some common features. These features are described below (Triantaphyllou et al., 1998):

Alternatives: Alternatives indicate potential decision options that decision makers can choose. The set of alternatives are generally finite and their numbers can vary based on the type of decision problem. Decision makers evaluate, prioritize, rank all available alternatives and ultimately select the most appropriate alternative.

Multiple criteria: MCDM problems consist of multiple criteria which allow alternatives to be evaluated from different perspective. The criterion as a word can also be expressed as goals, attributes. The number of criteria may be too much in some MCDM problems. In such a case, the criteria are arranged according to the hierarchical structure. While some criteria form the main criteria of the problem, others form the sub-criteria.

Conflict among criteria: There may be conflict among the criteria determined in MCDM problems. For example, when we buy a car, we want it to be both low priced and luxurious at the same time. Here, luxury and price are two conflicting criteria.

Incommensurable units: The criteria in MCDM problems may be qualitative or quantitative. While qualitative criteria cannot be expressed with numbers, numerical values are used for quantitative criteria. The units of quantitative criteria may also be different. For this reason, normalization is implemented to make unitless values of the criteria.

Weights of criteria: The criteria considered in MCDM problems may not have the same relative importance. Therefore, decision makers determine weights of criteria in terms of their importance. In order to determine these weights, many different techniques are put forward in the literature.

Decision matrix: Multi criteria decision making problems are generally expressed with mXn dimensional decision matrices. Figure 2.1 shows a typical decision matrix. Accordingly, while $\mathbf{A_i}$ indicates a finite set of alternatives (for i = 1, 2, 3, …., m), $\mathbf{C_j}$ shows a finite set of criteria or attributes (for j = 1, 2, 3, …., n). $\mathbf{a_{ij}}$ states the performance of alternative $\mathbf{A_i}$ according to criteria $\mathbf{C_j}$. Each criterion has different relative importance. Therefore, decision makers define the weights of criteria. $\mathbf{W_i}$ indicates the importance weights of each criterion.

	Criteria				
	$\mathbf{C_1}$	$\mathbf{C_2}$	$\mathbf{C_3}$	**….**	$\mathbf{C_n}$
Alt.	$\mathbf{W_1}$	$\mathbf{W_2}$	$\mathbf{W_3}$	**….**	$\mathbf{W_n}$
$\mathbf{A_1}$	a_{11}	a_{12}	a_{13}	**.....**	a_{1n}
$\mathbf{A_2}$	a_{21}	a_{22}	a_{23}	….	a_{2n}
$\mathbf{A_3}$	a_{31}	a_{32}	a_{33}	….	a_{3n}
….	….	….	….	….	**.....**
$\mathbf{A_m}$	a_{m1}	a_{m2}	a_{m3}	….	a_{mn}

Figure 2.1 A typical decision matrix

The basic steps of the solution of MCDM problems are as follows (Opricovic & Tzeng, 2004):

1) Evaluation criteria related to objectives is formed.
2) Alternative to achieve the goals are developed.
3) Alternatives are assessed according to evaluation criteria.
4) One of the MCDM methods is applied.
5) One alternative is accepted as optimal and this alternative is preferred.
6) New information is gathered and multi criteria optimization is repeated, unless the final solution is accepted.

Numerous methods have been proposed for MCDM problems. Asadabadi (2018) stated that the most commonly used methods are as follows:

- Analytic Hierarchy Process (AHP)
- Decision Making Trial and Evaluation Laboratory (DEMATEL)
- Elimination and Choice Expressing Reality (ELECTRE)
- Analytic Network Process (ANP)
- Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE)
- VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Multi criteria optimization and compromise solution)
- Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

Except these methods listed above, there are many other methods to solve MCDM problems. Moreover new methods are being proposed to solve these problems. With the use of these methods, successful applications have been made in the literature for decision problems in different fields and the use of these methods is becoming more widespread.

2.2 Dynamic Multi Criteria Decision Making

MCDM methods are often applied to solve decision making problems as noted in the previous subsection. In the literature, numerous MCDM methods have been suggested and these methods successfully implemented to decision making problems. Recently, however, it has been put forward by some researchers that they are not sufficient for solving some decision problems. The biggest deficiency in these methods is that it neglects the time factor in the decision making process (Baykasoglu & Golcuk, 2019a, 2019b).

In classical MCDM problems, decision makers define a fixed set of criteria and alternatives related to decision problems when they make a choice. Then they evaluate the available alternatives in terms of the criteria and obtain a score value for each alternative. Thus, according to the score values obtained, they rank alternatives and prefer the alternative which has maximum value (Campanella & Ribeiro, 2011). This is a general summary of classical MCDM methods.

Zulueta, Moreno, Pérez & Martìnez (2014) mentioned that past and present performance of alternatives should be considered together, while evaluating available alternatives in some multi criteria decision making problems. We can explain this with an example. We can assume that a company wants to determine the best employee and reward him or her. In such a case, the company evaluates its employee based on certain criteria and makes a decision according to them. MCDM methods can be considered as a suitable solution techniques for such decision problem. Here, the decision maker determines a range of criteria and defines the weights of these criteria to evaluate the employees. He/She looks at the performance of the employees and specifies the best employee by implementing one of the MCDM techniques. The most important question here: Which time period should the performance of employees be evaluated? MCDM methods do not consider the success of alternatives at different time periods. According to these methods, a single time period is considered. Such an assessment may not provide realistic results for such decision problems. For example, the performance of an employee is low for now, but it

showed great success in the past, or vice versa. Therefore, instead of focusing on a single time period in these decision problems, it will make more accurate decisions by thinking holistically. Similarly, time factor should be taken into consideration in many decision problems such as supplier selection and investment decisions.

MCDM models which consider time factor for making decision have been named as dynamic multi criteria decision making (DMCDM) in the literature. This topic has recently attracted the attention of researchers. Therefore, they have developed different methods to solve these problems.

In this thesis, system dynamics modeling approach is proposed to solve DMCDM problems.

2.3 System Dynamics

Human beings have made quick decisions and found good solutions against the problems they have faced based on their intuition since ancient times. From an evolutionary standpoint, for example, when we see a dangerous animal approaching us, we immediately decide and run away from there, otherwise we cannot survive forever. Thus people who make decision quickly will be survivor (Kirkwood, 1998). In the face of such simple events, it is easy to make right and quick decisions and to realize the causes and effects of these events. The human mind is an effective tool for such short term, uncomplicated decisions. However, it is incapable to address complex, long term strategic decision problems.

Nowadays, with the developments in technology and industry, the problems we face have become more complicated than ever. Overpopulation, unemployment, global warming, depletion of natural resources, educational problems, healthcare problems, conflicts between nations constitute only a few of these problems. In a constantly developing and changing world, the number of complex and dynamic problems in both public and private areas is increasing. The solution of these increasing complex problems may not be as easy as the above mentioned example.

System dynamics discipline is an effective approach to solve such critical, long term and strategic problems (Barlas, 2002).

System dynamics field was developed by Jay W. Forrester and a group of researchers at the Massachusetts Institute of Technology (M.I.T) in the late 1950s. The first application area of this methodology was to solve industrial management problems, thus it was named as *Industrial Dynamics* in the earliest time. The seminal book which name is "Industrial Dynamics", published by Forrester in 1961, was the main output of this research and introduced the methodology. The book is also the main reference book in industrial applications today. This study was followed by "Urban Dynamics" which researches the impacts of housing on urban areas and "World Dynamics" which deals with the relationship between increase in world population and depletion of natural resources respectively. Today, interest in the discipline of system dynamics is growing rapidly and it has a wide range of applications. It can be seen in national economic problems, project management, educational problems, sustainable development, health care problems, supply chain (Ekinci & Baykasoglu, 2019), energy systems, politics and many other areas (Barlas, 2002).

The meaning of the concept of system dynamics as a word is as follows: *"System"* is a whole, which consists of a set of components that come together to achieve a specific purpose. In other words, it refers an interdependent group of elements (Kirkwood, 1998). *"Dynamic"* means something changes over time. Dynamic problems are defined by variables that change continuously over time. Therefore, in order to solve these problems, continuous managerial activities are needed. For example, although choosing a location for a company is a very difficult problem, it is a static decision problem. After decision is made, the results of the decision are not monitored continuously and no new decision is made depending on the results of the decision. On the other hand, in dynamic decision problems, the results of decisions are continuously observed and evaluated. If necessary, new decisions are taken (Barlas, 2002). When system and dynamic words are used together, namely "*System Dynamics*", it is an approach that deals with the changes

that occur in the system as a result of the interaction of system components over time.

System dynamics used in different application areas for many years provide us with tools to better understand complex problems. At the same time, this approach allows us to change our perspective in response to the problems that arise in organizations. In other words, in the face of a problem in organizations, instead of investigating the causes of problems in an isolated environment, it shows the way to see the organization as an interactive system and find out how the problem originated (Kirkwood, 1998).

System dynamics which take complex systems from a holistic perspective provide two basic tools for understanding complex problems. These tools are causal loop diagrams and stock - flow diagrams.

2.3.1 Causal Loop Diagrams

Causal loop diagrams are visual maps which show the cause and effect relationship between system component. These diagrams present the relationship between the components that make up the system, feedback loops, time delays, and thus give us more explanatory information about the problems we face. They have not been used in the initial applications of system dynamics model. Therefore causal relations and feedback structures have been expressed by equations or stock-flow diagrams, which is more suitable for engineers. However, the use of these diagrams has become widespread in the following years to make system dynamics accessible to more audience (Richardson, 1986).

Causal loop diagrams consist of system components and arrows showing the relationship between these components. The relationship between the components is determined according to “+” and “-” signs shown on the arrows. The “+” sign means that the relationship between the two components is the same direction. Namely, if increasing one variable leads to enhance the other variable, the relationship between

these two variables is positive. On the other hand, the "-" sign means that the relationship between the two components is the opposite direction. In other words, if increasing one variable leads to decrease the other variable, the relationship between these two variables is negative. This will be better explained in the causal loop diagram of population below.

As a result of negative and positive relationships, feedback loops may occur. There are two different feedback loops, positive and negative in causal loop diagrams:

1) Positive feedback loops (Reinforcing): If the feedback loop shows a change in the direction of continuous improvement, this is called positive feedback loop. These feedback loops are indicated by "+", "R", or rolling snowball in the middle of the loop.

2) Negative feedback loops (Balancing): If the feedback loop is self balancing, these loops are called negative feedback loops. These feedback loops are indicated by "-", "B", or the balance symbol in the middle of the loop.

Figure 2.2 presents the causal loop diagram of population. There are two different feedback loops in this diagram. The left side of the diagram is the positive feedback loop, while the right side is the negative feedback loop. Accordingly, the population is affected by two different variables (births and deaths). As births increase, the number of population increases too. The relationship between them is positive. Incresing population will increase the births even more. This loop is pozitif feedback loop. On the other hand, while increasing population increases deaths, increasing number of deaths decreases the number of population. The relationship between them is negative. The resulting loop is the negative feedback loop.

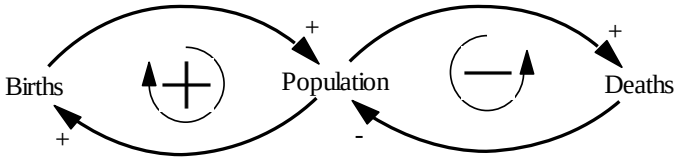


Figure 2.2 Causal loop diagram of population

Whether the feedback loops are positive or negative is determined by looking at the number of negative signs in the loops. If a loop has an odd number of negative signs, this loop is named as negative feedback loop. On the other hand, if there are an even number of negative sings in the loop, it is named as positive feedback loop. Namely, the sign of a loop is obtained by the algebraic product of the signs in the loop (Kirkwood, 1998).

2.3.2 Stock and Flow Diagrams

Although the causal loop diagram visualizes information about the system, it is not sufficient for system dynamics modeling. Since system dynamics is a computer aided approach, there is a need for diagrams that can be expressed mathematically. Therefore, in order to express system dynamics in simulation programs, stock and flow diagrams are implemented.

The causal loop diagram of population mentioned above has been formed in the Stella software program. Accordingly, while population is modeled as stock variable, births and deaths are modeled as flows. The model is shown in figure 2.3. While the births flow into the population, that is they increases the population, the deaths flow out the population, namely they decreases the population. In addition, convertor variable which shows rate for births and deaths are defined. The arrows shown between variables transmit information between variables.

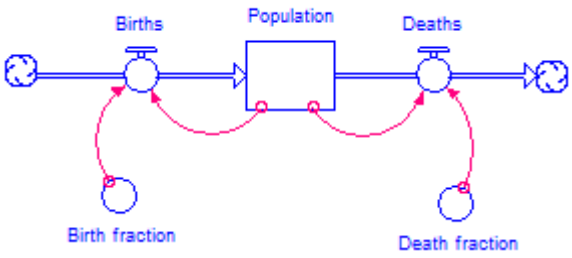


Figure 2.3 Stock-flow diagram of population (Barlas, 2002)

To model stock and flow diagrams, special computer software program is required. For this, a number of software packages, like Vensim, Powersim, Stella, Ithink are available.

CHAPTER THREE
LITERATURE REVIEW

In this chapter, researches related to the topic of the thesis in the literature are presented. This review is examined under two headings. In the first part, the studies about DMCDM models are discussed. In the second part, combination of system dynamics and MCDM approaches are provided.

3.1 Literature Review on Dynamic MCDM

Considering the time factor in decision making process has recently paid great attention in the literature. For this, many researchers have proposed different solution methods for such decision problems. These decision problems are called DMCDM problems in the literature. In this section, DMCDM methods proposed in the literature are discussed.

Some researchers have converted the decision matrices which belong to past and current time into a single decision matrix by aggregating them with an appropriate aggregation operator. Then they have applied one of the classical MCDM methods and specified the most suitable alternative.

Xu & Yager (2008) proposed two new aggregation operators called dynamic intuitionistic fuzzy weighted averaging and uncertain dynamic intuitionistic fuzzy weighted averaging in order to aggregate intuitionistic or uncertain fuzzy decision matrices which belong to past periods. In the study, they firstly aggregate all past decision matrices via dynamic intuitionistic fuzzy weighted averaging operator, and then they utilized from the TOPSIS to rank and determine the best alternative.

Xu (2008) proposed an approach based on the dynamic weighted averaging operator and uncertain dynamic weighted averaging operator to solve DMCDM problems. They illustrate the proposed method with an investment decision problem.

Chen & Li (2011) utilized from the weighted arithmetic averaging operator so as to aggregate the decision matrices expressed by triangular intuitionistic fuzzy numbers. The weights of criteria were specified by means of the entropy method. In order to exemplify the proposed method, an investment decision problem was presented.

Park, Cho, & Kwun (2013) developed two different aggregation operators which called as dynamic intuitionistic fuzzy weighted geometric and uncertain dynamic intuitionistic fuzzy weighted geometric. While these aggregation operators were applied to combine the decision matrices at different time periods, VIKOR was implemented to determine the ranking of alternatives.

Bali, Dagdeviren, & Gumus (2015) combined AHP and dynamic intuitionistic fuzzy weighted averaging operator developed by Xu & Yager (2008) for dynamic MCDM problems. In the study, whereas AHP was implemented to specify weights of criteria, dynamic intuitionistic fuzzy weighted averaging operator was used to aggregate the values of performance of alternatives over different time periods. So as to show the feasibility of their study, they solved a personnel promotion problem.

Some authors have found positive ideal and negative ideal sets of solutions for the decision matrices of different times, rather than combining these matrices at the beginning.

Lin, Lee, & Ting (2008) proposed a DMCDM method that integrates grey numbers and Minkowski distance function. The TOPSIS technique was considered as main structure in this study. Firstly negative and positive ideal solution sets were found for the decision matrices which are expressed with grey numbers in different time periods. Then negative and positive measurements calculated for all periods were aggregate. To show the effectiveness of the proposed method, a subcontractor selection example was provided.

Increasing complexity in decision making process has enhanced the uncertaintiness and vagueness. Therefore, decision makers benefit from approximate values instead of exact numbers to express the performance of existing alternatives. In the literature, expressions such as grey numbers, interval values, and fuzzy numbers are used in the evaluation process. With the help of these numbers, decision makers can express their feelings more accurately. In the following various numbers used by researchers are presented:

- Intuitionistic fuzzy numbers (Xu & Yager, 2008; Bali et al., 2015; Park et al., 2013)
- Interval-valued intuitionistic fuzzy numbers (Xu & Yager, 2008; Park et al., 2013)
- Grey numbers (Lin et al., 2008)
- Triangular intuitionistic fuzzy numbers (Chen & Li, 2011)

DMCDM approaches focus on decision making based on information collected from different time periods. However, this approach is not effective where there are large set of alternatives and criteria (Zulueta et al., 2014). For this reason, some researchers have proposed different approaches to overcome this weakness. For this, a rating value for alternatives has been calculated with classical MCDM methods at each time period. Then the rating value calculated in each period is transferred to the next period.

Campanella & Ribeiro (2011) proposed a framework based on the classic MCDM model in order to solve dynamic MCDM problems. In the study, first of all the non dynamic rating of each alternative is calculated by means of one of the classical MCDM methods. Then, the current performance rating and past performance rating of the alternatives are integrated by a suitable aggregation operator, and so the dynamic ratings of alternatives are obtained. The results of dynamic ratings are stored as historical information for the future and the historical rating value is updated with the dynamic rating value. In order to illustrate this framework, a landing site selection for a helicopter landing place was presented. It was also

pointed out that the framework could be applied to a variety of dynamic decision making problems, like medical diagnosis, emergency department operation, planetary landing site selection and supplier selection. One year later, Campanella, Pereira, Ribeiro, & Varela (2012) extended this proposed method and applied this model to a supplier selection problem.

Zulueta et al. (2014) mentioned some limitations of the framework proposed by Campanella & Ribeiro (2011). Because, when alternatives are evaluated, although non-dynamic ratings of alternatives are different, it can be obtained equal dynamic ratings. Therefore, they proposed a new discrete time variable index based on bipolar aggregation operator to support DMCDM models. To exemplify and show the feasibility of their proposal, a supplier selection example was presented.

Liu, Jiang, & Martínez (2018) utilized from the method proposed by Campanella & Ribeiro (2011) to solve DMCDM problems and applied this method a supplier selection problem. In this study, they used the bipolar linguistic values so as to evaluate alternatives according to criteria.

Chiang (2005) extended AHP method to solve dynamic decision making problems. A long term supplier selection problem was addressed to illustrate the proposed method. According to this study, three different suppliers was evaluated with AHP method separately in three different periods. Finally, which supplier will be selected was calculated by taking the averages of rating values of alternatives in these three different time periods.

Prida, Viveros, Barberá, & Márquez (2014) proposed a methodology which adopted AHP method to a continuously changing environment, taking into consideration that alternatives and criteria are changeable variables. They applied their methodology to evaluate electric engine components in a mining industry.

Some authors have stated that future estimation values should be considered in the evaluation of alternatives.

Jassbi, Ribeiro, & Varela (2014) advocated that future information should also be considered in dynamic multi criteria decision making models. For this reason, they extended DMCDM framework proposed by Campanella & Ribeiro (2011) with future knowledge. According to this study, weighted average aggregation function was used to merge past, current and future information of alternatives into one final score for each alternative. To demonstrate practicability of the proposed model, a supplier selection problem in an automotive industry was presented.

Orji & Wei (2015) proposed a new method integrating system dynamics and fuzzy logic in order to determine the best sustainable supplier whose performance changes over time. According to the study, performances of suppliers were assessed in terms of several sustainability criteria in different time periods, namely past, current and future. The new method was applied to a supplier selection problem for a gear manufacturing company in China.

Baykasoglu & Golcuk (2019a) proposed a new model by learning of fuzzy cognitive maps to solve DMCDM problems. In this study, it was benefit from Jaya algorithm to train fuzzy cognitive maps, so the patterns and trends in the historical data were obtained. According to this, future decision matrices for short, medium and long term were generated and these matrices were used to evaluate and rank the alternatives. In order to show applicability of the proposed model, a real-life supplier selection problem was solved.

In the same year, Baykasoglu & Golcuk (2019b) combined interval type-2 fuzzy regression and fuzzy functions approaches to solve DMCDM problems. In this study, they estimated current performance of alternatives based on the trends and patterns in the historical decision matrices. Finally, this study was applied to a personnel promotion problem.

3.2 Literature Review on Combination of System Dynamics and MCDM

The common feature of system dynamics and multi criteria decision making models is that both guides decision makers in decision making process. Some authors have used them together.

In order to deal with DMCDM problems, Vo, Chae, & Olson (2002) put forward a procedure which combines MCDM with system dynamics modeling and named this Dynamic Multi Criteria Decision Making. They exemplified this via a case of urban infrastructure planning, which supports sustainable development in urban areas.

Sonawane & Rodrigues (2015) developed System Dynamics model based on Analytic Hierarchy Process to evaluate suppliers' quality performance for a washing machine company.

Tesfamariam & Lindberg (2005) proposed System dynamics model and Analytic Network Process to make decision strategically consistent. They illustrated the approach by means of a case selecting the best system configuration among other competitive configurations in manufacturing system design.

Cruz, Naderpour, & Ramezani (2018) proposed a method combining MCDM with system dynamics to specify the best water resource needed for extraction of shale gas. Firstly, AHP was applied to select the best water resources and then the long term effects of consumption of selected water resources were analyzed via system dynamics modeling.

Xi & Poh (2015) proposed a decision support tool which integrates system dynamics and analytic hierarchy process to select a suitable plan to reduce the risks of urban flooding and vary water supply sources. After the consequences of different plans under population growth were simulated by means of system dynamics modeling, AHP was used to choose the best plan according to system dynamics analysis result.

In this chapter, the proposed solution methods for DMCDM problems in the literature are presented. In addition, combining SD with MCDM is mentioned. In contrast to the studies in the literature, the contribution of this thesis to the literature is as follows:

- Predicting the future performances of alternatives: When the literature is examined, they are tried to make appropriate decisions considering the past and present performance of alternatives. In addition to this, few researchers have proposed to predict their future performances based on their past performances. In this thesis study, SD simulation modeling is used to estimate future performance of alternatives. The aim of the study is to consider the historical data of alternatives as a statistical distribution and provide to understand the changing behavior of alternatives over time by using SD simulation model.

- Changing weights of evaluation criteria: The studies in the literature have argued that time factor should be taken into account in MCDM problems. However, the studies have only conducted to evaluate the change in performance of alternatives. Not only the change in the performance of alternatives, but also the changes in the weight of the evaluation criteria should be considered in decision making process. In this thesis, the changes in the weight of the criteria in different time periods are also taken into consideration.

- Determining the best alternative for the long term: In the literature, it is intended to determine the best alternative for the future. However, it is not enough to evaluate the past and present performances of alternatives. As mentioned at the beginning, it is crucial to be able to predict the future. Here, SD modeling is identified as a suitable tool to predict the performance of alternatives in the future. When the literature is examined, it is seen that SD is used together with MCDM models. In these studies, after determining an alternative by means of any MCDM method, the long term performance of

the chosen alternative has been examined with the help of SD simulation model. Besides, after all alternatives are evaluated via SD simulation model, the outputs of the simulation are utilized as input for MCDM models. The purpose of this thesis is to use SD as a solution method for MCDM problems. Thanks to SD, it is possible to assess MCDM problems dynamically.

CHAPTER FOUR
THE PROPOSED METHOD

4.1 Introduction

In the previous chapter, the methods proposed in the literature for DMCDM problems are discussed. In general, when the proposed methods are examined, the past and current performance information of alternatives are collected with an appropriate aggregation operator, and so the performance value is determined for each alternative. Accordingly, the best performing alternative for all periods has been preferred. Evaluating the success of the alternatives in different time periods is a good approach to make right decisions. However, it may not be sufficient to just consider past and current performance in the evaluation of decision options. In addition, it is necessary to foresee the future of performances, since decisions are related to the future. However, predicting the future is a very difficult process. For this purpose, it is benefit from system dynamics software in this thesis to predict future performance of alternatives.

System dynamics has been a guiding tool for decision makers to solve complex problems. So far, it has been utilized in many areas. The basic logic of system dynamics is that analyzes the changes in the system over time by considering the relationships between the system components, and help us understand the system as a whole.

In order to understand the changing behavior of alternatives in MCDM problems, it is necessary to specify the factors which affect the performance of alternatives and evaluate them from a holistic perspective. Therefore, the system dynamics methodology can be an appropriate approach to deal with such problems.

The steps of proposed method for solving DMCDM problems will be explained in the following subsection respectively.

4.2 Phases of the Proposed Method

In this thesis, system dynamics modelling is implemented to solve DMCDM problems. The flow chart of the proposed method is clearly presented in figure 4.1. The steps of proposed method are described below one by one.

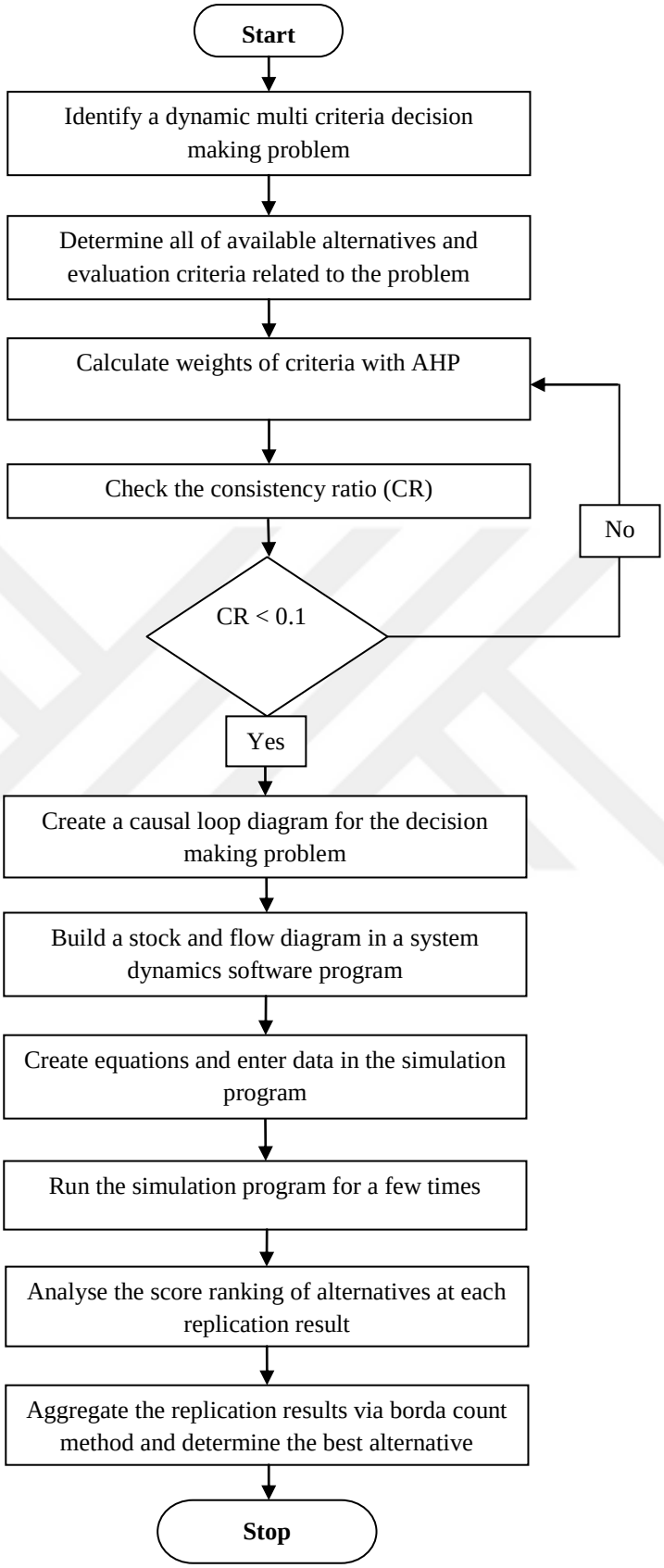


Figure 4.1 Flow chart of the proposed method

4.2.1 Description of Dynamic Multi Criteria Decision Making Problem

The first stage of the proposed method is the determination of a DMCDM problem. At this stage, the decision makers clearly define the problem and determine the objectives they want to achieve. They specify the evaluation criteria appropriate for their purposes. As mentioned previously, the number of evaluation criteria varies based on the nature of the decision problem. If the number of criteria is large, then these criteria are arranged by means of a hierarchical structure. At this stage, besides the determination of the criteria, a set of alternative solutions are specified for the decision problem.

4.2.2 Calculation Weights of Evaluation Criteria

AHP which is one of the multi criteria decision making methods was developed by Thomas Saaty in the mid 1970s. It is a mathematical theory, which used for measuring and decision making (Saaty & Niemira, 2006). This method has been implemented to the decision making problems in different fields successfully since its emergence. In this thesis, AHP is implemented to determine the weights of criteria.

AHP is a measurement theory that enables obtaining priority values between two things through pair wise comparisons based on decision makers' opinition. The comparisons are made to determine how much more important one criterion than the other criterion, so an absolute judgment scale is needed to make comparisons (Saaty, 2008a). Table 4.1 provides the fundamental scale of absolute numbers proposed by Saaty.

Table 4.1 The fundamental scale of absolute numbers (Saaty, 2008a)

Intensity of importance	**Definition**	**Explanation**
1	Equal importance	Two factors are equally important
3	Moderate importance	One factor is more important than the other
5	Strong importance	One factor is strong importance than the other
7	Very strong or demonstrated importance	One factor is very strong importance than the other
9	Extreme importance	One factor is extreme importance than the other
2, 4, 6 and 8	Intermediate values	They are used for values between two values

The steps of the AHP method to specify the weights of criteria in decision making problems are explained individually below:

Step 1: Forming a pairwise comparison matrix between decision criteria

In this step, decision makers form a pair wise comparison matrix to specify the relative importance of the criteria using the scale of 1-9 proposed by Thomas Saaty. Table 4.1 provides the scale of 1-9 which will be used to create the pair wise comparison matrix. Using the scale of 1-9, the criteria are compared in pairs and obtained degrees of superiority. Equation 4.1 shows the pairwise comparison matrix in size nxn.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{4.1}$$

Step 2: Normalization of the pairwise comparison matrix

After the pair wise comparison matrix is created, normalization is implemented for this matrix. To do this, after each column is added, each element of the matrix is divided by the sum of their columns. While equation 4.2 provides the normalization formula, equation 4.3 presents the normalized matrix.

$$d_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{4.2}$$

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ d_{n1} & d_{n2} & \cdots & d_{nn} \end{bmatrix} \tag{4.3}$$

Step 3: Calculation of weights of the criteria

After the normalization, the average of each row of the normalized matrix is calculated based on equation 4.4 and obtained the weights of criteria. Equation 4.5 presents weight vector.

$$w_i = \frac{\sum_{j=1}^{n} d_{ij}}{n} \tag{4.4}$$

$$w = \begin{bmatrix} w_1 \\ w_2 \\ \cdots \\ w_n \end{bmatrix} \tag{4.5}$$

Step 4: Calculation of consistency ratio (CR)

Since AHP is an evaluation method that depends on the decision makers' opinions, it is possible that there are inconsistencies in the evaluations. Since inconsistent assessment will affect the accuracy of the results, it should be checked whether it is consistent. In cases of inconsistency, decision makers should review the pairwise comparison matrix.

The consistency ratio is computed with the equation 4.6.

$$CR = \frac{CI}{RI} \tag{4.6}$$

CR: Consistency ratio
CI: Consistency index
RI: Random indicator

Consistency index is computed with the equation 4.7.

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{4.7}$$

$\lambda_{\max}$: The largest eigenvalue in the matrix
n: numbers of criteria

In order to find the largest eigenvalue ($\lambda_{\max}$) in the matrix:

- Multiply the pairwise comparison matrix (A) formed by the decision maker at the beginning by the weight vector (W).
- The resulting matrix is divided by the weight vector (W).
- The obtained values are averaged, and thus the largest eigenvalue is found.

The random index values determined for each nxn dimension matrix are found in table 4.2.

Table 4.2 Random index (Saaty, 2008b)

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

If the consistency ratio is less than 0.10, then the comparison of the decision maker is consistent. On the other hand, if this value is greater than 0.10, the comparison process should be reviewed.

4.2.3 Creating a Causal Loop Diagram for the Decision Problem

In DMCDM problems, decision makers define criteria related to the decision problem and the variables that affect these criteria. Then the relationships between variables are determined and a causal loop diagram is established. Thanks to these diagram, we can understand visually that relationships between variables, feedback loops and time delays. Since the detailed information about these diagrams is given in chapter 2, it is not mentioned it here again. See chapter 2 for more information.

4.2.4 Building a Stock and Flow Diagram

As mentioned earlier, even though causal loop diagrams are appropriate tools to demonstrate mutual relationships and feedback loops in problems, they don't provide mathematical operations to be performed. This requires stock and flow diagrams. Many system dynamics software like Vensim, Powersim, Stella, I-think is available to create stock and flow diagrams.

After developing stock and flow diagrams in a suitable system dynamics simulation software, mathematical equations related to the problem are formed to run the program. After the necessary conditions are met, it is decided how long the program will run and the program runs.

4.2.5 Analyzing the Result and Determine the Best Alternative

In this study, since it is aimed to make an estimation about the future performance of alternatives, firstly the statistical distributions of past performance values of alternatives are examined. Accordingly, it is tried to predict how one of alternatives will perform in the future. Therefore, the simulation program is run several repetitions to estimate this. As a result, different ranking values are obtained for each repetition. In order to convert these raking values into a single ranking value, the borda count method is utilized here. As a result of this process, the best alternative is estimated.

4.2.5.1 Borda Count Method

The Borda count method provides a single ranking by combining two or more different ranking lists. This method is generally used in group decision making methods. Scoring technique is implemented in this method. In the ranking where there are N alternatives, while 1 point is given to the lowest alternative, N point is given to the top alternative. We can explain this with an example. Table 4.3 presents that four different voters rank four different candidates. The borda count method is applied to obtain a single ranking from these different rankings. According to this, 4 points for each first ranked candidate, 3 points for each second ranked candidate, 2 points for each third ranked candidate and 1 points for each fourth candidate are given. Finally, score values are calculated.

Let’s look at the score calculation of candidate A as an example.

- Multiplied by 2 and 4, since it takes two times in the first rank.
- Multiplied by 3 and 1, since it takes one time in the second rank.
- Multiplied by 2 and 1, since it takes one time in the third rank.
- Multipled by 1 and 0, since it takes no time in the forth rank.

The calculated product values are summed and a score for A is obtained. The same procedures are implemented to all other candidates. Finally, all the results obtained are compared and ranked from the highest to the lowest score.

Table 4.3 Borda count method

	Voters			
Ranking	**V_1**	**V_2**	**V_3**	**V_4**
1st	A	C	A	D
2nd	C	B	B	A
3rd	D	A	D	C
4th	B	D	C	B

A: (4 x 2) + (3 x 1) + (2 x 1) + (1 x 0) = 13

B: (4 x 0) + (3 x 2) + (2 x 0) + (1 x 2) = 8

C: (4 x 1) + (3 x 1) + (2 x 1) + (1 x 1) = 10

D: (4 x 1) + (3 x 0) + (2 x 2) + (1 x 1) = 9

A > C > D > B

CHAPTER FIVE
APPLICATION

In this chapter, an example of supplier selection with a DMCDM problem is discussed to show the applicability of the method proposed in chapter four.

5.1 Long Term Supplier Selection Problem

Nowadays, with the impact of globalization and the increase of competitive environment, it becomes more difficult for companies to survive. In such environment, the survival of companies could be possible by adapting themselves to changing needs and continuous improvement. With the help of responding quickly to customer needs and adopting themselves to the changing environment will support the organizations to successfully maintain their presence in the market for many years.

One of the most important factors for the success of companies is the effective management of the supply chain. Especially, in such competitive environment, the better the company manages the supply chain, the more powerful it becomes among their competitors. The most critical factor in supply chain management is the management of suppliers effectively. No matter how successful a company is, its success can be adversely affected by its supplier related problems. If we want to explain this with an example, although the company produces very high quality products, late delivery of a supplier can delay production process. This causes that the company to fail delivery of the products on time. Eventually, this type of problem can lead to loss of customers.

In terms of competitive advantage, it is crucial to select right suppliers we work together. The problem of supplier selection is one of the most important strategic decision problem of companies. In this decision problem, enterprises try to determine the most suitable supplier for their objectives. Companies in the trend of global supply chain management want to cooperate with their chosen suppliers for a long

period of time as well as choosing the right supplier (Chiang, 2005). Supplier evaluation and selection means evaluating and ranking suppliers' performances and selecting the most appropriate. In order to evaluate the performances of suppliers, companies establish evaluation criteria that are suitable to their objectives and compare the supplier performance according to these criteria (Sonawane & Rodrigues, 2013).

Supplier evaluation and selection problems are MCDM problems where multiple qualitative and quantitative factors are considered together. Numerous MCDM methods have been suggested in the literature about the solution of these problems (Ho, Xu, & Dey, 2010, Yıldız & Yayla, 2015). However, as mentioned in the previous sections, some decision making problems should be decided by considering the time factor. Since supplier selection problems are decision problem in a changing dynamic environment where their success based on a criterion can change over time, we need to consider time factor in the evaluation process. In the literature, just few researchers have emphasized time factor for decision making problems and suggested some new approaches that add time factor to classical MCDM methods. They have named this type of problems as DMCDM.

Until today, static and dynamic decision making methods have been applied in supplier evaluation and selection problems. However, none of these studies have addressed reasons how behavior of suppliers changing over time. In this thesis, supplier performance change is accepted as a system with nonlinear behaviors, feedback loops and time delays. Therefore, it is aimed to observe the change of performance of suppliers over time. In addition, it is intended to create a model that supports DMCDM.

5.2 Definition of Supplier Evaluation Criteria and Alternatives

As previously mentioned, supplier selection problems are MCDM problems, in other words when assessing a supplier performance most of factors (qualitative and quantitative) are taken into consideration. Dickson (1966) determined 23 important

criteria to evaluate the performance of suppliers and ranked them based on their priorities. According to this study; quality, on time delivery and performance history are the most important criteria. Weber, Current, & Benton (1991) investigated 74 articles about supplier selection criteria and methods from 1966 to 1991. They indicated that net price, delivery performance and quality are the most crucial factors. Deshmukh & Chaudhari (2011) analysed 49 articles from 1992 to 2007. According to their study, net price, quality and on time delivery are very important criteria for evaluation of suppliers' performance.

In the light of the information obtained from the literature, in this study, six different evaluation criteria have been determined to evaluate the performance of supplier. Furthermore, five different suppliers are considered as alternatives. Figure 5.1 presents the problem of supplier evaluation and selection in a hierarchical order.

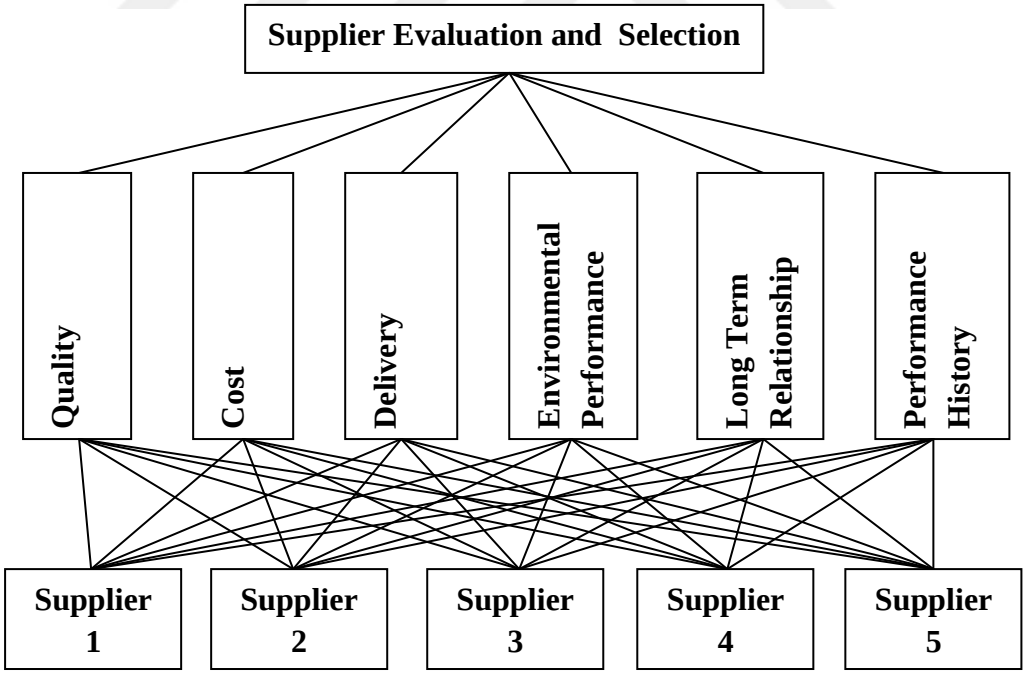


Figure 5.1 Hierarchy of supplier evaluation and selection

5.3 Calculation of Weights of Supplier Evaluation Criteria

Each of the supplier evaluation criteria has different weights or relative importance. To determine weights of the criteria, the AHP is applied in this thesis. The computation of weights of criteria is provided step by step below.

Step 1: Forming a pairwise comparison matrix between supplier evaluation criteria

Pairwise comparison matrices are formed to define the degree of importance between criteria based on the opinions of decision makers. It is assumed that there is only one decision maker in this decision problem. Accordingly, the pairwise comparison matrix created by the decision maker is presented in table 5.1.

Table 5.1 Pairwise comparison matrix of the supplier evaluation criteria

	Quality	**Cost**	**Delivery**	**Environmental Performance**	**Long Term Relationship**	**Performance History**
Quality	1	3	3	3	5	4
Cost	1/3	1	1/3	3	4	3
Delivery	1/3	3	1	3	4	4
Environmental Performance	1/3	1/3	1/3	1	4	3
Long Term Relationship	1/5	1/4	1/4	1/4	1	1/3
Performance History	1/4	1/3	1/4	1/3	3	1

Step 2: Normalization of the pairwise comparison matrix

The pair wise comparison matrix formed in the first step is normalized using the Formula in 4.2. Table 5.2 provides the normalized matrix.

Table 5.2 Normalization of the pairwise comparison matrix

	Quality	Cost	Delivery	Environmental Performance	Long Term Relationship	Performance History
Quality	0.42	0.38	0.58	0.28	0.24	0.26
Cost	0.14	0.11	0.06	0.28	0.19	0.20
Delivery	0.14	0.34	0.19	0.28	0.19	0.26
Environmental Performance	0.14	0.04	0.06	0.09	0.19	0.20
Long Term Relationship	0.08	0.03	0.05	0.02	0.05	0.02
Performance History	0.11	0.04	0.05	0.03	0.14	0.07

Step 3: Calculation weights of criteria

After the normalization process, the formula in 4.4 is applied to obtain the weights of supplier evaluation criteria shown in table 5.3.

Table 5.3 Weights of the supplier evaluation criteria

	W
Quality	0.36
Cost	0.17
Delivery	0.24
Environmental Performance	0.12
Long Term Relationship	0.04
Performance History	0.07

Step 4: Calculation of consistency ratio

The consistency ratio is computed to specify whether the weights of criteria found are consistent. Consistency ratio is calculated by using the formula 4.6. In this study, the consistency ratio was found to be 0.088. Since the value is less than 0.1, the evaluation is consistent.

5.4 Creating Causal Loop Diagram to Analyze the Behavior of Suppliers

After the weights of supplier evaluation criteria are determined, the variables that affect the performance of the suppliers are identified and a causal loop diagram showing the relationships between these variables and feedback loops together is created. As mentioned before, causal loop diagrams are very useful visual tools that allow us to see easily the relationships between the components and loops in the system. These diagrams also provide a basis for creating stock and flow diagrams. In this thesis, Vensim PLE x32 software program which makes a good presentation visually is used to create causal loop diagrams. In order to clearly represent the causal loop diagrams, each feedback loop is described individually and ultimately the complete causal loop diagram is presented in APPENDIX 2.

5.4.1 Feedback Loop of Quality Improvement

One of the most important issue in supplier evaluation is that the supplier can provide quality goods and services. Therefore, suppliers attempt to continuously improve their quality so as to survive in a competitive environment. Thus, they increase the probability of being selected by the companies. Figure 5.2 shows the relationships between factors and feedback loop related to suppliers' quality improvement. According to this loop, as the performance score of the supplier improves, the company will order more from that supplier. If the order quantity from the supplier increases, then income level of preferred supplier raises. The supplier whose income level rising will start to invest in itself. Therefore, it can improve its performance and keep up with competitive environment. These investments are made based on the weight rations of the criteria that companies attach importance to. The whole of the causal loop diagram of this study which clearly shows the direction where investments will be allocated is provided in APPENDIX 2. Figure 5.2 only shows investment in quality. Accordingly, as the weight of quality criteria increases, investment in quality increases too. However, seeing the investment results may not happen immediately. Namely, after making investment, the return on investment takes a certain time. The sign on the arrow between investment of quality and quality

score represents the delay. At the end of a certain time period, quality score of the supplier will increase. Both of quality score and weight of quality criteria increase quality performance effect. As quality performance effect increases, supplier performance score rises too. The feedback loop is positive. The rolling snow ball shown in the middle of the loop indicates that the loop is a positive feedback loop.

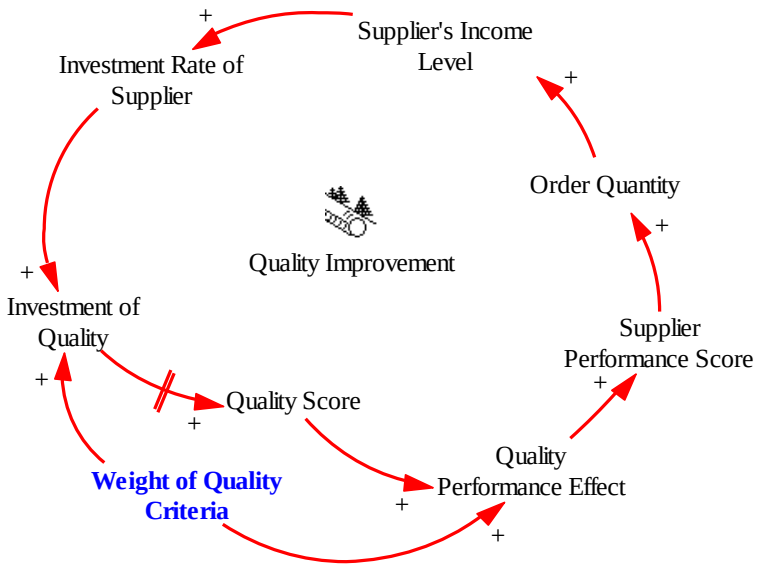


Figure 5.2 Feedback loop of quality improvement

5.4.2 Feedback Loop of Cost Improvement

One of the goals of the company is to reduce costs. Therefore, when evaluating suppliers, supplier with low cost is a preferable reason. For this reason, suppliers give importance to this criterion not to lose their customers. Otherwise, companies start to work with another competing supplier. All of the situations that occurred quality improvement feedback loop stated above will be the same in this loop. The cost improvement feedback loop is provided in figure 5.3. As the supplier performance score increases, the order quantity given to that supplier will increase. The amount of the order will enhance the income level of supplier. Higher the income level means higher investment rate of the supplier. Here, the supplier will try to develop various ways to reduce its costs. For example, it may plan to reduce its energy consumption by investing in alternative energy resources, and thus reducing

its costs. Similar to delays in quality return on investment, there will be delays in the impact of the cost reducing investments. After a certain time delay feedback on the investment, these investments will augment the cost score. Here, the increase in the cost score means a decrease in the cost level. It mustn't be confused with the meaning that the cost increases as the investment increases. Cost score and weight of cost criteria pile up cost performance effect, and so supplier performance score go up.

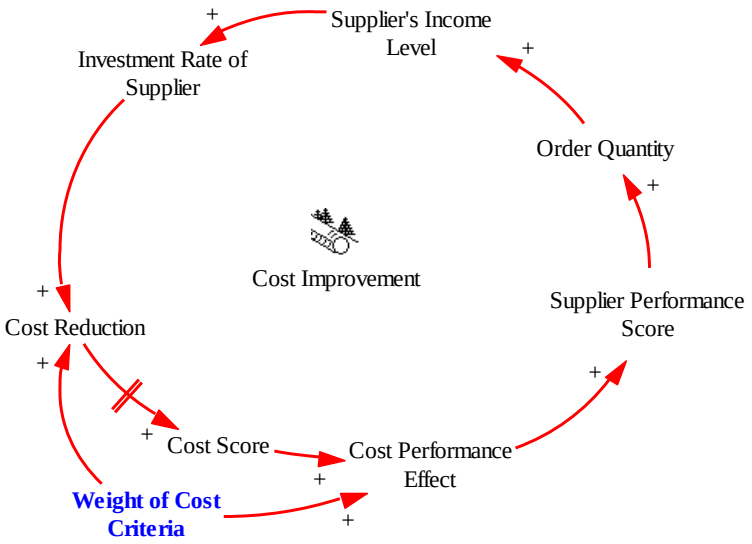


Figure 5.3 Feedback loop of cost improvement

5.4.3 Feedback Loop of Delivery Improvement

Another crucial issue for the companies is the delivery performance of the suppliers. If a supplier delivers the product to the company in the right amount, undamaged and just in time, then the success of the company will be positively affected. Therefore, companies prioritize this criterion in supplier evaluation. For this reason, suppliers try to improve their delivery performance. So they can increase their chances of to be selected. Figure 5.4 presents the feedback loop of delivery performance improvement, which is similar to the feedback loop of quality improvement and the feedback loop of cost improvement mentioned above. The investment made here is based on the weight of delivery criteria to improve delivery

score of supplier. Here, the supplier can increase the number of product distribution centers and purchase new transportation vehicles by means of the investment made to improve delivery performance. Again, the return on investment takes a certain time. As a result, the delivery performance of the supplier will increase and this will have a positive effect on the total performance score.

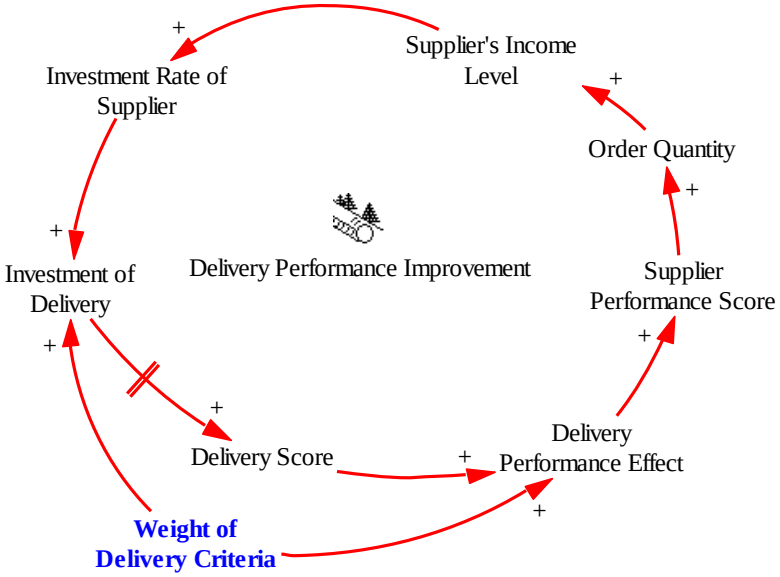


Figure 5.4 Feedback loop of delivery performance improvement

5.4.4 Feedback Loop of Environmental Improvement

With the increase in environmental pollution and the necessities and sanctions imposed by the legal regulations, companies have started to give importance to environmental issues. Although the company give importance to this issue, because of the fact that the supplier does not pay the same attention to this affects the performance of the company negatively. Therefore, environmental performance of the suppliers is an important factor when suppliers evaluated. For this reason, suppliers must meet certain standards about environment, which should develop themselves in the field of environmental awareness and have certain environmental certificates. Figure 5.5 shows the feedback loop of environmental performance of the supplier. The loop is similar to other feedback loops of quality improvement, cost improvement and delivery improvement. The investment is made to improve the

environmental performance of the supplier. As any investment, delays in return on investment occur here. The investment affects environmental score positively. Consequently, total performance of the supplier will improve.

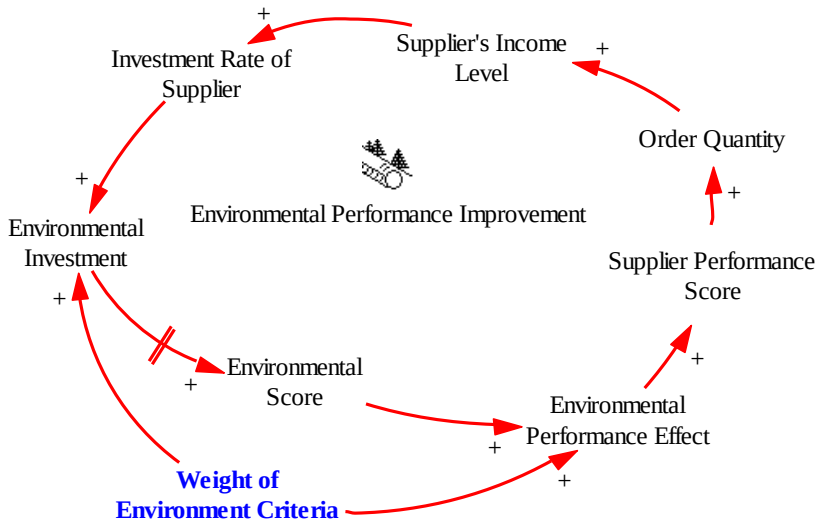


Figure 5.5 Feedback loop of environmental improvement

5.4.5 Feedback Loop of Past Performance Effect

One of the issues criticized in classical MCDM problems is the lack of consideration of the time factor. A number of alternatives are evaluated according to a set of criteria, ranked and the best one is preferred. This form of evaluation is static. Therefore, DMCDM methods which take into account the time factor have been proposed to overcome this deficiency in the literature. For this, in this study past performance of suppliers is taken into consideration instead of just thinking their performance in a single period. The feedback loop of past performance effect is provided in figure 5.6. Accordingly, the supplier performance score calculated at the end of each period constitutes the past performance score for the following period. For example, the performance score of supplier in April is considered as past performance score for supplier assessment in May. This is similar to the DMCDM framework proposed by Campanella and Ribeiro (2011). The difference here is that

past performance is considered as a criterion and multiplied by a weights of criteria and then the obtained value is put into evaluation.

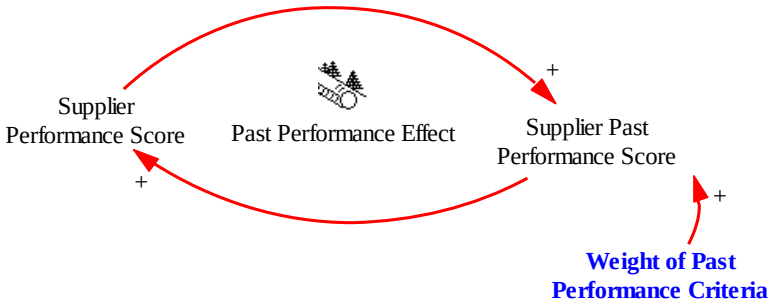


Figure 5.6 Feedback loop of past performance effect

5.4.6 Feedback Loop of Long Term Relationship Effect

In the selection of suppliers, long term relations are preferred rather than short term relations with suppliers. The longer a company work with a supplier, the more information about that supplier, and so the more likely risks are avoided. Here, long term work with the supplier is considered to be proportional to the order quantity given to it. A high performance score of the supplier is preferred by companies. More orders are made from the supplier with the highest performance compared to other suppliers. This strengthens long term relationships with the supplier. Figure 5.7 provides a feedback loop showing the behavior of suppliers in the long term relationship.

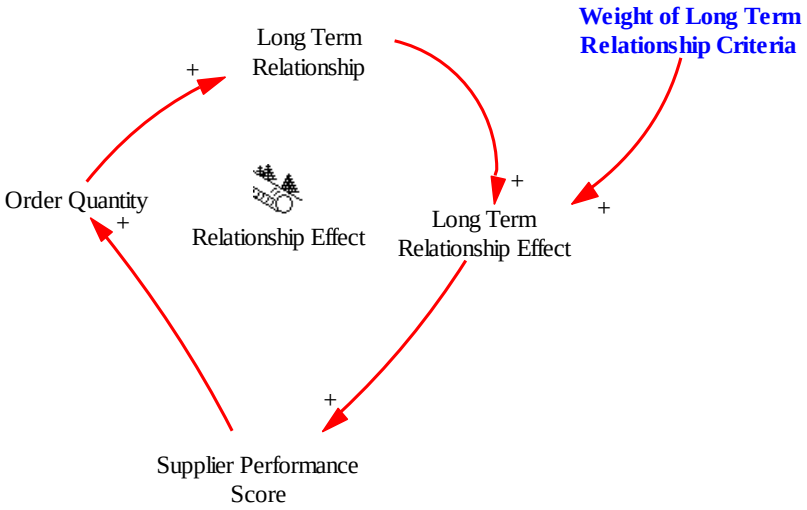


Figure 5.7 Feedback loop of relationship effect

5.5 Building Stock and Flow Diagram

After creating the causal loop diagram of the supplier behavior change, a stock and flow diagram was developed to simulate this behavior change based on the causal loop diagram. Stella 10.0.4 software, which is one of the system dynamics software, was used to build the stock and flow diagram which is shown in APPENDIX 3. The running time of the model was determined as 84 months, namely 7 years. The equations created in the installation of the model are explained below one by one. In addition, a complete version of the equations in the model is provided in APPENDIX 4.

5.5.1 Assumptions

Before the equations created in the model, some assumptions were made. These assumptions are as follows:

1. Since the example of supplier performance evaluation in this thesis is a hypothetical example and there is not any real data about suppliers, the initial value of each criteria of each supplier is assigned normal distribution.

2. The success of suppliers in each criterion is considered normalized. All values range from 0 to 1.
3. The return on investment of suppliers is indicated by monthly delays which are assigned randomly.
4. It is assumed that the impact of each investment is not 100 %. For this reason, it is multiplied by a random number.
5. Other factors affecting supplier behavior have been ignored here.

5.5.2 Equation of the Model

After developing the stock and flow diagram, equations are created to run the simulation model. Now, these equations will be explained step by step.

Stocks, one of the main elements of Stella software, accumulate everything that flows through the model. By looking at the stocks, we learn about the state of the system at a given time. In the model, total performance, quality, cost, delivery and environmental scores of suppliers are defined as stocks. Initial values of these stock variables are determined and presented in table 5.4.

Another main element of the Stella software is *flows* which fill or drain the stocks. In the model, increases and decreases in the criteria scores of suppliers and total performance changes of suppliers are defined by flow variable. Table 5.5 provides equations of the flow variables in the model.

Converters are the auxiliary element of system dynamics. The creation of fixed numerical values, the use of graphical functions and importing external inputs into the model is performed with these elements. Table 5.6 presents equations of the converters in the model.

Values in table 5.4, 5.5, and 5.6 belong to supplier 1. If you want to see equations for other suppliers, you can look at APPENDIX 4.

Table 5.4 Equations of stock variables

Stock Variable	Equation	Explanation
Supplier Per Score	Quality Score * weight of quality criteria + Cost Score * weight of cost criteria + Delivery Score * weight of delivery criteria + Environmental Score* weight of environment criteria	At the beginning of the simulation model, all suppliers have a total score value. This equation calculates the initial scores of suppliers which was calculated before starting the simulation model. Here the initial score value of each criterion is multiplied by its weights and then all multiplication values obtained are summed. That is, the formula of the weighted sum method which is one of MCDM techniques is applied. While the scores of all criteria are taken into consideration in this equation, long term relationship and past performance criteria are not considered. Because there is no historical information and long term working experience with suppliers at the beginning, so the effect of past performance and long term relationship are ignored there.
Quality Score	NORMAL (0.72, 0.10)	Each one demonstrates the success of supplier 1 in the relevant criteria at the beginning. The initial values of these variables are presumptively assigned to normal distribution. For example, quality score of the supplier at the beginning is NORMAL (0.72, 0.10) which means average value is 0.72, standart deviation is 0.10.
Cost Score	NORMAL (0.63, 0.10)	
Delivery Score	NORMAL (0.75, 0.11)	
Environmental Score	NORMAL (0.76, 0.11)	

Table 5.5 Equations of flow variables

Flow Variable	Equation	Explanation
quality score increase	(investment of quality * (1 - Quality Score)) / quality investment delay	The increases in criteria scores of suppliers are calculated by these equations which are logically similar. For example, the increase in quality score is affected by investment of quality, quality score and investment delay. The investment in quality affects quality based on current quality score. Namely, if quality score is low, the impact of investment is more.
cost score increase	(investment of cost * (1 - Cost Score)) / cost reduction delay	
delivery score increase	(investment of delivery * (1 - Delivery Score)) / delivery investment delay	
environmental score increase	(environmental investment * (1 - Environmental Score)) / environmental investment delay	
quality score decrease	Quality Score * RANDOM (0.001, 0.005)	The scores of criteria will decrease as well as increase. This means that the supplier may not be in a state of continuous improvement. For this, an outflow variable that reduces each criterion score is defined. According to the equations, the score of each criterion decreases by any random.
cost score decrease	Cost Score * RANDOM (0.001, 0.005)	
delivery score decrease	Delivery Score * RANDOM (0.001, 0.005)	
environmental score decrease	Environmental Score * RANDOM (0.001, 0.005)	
Total score of supplier performance change	((delivery performance effect + quality performance effect + past performance effect + environmental performance effect + cost performance effect) – Supplier Per Score) * (1 – Supplier Per Score)	The effects of all criteria are summed to obtain the total performance score change. In this equation the meaning of "1 – Supplier Per Score" is never intended to exceed 1. To achieve this, the equation is finally multiplied by this value.

Table 5.6 Equations of convertor

Convertor	Equation	Explanation
order quantity	Supplier Per Score [1] / (Supplier Per Score [1] + Supplier Per Score [2] + Supplier Per Score [3] + Supplier Per Score [4] + Supplier Per Score [5])	The quantity of products ordered from suppliers which is indicated as "order quantity" in the simulation model is influenced by the total performance score of the suppliers. The highest quantity of products will be ordered from the best performance score of supplier.
supplier's income level	order quantity	If the quantity of products purchased from a supplier increase, the income level of the supplier rises. Namely, the income level is directly proportional to the order quantity.
investment rate of supplier	supplier's income level	In a changing competitive environment, suppliers have to adapt themselves to this environment and constantly improve themselves. Otherwise, they lag behind other competitors. For this reason, a supplier whose income level increases will start to invest in itself so as to keep up with competitive environment. Investment rates of suppliers will vary based on their income level. The higher income level means the higher investment rate.
investment of quality	weight of quality criteria * investment rate of supplier * RANDOM (0.2, 0.6)	When suppliers will invest, they will decide what to invest in according to the weights of criteria determined by the company. For instance, if the company pays much more attention to quality criteria than other criteria when evaluating its suppliers, the suppliers will want to improve quality performance to be better than other competing suppliers. In this case, the supplier will allocate its investments according to the importance of the criteria. A notable case in the equations is that each one is multiplied by
investment of cost reduction	weight of cost criteria * investment rate of supplier * RANDOM (0.2, 0.6)	
investment of delivery	weight of delivery criteria * investment rate of supplier * RANDOM (0.2, 0.6)	

Table 5.6 continues

environmental investment	weight of environment criteria * investment rate of supplier * RANDOM (0.2, 0.6)	RANDOM (0.2, 0.6). This randomness can be think as investment efficiency. That is, not every investment affects quality as planned, but at a certain rate.
quality investment delay	RANDOM (2, 4)	Investments are made to improve things, make it better. However, when investments are made, it may not be possible to see their effects immediately. Return on investment happens after a certain period of time. It is assumed that each investment will be delayed and delay time is specify as random. Thanks to investments of suppliers, their scores in each criterion will become better.
cost reduction delay	RANDOM (2, 4)	
delivery investment delay	RANDOM (2, 4)	
environmental investment delay	RANDOM (2, 4)	
weight of quality criteria	0.36	The weights of criteria determined by the decision maker with AHP method.
weight of cost criteria	0.17	
weight of delivery criteria	0.24	
weight of environment criteria	0.12	
weight of past performance	0.07	

Table 5.6 continues

weight of long term relationship criteria	0.04	
long term relationship	order quantity	As the quantity ordered from the suppliers increases, the company will work with this suppliers long period of time.
quality performance effect	Quality Score * weight of quality criteria	In order to calculate the total scores of suppliers, firstly the impact each criterion on total performance is computed. Therefore, each criterion score is multiplied by its weights. In order to calculate the past performance effect of suppliers, the total performance score of the suppliers in the previous period is taken into consideration.
cost performance effect	Cost Score * weight of cost criteria	
delivery performance effect	Delivery Score * weight of delivery criteria	
environmental performance effect	Environmental Score * weight of environment criteria	
past performance effect	Supplier Per Score * weight of past performance	
long term relationship effect	long term relationship * weight of long term relationship criteria	

5.6 Analyzing the Results and Determine the Best Supplier

After running the simulation program, the time dependent performance change graph of each supplier is obtained. Figure 5.10 provides this graph. As mentioned before, the duration of the simulation model is specified 84 months, namely 7 years.

Since we use random numbers to create simulation equations, the graphs obtained each time when we run the simulation will give different values. Accordingly, this simulation program was run with 100 replications in order to estimate the performance values of the supplier 7 years later. At the end of each run, a table was created by considering the ranking values in 7th year. This table is presented in APPENDIX 5. Figure 5.8 represents the results of a replication. According to this graph, the ranking of the suppliers are as follows: S5 > S2 > S3 > S4 > S1

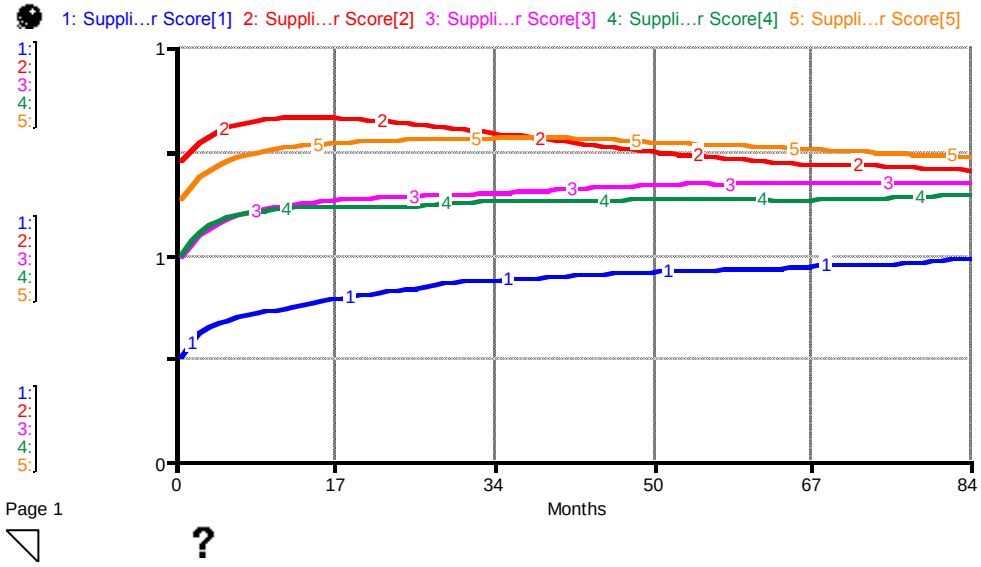


Figure 5.8 Change of performance scores of suppliers over time

Borda count method is an appropriate approach to convert different ranking values obtained from 100 replications into a single ranking value. Therefore, a single ranking value is obtained from all rankings by using borda count method. Thus, the best alternative for the future can be predicted. Table 5.7 gives the calculation of the borda count method ranking of the supplier. As a result of the calculations, the new

order of suppliers is as follows: S4 > S2 > S1 > S3 > S5. Accordingly, the best supplier has been identified as S4.

Table 5.7 Results of the borda count method for the first simulation model

	1st	**2nd**	**3rd**	**4th**	**5th**	
S1	17	22	21	25	15	(17x5) + (22x4) + (21x3) + (25x2) + (15x1) = 301
S2	24	17	22	19	18	(24x5) + (17x4) + (22x3) + (19x2) + (18x1) = 310
S3	17	21	25	19	18	(17x5) + (21x4) + (25x3) + (19x2) + (18x1) = 300
S4	27	23	13	15	22	(27x5) + (23x4) + (13x3) + (15x2) + (22x1) = 318
S5	15	17	19	22	27	(15x5) + (17x4) + (19x3) + (22x2) + (27x1) = 271

5.7 Changing of Weights of Criteria

In classical multi criteria decision making methods, it is assumed that weights of criteria are constant when evaluating alternatives. However, it is not realistic assumption in real life decision problems, because weights of criteria can change over time. If a criterion develops significantly, then the relative importance of this criterion decreases (Vo et al., 2002). To illustrate this, delivery is not a distinguishing variable for a company if all suppliers of a company deliver products on time. Therefore, the weight value of delivery criteria in supplier evaluation process will be less than weights of other criteria. However, when the problems related to the delivery performance start to emerge, the weight value given to this criterion increases. Therefore, there is an opposite relationship here.

In this study, the weights of the supplier evaluation criteria were calculated with the help of AHP in chapter 5.3 and it was assumed that these values did not change

over time. Here, the weight of the evaluation criterion depends on the performance of the suppliers in this criterion. (APPENDIX 6 presents new created causal loop diagram.) For this, the average value of the criteria is calculated. While the criterion which has the lowest average score is given the highest weight value, criterion which has the highest average score is given the lowest weight value. Thus, changes of weight values have been observed over time. Figure 5.9 and figure 5.10 illustrate this. In figure 5.9, since the average of quality score of suppliers is excellent, the weight given to the quality criteria is decreased over time. On the other hand, in figure 5.10, as the average of environmental score of suppliers decreased, weight of environment criteria increased. In the study, weights of long term relationship and past performance criteria are not included in this change and they are kept fixed, since there is no factor to change the performance of these criteria. Figure 5.11 shows changes of all criteria weights over time. The stock and flow diagram for changing of criterion weights is presented in APPENDIX 7. In addition new equations of the model are provided in APPENDIX 8.

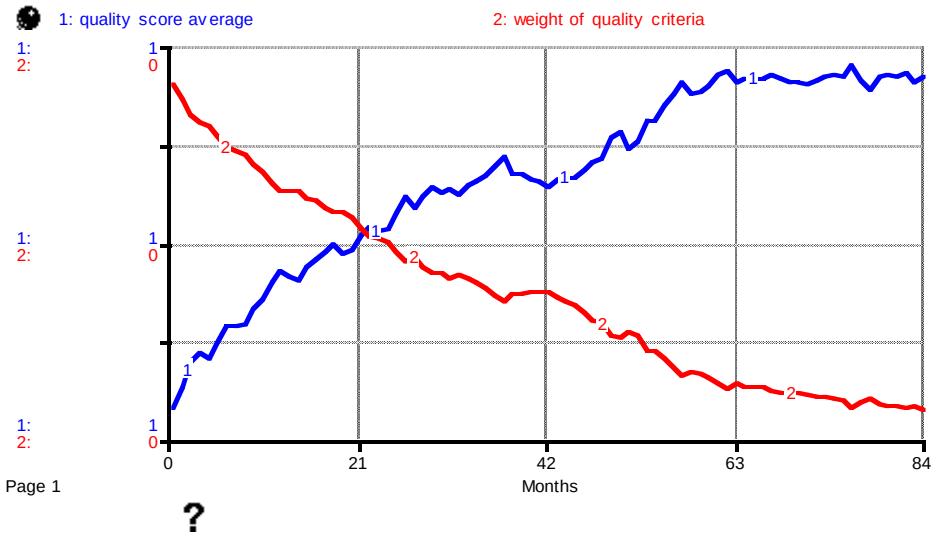


Figure 5.9 Changes of weight of quality criteria



Figure 5.10 Changes of weight of environment criteria



Figure 5.11 Changes of weights of criteria

There may also be changes in the order of alternatives as the weights of criteria change. In order to observe this, the model has been run 100 replications again. The results of replications are presented in APPENDIX 9. The obtained ranking values from the simulation have aggregated with the borda count method. Table 5.8 presents the calculation of the borda count method.

Table 5.8 Results of the borda count method for the second simulation model

	1st	**2nd**	**3rd**	**4th**	**5th**	
S1	1	7	19	46	27	(1x5) + (7x4) + (19x3) + (46x2) + (27x1) = 255
S2	29	30	28	8	5	(29x5) + (30x4) + (28x3) + (8x2) + (5x1) = 370
S3	0	0	4	30	66	(0x5) + (0x4) + (4x3) + (30x2) + (66x1) = 138
S4	38	34	20	7	1	(38x5) + (34x4) + (20x3) + (7x2) + (1x1) = 401
S5	32	29	29	9	1	(32x5) + (29x4) + (29x3) + (9x2) + (1x1) = 382

As a result of the calculations in table 5.8, the new order of suppliers is as follows: S4 > S5 > S2 > S1 > S3. Accordingly, the best supplier has been identified as S4.

5.8 Results

In this study, the performance of suppliers after 7 years is estimated based on their previous performance values. Here, with the help of system dynamics simulation, it is observed how the behavior changes of suppliers over time. When a company chooses a supplier to work together, the income level of this supplier will increase. Thus this supplier will start to invest in itself to keep up with the competitive environment, which will improve its performance. In other words, the change in the performance of the supplier is related to the selection by the company.

In the study, two different simulation models have been established. In the first model, it has been assumed that the weight values of the criteria used to evaluate the performances of suppliers are fixed and these values have been calculated with AHP. On the other hand, the weight values of criteria have been changed according to the average performance of suppliers in the second model. The simulation program has

been run with 100 replicates for two different models separately. Therefore, the ranking values of suppliers have been obtained as a result of each replication. These ranking values have been aggregated by the borda count method and a single ranking has been obtained for the two simulation models separately. When the ranking values obtained from two different simulation models are compared, S4 is the best supplier in both. However, it is seen differences in the ranking of other suppliers. Namely, if the weights of criteria are changed, the order of suppliers can change.

CHAPTER SIX
CONCLUSIONS

Making decision is an action which occurs every moment of our lives. In particular, the decisions that managers make to achieve the objectives of the organizations are strategically important. Decisions of investment, supplier selection, personel promotion are some of the strategic decisions made for organizations. In these decision problems, multiple qualitative and quantitative factors which may be conflict each other are considered together, when making a decision. Since these decisions are very difficult and complex decision problems, scientific methods are needed to support decision makers. For this, the most preferred method in the literature is MCDM methods. However, these methods have been criticized by many researchers, because the time factor is ignored. For this reason, a new decision making approach has been developed by adding time factor to MCDM methods by the researchers. Many solution methods have been proposed for the new modeling approach called DMCDM. In these methods, the past and current performances of alternatives are evaluated together and the most suitable alternative is determined.

Studies in the field of DMCDM are often concern with assessing the past and current performances of alternatives. Just few researchers have suggested that future performances of alternatives should be considered. System dynamics modeling may be an appropriate approach to estimate the changing performance of alternatives over time. In this thesis, system dynamics approach is proposed to solve DMCDM problems. Thus, it is aimed to determine the most suitable alternative for long period of time in dynamic decision making.

To demonstrate the applicability of the proposed method, a supplier selection problem has been solved. With the help of the system dynamics simulation, the performances of five different suppliers after 7 years have been predicted based on their historical data. In the study, two different simulation models have been created. In the first model, weights of the criteria used to evaluate alternatives are assumed to be constant throughout the simulation. The model has been run with 100 repetitions

and as a result different ranking values have been obtained for each repetition. In order to convert these order values into a single order, the borda count method has been applied. Thus, the single order of alternatives has been obtained. In the second model, weights of evaluation criteria have been considered to vary depending on the performance of alternatives throughout the simulation program. Similar to the first program, the program has been run 100 times and different ranking values have been obtained in each repetition. In order to aggregate the ranking values the borda count method has been applied. Finally, when we compare the results of two models, we can interpret that changing weights of criteria also alters the order of alternatives.

This thesis provides a different perspective for the solution of DMCDM problems. According to the results obtained, this proposed method is very effective for making decisions in a constantly changing environment. In the future, this study can be applied to real life supplier selection problems. Moreover it is a suitable solution method not only for supplier selection problems, but also for the problems such as investment decisions, personnel promotion problems, which are all dynamic decision making problems.

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APPENDICES

APPENDIX 1: List of abbreviations

AHP	Analytical Hierarchy Process
DMCDM	Dynamic Multi Criteria Decision Making
MCDM	Multi Criteria Decision Making
SD	System Dynamics

APPENDIX 2

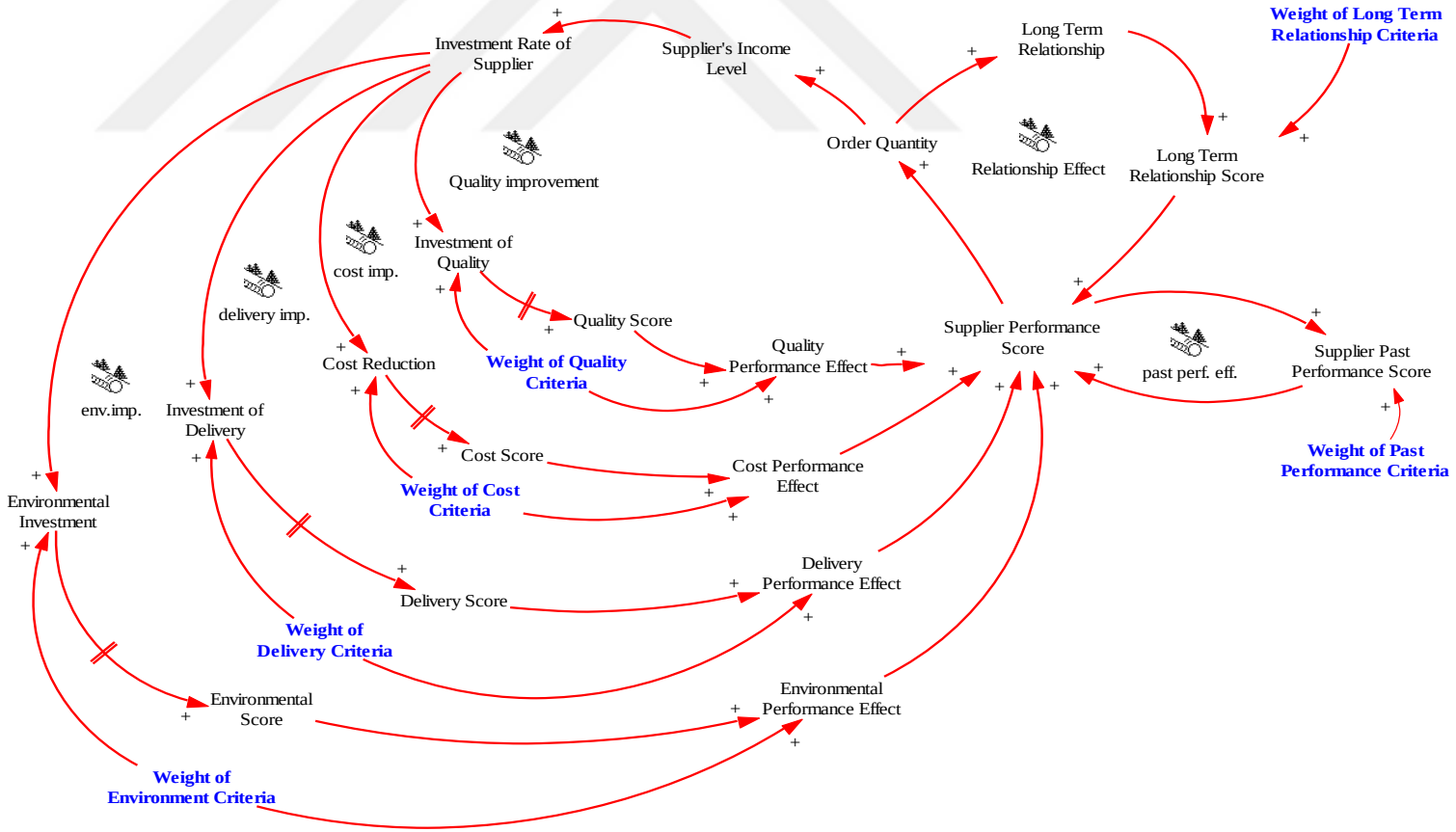


Figure A.1 Causal loop diagram of the performance changing of the supplier (for static weights of criteria)

APPENDIX 3

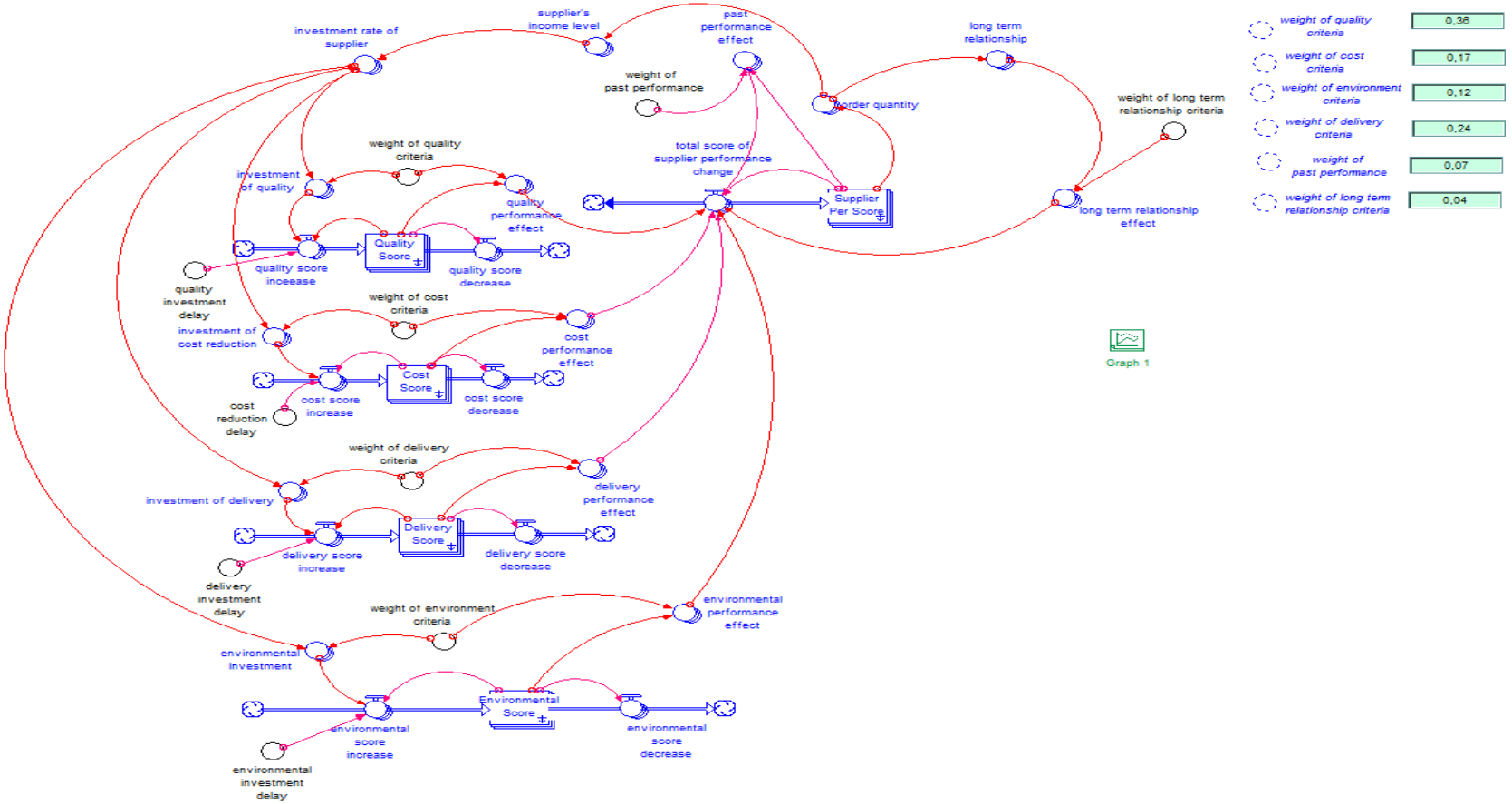


Figure A.2 Stock and flow diagram of supplier evaluation (for static weights of criteria)

APPENDIX 4: Stella model equations for static weights of supplier evaluation criteria

```
Cost_Score[1](t)=Cost_Score[1](t-dt)+(cost_score_increase[Tedarikci]
  -cost_score_decrease[Tedarikci]) * dt

INIT Cost_Score[1] = NORMAL(0.63, 0.1)

Cost_Score[2](t)=Cost_Score[2](t-dt)+(cost_score_increase[Tedarikci]
  - cost_score_decrease[Tedarikci]) * dt

INIT Cost_Score[2] = NORMAL(0.75, 0.1)

Cost_Score[3](t)=Cost_Score[3](t-dt)+(cost_score_increase[Tedarikci]
  - cost_score_decrease[Tedarikci]) * dt

INIT Cost_Score[3] = NORMAL(0.65, 0.1)

Cost_Score[4](t)=Cost_Score[4](t-dt)+(cost_score_increase[Tedarikci]
  - cost_score_decrease[Tedarikci]) * dt

INIT Cost_Score[4] = NORMAL(0.82, 0,12)

Cost_Score[5](t)=Cost_Score[5](t-dt)+(cost_score_increase[Tedarikci]
  - cost_score_decrease[Tedarikci]) * dt

INIT Cost_Score[5] = NORMAL(0.84, 0.1)

INFLOWS:

cost_score_increase[Tedarikci]=(investment_of_cost_reduction*(1-
  Cost_Score) )/cost_reduction_delay

OUTFLOWS:

cost_score_decrease[Tedarikci]=Cost_Score * RANDOM(0.001,0.005)

Delivery_Score[1](t)=Delivery_Score[1](t-dt)+
  (delivery_score_increase[Tedarikci]-
  delivery_score_decrease[Tedarikci]) * dt

INIT Delivery_Score[1] = NORMAL(0.75, 0.11)

Delivery_Score[2](t)=Delivery_Score[2](t-dt)+
  (delivery_score_increase[Tedarikci]-
  delivery_score_decrease[Tedarikci]) * dt

INIT Delivery_Score[2] = NORMAL(0.82, 0.12)

Delivery_Score[3](t)=Delivery_Score[3](t-dt)+
  (delivery_score_increase[Tedarikci]-
  delivery_score_decrease[Tedarikci]) * dt

INIT Delivery_Score[3] = NORMAL(0.71, 0.1)
```

```
Delivery_Score[4](t)=Delivery_Score[4](t-dt)+
  (delivery_score_increase[Tedarikci]-
  delivery_score_decrease[Tedarikci]) * dt

INIT Delivery_Score[4] = NORMAL(0.81, 0.13)

Delivery_Score[5](t)=Delivery_Score[5](t-dt)+
  (delivery_score_increase[Tedarikci]-
  delivery_score_decrease[Tedarikci]) * dt

INIT Delivery_Score[5] = NORMAL(0.74, 0.13)

INFLOWS:

delivery_score_increase[Tedarikci]=(investment_of_delivery*(1-
  Delivery_Score ))/delivery_investment_delay

OUTFLOWS:

delivery_score_decrease[Tedarikci]=Delivery_Score*
  RANDOM(0.001,0.005)

Environmental_Score[1](t)=Environmental_Score[1](t-dt)+
  (environmental_score_increase[Tedarikci]-
  environmental_score_decrease[Tedarikci]) * dt

INIT Environmental_Score[1] = NORMAL(0.76, 0.11)

Environmental_Score[2](t)=Environmental_Score[2](t-dt)+
  (environmental_score_increase[Tedarikci]-
  environmental_score_decrease[Tedarikci]) * dt

INIT Environmental_Score[2] = NORMAL(0.78, 0.1)

Environmental_Score[3](t)=Environmental_Score[3](t-dt)+
  (environmental_score_increase[Tedarikci]-
  environmental_score_decrease[Tedarikci]) * dt

INIT Environmental_Score[3] = NORMAL(0.70, 0.1)

Environmental_Score[4](t)=Environmental_Score[4](t-dt)+
  (environmental_score_increase[Tedarikci]-
  environmental_score_decrease[Tedarikci]) * dt

INIT Environmental_Score[4] = NORMAL(0.81, 0.13)

Environmental_Score[5](t)=Environmental_Score[5](t-dt)+
  (environmental_score_increase[Tedarikci]-
  environmental_score_decrease[Tedarikci]) * dt

INIT Environmental_Score[5] = NORMAL(0.75, 0.11)

INFLOWS:

environmental_score_increase[Tedarikci] = ( environmental_investment
  *(1-Environmental_Score) )/environmental_investment_delay
```

```
OUTFLOWS:

environmental_score_decrease[Tedarikci]=Environmental_Score*
  RANDOM(0.001,0.005)

Quality_Score[1](t)=Quality_Score[1](t-dt)+
  (quality_score_inceease[Tedarikci]-
  quality_score_decrease[Tedarikci]) * dt

INIT Quality_Score[1] = NORMAL(0.72,0.10)

Quality_Score[2](t)=Quality_Score[2](t-dt)+
  (quality_score_inceease[Tedarikci]-
  quality_score_decrease[Tedarikci]) * dt

INIT Quality_Score[2] = NORMAL(0.80,0.15)

Quality_Score[3](t)=Quality_Score[3](t-dt)+
  (quality_score_inceease[Tedarikci]-
  quality_score_decrease[Tedarikci]) * dt

INIT Quality_Score[3] = NORMAL(0.62,0.12)

Quality_Score[4](t)=Quality_Score[4](t-dt)+
  (quality_score_inceease[Tedarikci]-
  quality_score_decrease[Tedarikci]) * dt

INIT Quality_Score[4] = NORMAL(0.75, 0.13)

Quality_Score[5](t)=Quality_Score[5](t-dt)+
  (quality_score_inceease[Tedarikci]-
  quality_score_decrease[Tedarikci]) * dt

INIT Quality_Score[5] = NORMAL(0.80, 0.14)

INFLOWS:

quality_score_inceease[Tedarikci]=(investment_of_quality*(1-
  Quality_Score) )/quality_investment_delay

OUTFLOWS:

quality_score_decrease[Tedarikci]=Quality_Score* RANDOM(0.001,0.005)

Supplier_Per_Score[1](t)=Supplier_Per_Score[1](t-dt)+
  (total_score_of_supplier_performance_change[Tedarikci]) * dt

INIT Supplier_Per_Score[1]=
  (Quality_Score[1]*weight_of_quality_criteria+
  Cost_Score[1]*weight_of_cost__criteria+
  Delivery_Score[1]*weight_of_delivery_criteria+
  Environmental_Score[1] *weight_of_environment_criteria)

Supplier_Per_Score[2](t)=Supplier_Per_Score[2](t-dt)+
  (total_score_of_supplier_performance_change[Tedarikci]) * dt
```

```
INIT Supplier_Per_Score[2]=
   (Quality_Score[2]*weight_of_quality_criteria+
   Cost_Score[2]*weight_of_cost__criteria+
   Delivery_Score[2]*weight_of_delivery_criteria+
   Environmental_Score[2] *weight_of_environment_criteria)

Supplier_Per_Score[3](t)=Supplier_Per_Score[3](t-dt)+
   (total_score_of_supplier_performance_change[Tedarikci]) * dt

INIT Supplier_Per_Score[3]=
   (Quality_Score[3]* weight_of_quality_criteria+
   Cost_Score[3]*weight_of_cost__criteria+
   Delivery_Score[3]*weight_of_delivery_criteria+
   Environmental_Score[3] *weight_of_environment_criteria)

Supplier_Per_Score[4](t)=Supplier_Per_Score[4](t-dt)+
   (total_score_of_supplier_performance_change[Tedarikci]) * dt

INIT Supplier_Per_Score[4]=
   (Quality_Score[4]* weight_of_quality_criteria+
   Cost_Score[4]*weight_of_cost__criteria+
   Delivery_Score[4]*weight_of_delivery_criteria+
   Environmental_Score[4] *weight_of_environment_criteria)

Supplier_Per_Score[5](t)=Supplier_Per_Score[5](t-dt)+
   (total_score_of_supplier_performance_change[Tedarikci]) * dt

INIT Supplier_Per_Score[5]=
   (Quality_Score[5]* weight_of_quality_criteria+
   Cost_Score[5]*weight_of_cost__criteria+
   Delivery_Score[5]*weight_of_delivery_criteria+
   Environmental_Score[5] *weight_of_environment_criteria)

INFLOWS:

total_score_of_supplier_performance_change[Tedarikci]=
((delivery_performance_effect+
quality_performance_effect+
past_performance_effect+ environmental_performance_effect+
long_term_relationship_effect+
cost__performance_effect)-Supplier_Per_Score)*(1-Supplier_Per_Score)

cost_reduction_delay = RANDOM(2, 4)

cost__performance_effect[Tedarikci]=
   Cost_Score*weight_of_cost__criteria

delivery_investment_delay = RANDOM(2, 4)

delivery_performance_effect[Tedarikci]=
   Delivery_Score*weight_of_delivery_criteria
```

```
environmental_investment[Tedarikci]=
  investment_rate_of_supplier*weight_of_environment_criteria
  *RANDOM(0.2, 0.6)

environmental_investment_delay = RANDOM(2, 4)

environmental_performance_effect[Tedarikci]=
  Environmental_Score*weight_of_environment_criteria

investment_of_cost_reduction[Tedarikci] =
  weight_of_cost__criteria*investment_rate_of_supplier*RANDOM(0.2,
  0.6)

investment_of_delivery[Tedarikci] =
  weight_of_delivery_criteria*investment_rate_of_supplier*RANDOM(0.2
  ,0.6)

investment_of_quality[Tedarikci] =
  weight_of_quality_criteria*investment_rate_of_supplier*RANDOM(0.2,
  0.6)

investment_rate_of_supplier[Tedarikci] = supplier's_income_level

long_term_relationship[Tedarikci] = order_quantity

long_term_relationship_effect[Tedarikci]=
  weight_of_long_term__relationship_criteria* long_term_relationship

order_quantity[1] = Supplier_Per_Score[1] / (Supplier_Per_Score[1]
  +Supplier_Per_Score[2]+Supplier_Per_Score[3]+Supplier_Per_Score[4]
  +Supplier_Per_Score[5])

order_quantity[2] = Supplier_Per_Score[2] / (Supplier_Per_Score[1]
  +Supplier_Per_Score[2]+Supplier_Per_Score[3]+Supplier_Per_Score[4]
  +Supplier_Per_Score[5])

order_quantity[3] = Supplier_Per_Score[3] / (Supplier_Per_Score[1]
  +Supplier_Per_Score[2]+Supplier_Per_Score[3]+Supplier_Per_Score[4]
  +Supplier_Per_Score[5])

order_quantity[4] = Supplier_Per_Score[4] / (Supplier_Per_Score[1]
  +Supplier_Per_Score[2]+Supplier_Per_Score[3]+Supplier_Per_Score[4]
  +Supplier_Per_Score[5])

order_quantity[5] = Supplier_Per_Score[5] / (Supplier_Per_Score[1]
  +Supplier_Per_Score[2]+Supplier_Per_Score[3]+Supplier_Per_Score[4]
  +Supplier_Per_Score[5])

past_performance_effect[Tedarikci] =
  weight_of__past_performance * Supplier_Per_Score

quality_investment_delay = RANDOM(2, 4)

quality_performance_effect[Tedarikci]=
  Quality_Score*weight_of_quality_criteria
```

```
supplier's_income_level[Tedarikci] = order_quantity

weight_of_cost__criteria = 0.17

weight_of_delivery_criteria = 0.24

weight_of_environment_criteria = 0.12

weight_of_long_term__relationship_criteria = 0.04

weight_of_quality_criteria = 0.36

weight_of__past_performance=0.07
```

APPENDIX 5

Table A.1 Simulation results for static weights of criteria

1 st run		2 nd run		3 rd run		4 th run		5 th run		6 th run		7 th run		8 th run		9 th run		10 th run	
S 1	0.77	S 4	0.76	S 3	0.76	S 1	0.77	S 1	0.79	S 2	0.76	S2	0.77	S4	0.77	S3	0.78	S2	0.77
S 4	0.77	S 1	0.75	S 4	0.75	S 4	0.75	S 2	0.76	S 4	0.76	S1	0.75	S1	0.75	S2	0.76	S4	0.77
S 3	0.75	S 2	0.75	S 1	0.74	S 5	0.74	S 5	0.76	S 1	0.75	S4	0.74	S2	0.73	S5	0.76	S5	0.76
S 5	0.73	S 5	0.74	S 5	0.74	S 2	0.73	S 4	0.75	S 3	0.72	S3	0.73	S3	0.73	S1	0.74	S3	0.73
S 2	0.72	S 3	0.73	S 2	0.73	S 3	0.73	S 3	0.71	S 5	0.70	S5	0.73	S5	0.71	S4	0.73	S1	0.70
11 th run		12 th run		13 th run		14 th run		15 th run		16 th run		17 th run		18 th run		19 th run		20 th run	
S2	0.78	S4	0.77	S1	0.77	S2	0.76	S1	0.77	S4	0.78	S5	0.78	S3	0.80	S1	0.78	S4	0.78
S5	0.77	S3	0.75	S4	0.77	S1	0.75	S4	0.77	S3	0.77	S3	0.75	S2	0.76	S3	0.77	S3	0.76
S3	0.75	S5	0.73	S2	0.75	S4	0.74	S3	0.76	S5	0.74	S1	0.74	S4	0.75	S4	0.76	S1	0.74
S4	0.73	S1	0.73	S3	0.74	S3	0.72	S2	0.74	S2	0.73	S2	0.73	S1	0.72	S5	0.75	S5	0.73
S1	0.72	S2	0.70	S5	0.69	S5	0.72	S5	0.73	S1	0.72	S4	0.71	S5	0.72	S2	0.68	S2	0.72
21 st run		22 nd run		23 rd run		24 th run		25 th run		26 th run		27 th run		28 th run		29 th run		30 th run	
S3	0.77	S3	0.77	S1	0.76	S5	0.76	S4	0.77	S3	0.79	S5	0.77	S1	0.78	S2	0.78	S4	0.77
S4	0.77	S1	0.76	S3	0.76	S3	0.75	S3	0.76	S4	0.76	S2	0.75	S5	0.78	S5	0.77	S2	0.76
S2	0.76	S2	0.75	S2	0.74	S1	0.75	S2	0.75	S1	0.73	S3	0.74	S2	0.75	S1	0.75	S1	0.75
S1	0.73	S5	0.74	S4	0.74	S4	0.73	S5	0.74	S5	0.73	S1	0.74	S3	0.73	S3	0.73	S3	0.74
S5	0.71	S4	0.71	S5	0.73	S2	0.70	S1	0.73	S2	0.72	S4	0.71	S4	0.70	S4	0.73	S5	0.73
31 st run		32 nd run		33 rd run		34 th run		35 th run		36 th run		37 th run		38 th run		39 th run		40 th run	
S3	0.77	S3	0.79	S2	0.77	S5	0.78	S5	0.78	S2	0.77	S1	0.77	S2	0.77	S4	0.78	S2	0.77
S1	0.76	S2	0.77	S1	0.76	S2	0.77	S1	0.77	S4	0.76	S2	0.76	S4	0.74	S5	0.78	S1	0.74
S4	0.75	S5	0.75	S3	0.75	S3	0.75	S3	0.76	S3	0.75	S3	0.74	S5	0.74	S2	0.74	S4	0.74
S5	0.73	S4	0.72	S5	0.75	S4	0.74	S2	0.74	S1	0.74	S5	0.74	S1	0.73	S1	0.73	S3	0.73
S2	0.71	S1	0.70	S4	0.72	S1	0.70	S4	0.72	S5	0.73	S4	0.72	S3	0.72	S3	0.72	S5	0.69

Table A.1 continues

41 st run		42 nd run		43 rd run		44 th run		45 th run		46 th run		47 th run		48 th run		49 th run		50 th run	
S4	0.77	S2	0.79	S4	0.77	S3	0.77	S2	0.78	S3	0.77	S3	0.79	S1	0.78	S3	0.78	S4	0.78
S3	0.75	S5	0.75	S1	0.76	S2	0.76	S3	0.77	S1	0.77	S1	0.78	S5	0.75	S1	0.77	S5	0.77
S1	0.74	S3	0.74	S5	0.74	S1	0.75	S1	0.73	S2	0.74	S5	0.75	S3	0.74	S2	0.75	S3	0.75
S5	0.74	S4	0.74	S2	0.73	S5	0.74	S5	0.72	S5	0.73	S2	0.73	S4	0.73	S5	0.72	S1	0.74
S2	0.72	S1	0.70	S3	0.70	S4	0.72	S4	0.70	S4	0.72	S4	0.72	S2	0.71	S4	0.71	S2	0.70
51 st run		52 nd run		53 rd run		54 th run		55 th run		56 th run		57 th run		58 th run		59 th run		60 th run	
S4	0.77	S4	0.79	S4	0.77	S2	0.77	S5	0.79	S4	0.77	S1	0.77	S4	0.78	S3	0.78	S5	0.77
S5	0.75	S3	0.76	S1	0.75	S3	0.76	S3	0.78	S5	0.75	S2	0.74	S5	0.76	S2	0.77	S3	0.76
S3	0.74	S5	0.75	S3	0.75	S4	0.74	S4	0.75	S3	0.73	S3	0.73	S1	0.73	S1	0.75	S4	0.74
S2	0.72	S2	0.74	S2	0.74	S5	0.74	S2	0.73	S1	0.72	S5	0.73	S2	0.73	S4	0.72	S2	0.73
S1	0.71	S1	0.69	S5	0.71	S1	0.73	S1	0.73	S2	0.72	S4	0.72	S3	0.69	S5	0.71	S1	0.72
61 st run		62 nd run		63 rd run		64 th run		65 th run		66 th run		67 th run		68 th run		69 th run		70 th run	
S4	0.78	S3	0.78	S1	0.77	S2	0.77	S1	0.77	S4	0.77	S4	0.79	S1	0.79	S4	0.77	S5	0.77
S1	0.76	S1	0.76	S4	0.75	S5	0.75	S4	0.76	S2	0.76	S1	0.76	S3	0.76	S5	0.76	S3	0.76
S3	0.76	S2	0.74	S2	0.74	S3	0.73	S5	0.75	S1	0.75	S2	0.75	S2	0.75	S1	0.75	S2	0.74
S2	0.73	S5	0.74	S3	0.73	S4	0.72	S3	0.74	S3	0.73	S3	0.75	S4	0.73	S3	0.73	S1	0.73
S5	0.72	S4	0.73	S5	0.72	S1	0.71	S2	0.72	S5	0.71	S5	0.72	S5	0.71	S2	0.72	S4	0.72
71 st run		72 nd run		73 rd run		74 th run		75 th run		76 th run		77 th run		78 th run		79 th run		80 th run	
S4	0.78	S3	0.78	S3	0.76	S2	0.77	S1	0.79	S4	0.78	S5	0.77	S5	0.77	S5	0.79	S5	0.78
S1	0.78	S4	0.76	S1	0.75	S4	0.77	S4	0.76	S5	0.78	S1	0.76	S4	0.75	S3	0.77	S3	0.75
S5	0.76	S2	0.75	S2	0.75	S5	0.75	S2	0.74	S3	0.76	S2	0.76	S1	0.74	S4	0.76	S1	0.73
S3	0.73	S1	0.75	S4	0.73	S1	0.73	S3	0.73	S2	0.75	S3	0.74	S2	0.72	S1	0.75	S2	0.71
S2	0.72	S5	0.73	S5	0.71	S3	0.72	S5	0.72	S1	0.73	S4	0.72	S3	0.71	S2	0.74	S4	0.71

Table A.1 continues

81 st run		82 nd run		83 rd run		84 th run		85 th run		86 th run		87 th run		88 th run		89 th run		90 th run	
S2	0.77	S5	0.79	S5	0.76	S4	0.77	S3	0.78	S1	0.76	S2	0.78	S2	0.79	S2	0.77	S2	0.79
S4	0.77	S4	0.77	S1	0.76	S2	0.76	S5	0.76	S4	0.75	S5	0.77	S5	0.75	S3	0.76	S1	0.75
S1	0.76	S1	0.76	S3	0.75	S5	0.75	S1	0.76	S3	0.74	S4	0.74	S3	0.73	S4	0.75	S3	0.74
S5	0.74	S3	0.75	S2	0.74	S1	0.74	S4	0.73	S2	0.73	S1	0.73	S1	0.72	S5	0.75	S4	0.73
S3	0.74	S2	0.74	S4	0.71	S3	0.73	S2	0.70	S5	0.70	S3	0.72	S4	0.69	S1	0.71	S5	0.71
91 st run		92 nd run		93 rd run		94 th run		95 th run		96 th run		97 th run		98 th run		99 th run		100 th run	
S2	0.77	S1	0.78	S4	0.78	S2	0.77	S2	0.77	S4	0.77	S4	0.79	S4	0.77	S5	0.77	S2	0.77
S4	0.76	S2	0.75	S2	0.75	S4	0.76	S3	0.76	S2	0.76	S5	0.76	S2	0.75	S4	0.76	S3	0.77
S3	0.73	S4	0.74	S5	0.74	S5	0.75	S1	0.75	S3	0.75	S2	0.75	S5	0.74	S2	0.75	S5	0.75
S1	0.71	S5	0.71	S1	0.73	S1	0.73	S4	0.75	S1	0.74	S1	0.73	S1	0.71	S1	0.74	S1	0.74
S5	0.68	S3	0.70	S3	0.70	S3	0.73	S5	0.73	S5	0.70	S3	0.71	S3	0.68	S3	0.73	S4	0.72

APPENDIX 6

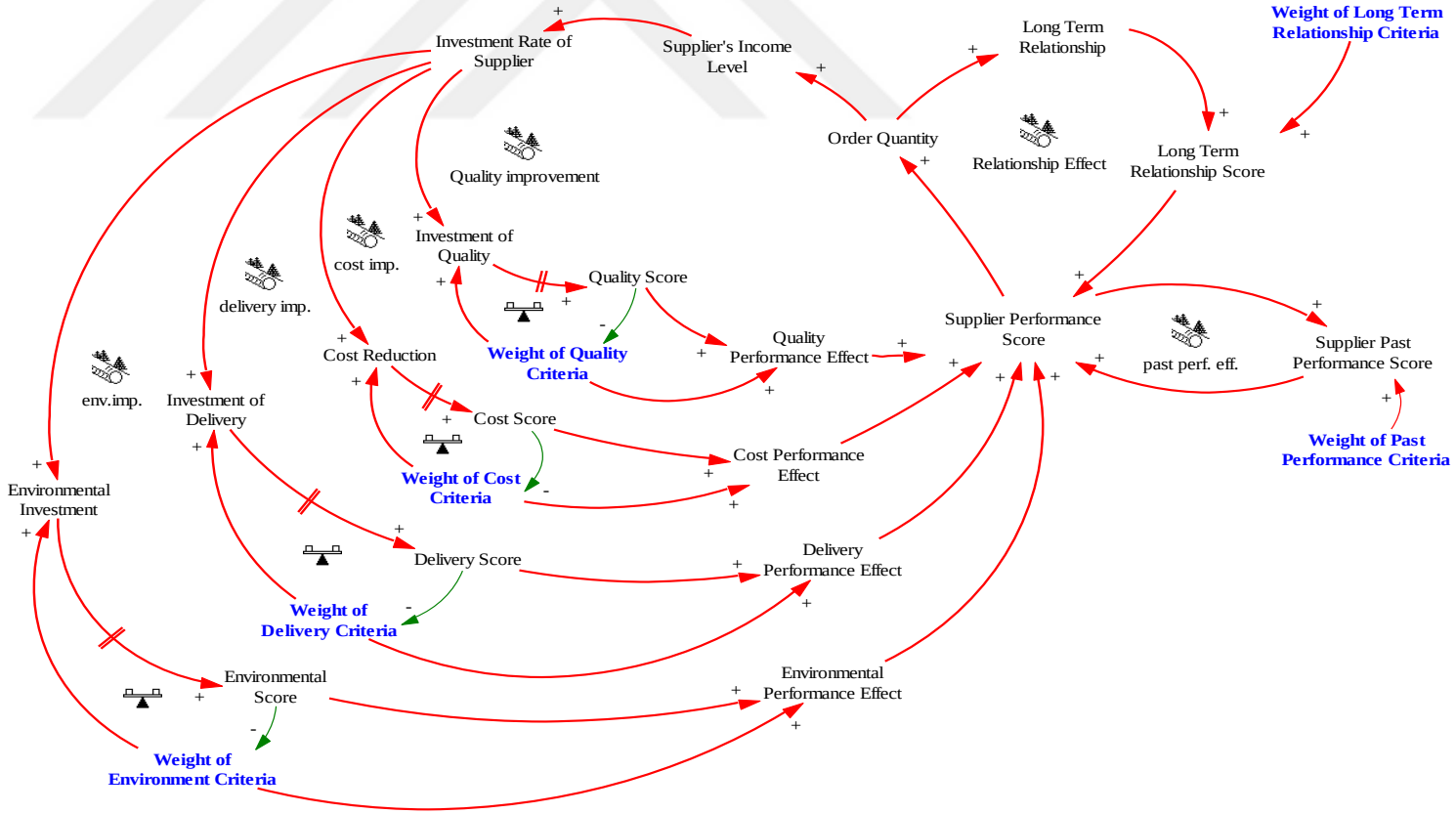


Figure A.3 Causal loop diagram of the performance changing of the supplier (for dynamic weights of criteria)

APPENDIX 7

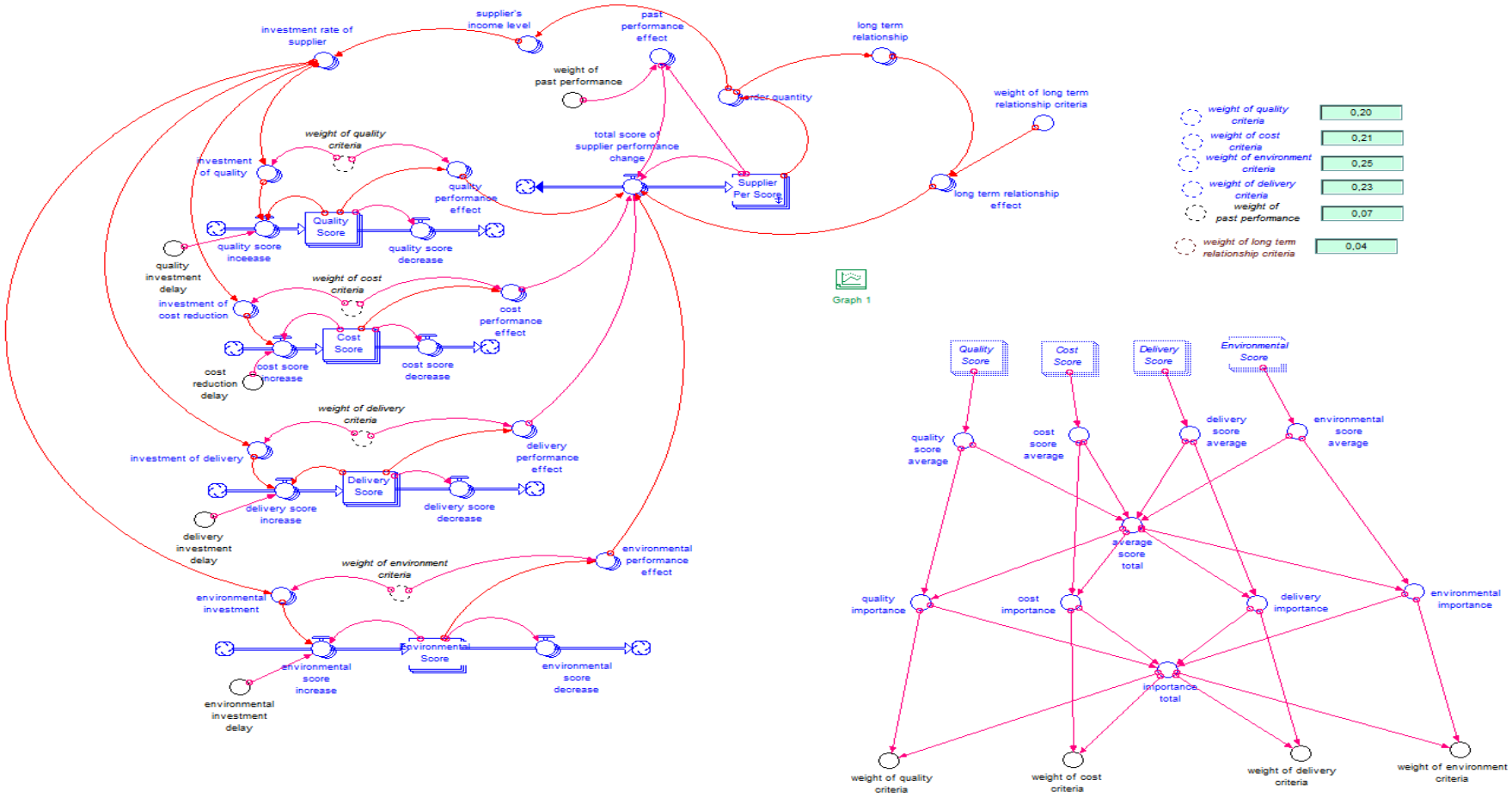


Figure A.4 Stock and flow diagram of supplier evaluation (for dynamic weights of criteria)

APPENDIX 8: Stella model equations for dynamic weights of supplier evaluation criteria

```
Supplier_Per_Score[1](t) = Supplier_Per_Score[1](t - dt) +
   (total_score_of_supplier_performance_change[Tedarikci]) * dt

INIT Supplier_Per_Score[1] = (Quality_Score[1] *
   weight_of_quality_criteria +Cost_Score[1] *
   weight_of_cost__criteria +Delivery_Score[1] *
   weight_of_delivery_criteria + Environmental_Score[1]*
   weight_of_environment_criteria)

Supplier_Per_Score[2](t) = Supplier_Per_Score[2](t - dt) +
   (total_score_of_supplier_performance_change[Tedarikci]) * dt

INIT Supplier_Per_Score[2] = (Quality_Score[2] *
   weight_of_quality_criteria +Cost_Score[2] *
   weight_of_cost__criteria +Delivery_Score[2] *
   weight_of_delivery_criteria +Environmental_Score[2]*
   weight_of_environment_criteria)

Supplier_Per_Score[3](t) = Supplier_Per_Score[3](t - dt) +
   (total_score_of_supplier_performance_change[Tedarikci]) * dt

INIT Supplier_Per_Score[3] = (Quality_Score[3] *
   weight_of_quality_criteria +Cost_Score[3] *
   weight_of_cost__criteria +Delivery_Score[3] *
   weight_of_delivery_criteria + Environmental_Score[3]*
   weight_of_environment_criteria)

Supplier_Per_Score[4](t) = Supplier_Per_Score[4](t - dt) +
   (total_score_of_supplier_performance_change[Tedarikci]) * dt

INIT Supplier_Per_Score[4] = (Quality_Score[4] *
   weight_of_quality_criteria + Cost_Score[4] *
   weight_of_cost__criteria +Delivery_Score[4] *
   weight_of_delivery_criteria +Environmental_Score[4]*
   weight_of_environment_criteria)

Supplier_Per_Score[5](t) = Supplier_Per_Score[5](t - dt) +
   (total_score_of_supplier_performance_change[Tedarikci]) * dt
```

```
INIT Supplier_Per_Score[5] = (Quality_Score[5] *
  weight_of_quality_criteria +Cost_Score[5] *
  weight_of_cost__criteria +Delivery_Score[5] *
  weight_of_delivery_criteria +Environmental_Score[5]*
  weight_of_environment_criteria)

INFLOWS:

total_score_of_supplier_performance_change[Tedarikci] =
  ((delivery_performance_effect+
  quality_performance_effect+
  past_performance_effect +
  environmental_performance_effect+
  long_term_relationship_effect+
  cost__performance_effect) -Supplier_Per_Score)*
  (1-Supplier_Per_Score)

Cost_Score[1](t) = Cost_Score[1](t - dt) +
  (cost_score_increase[Tedarikci] - cost_score_decrease[Tedarikci])
  * dt

INIT Cost_Score[1] = NORMAL(0.63, 0.1)

Cost_Score[2](t) = Cost_Score[2](t - dt) +
  (cost_score_increase[Tedarikci] - cost_score_decrease[Tedarikci])
  * dt

INIT Cost_Score[2] = NORMAL(0.75, 0.1)

Cost_Score[3](t) = Cost_Score[3](t - dt) +
  (cost_score_increase[Tedarikci] - cost_score_decrease[Tedarikci])
  * dt

INIT Cost_Score[3] = NORMAL(0.65, 0.1)

Cost_Score[4](t) = Cost_Score[4](t - dt) +
  (cost_score_increase[Tedarikci] - cost_score_decrease[Tedarikci])
  * dt

INIT Cost_Score[4] = NORMAL(0.82, 0,12)

Cost_Score[5](t) = Cost_Score[5](t - dt) +
  (cost_score_increase[Tedarikci] - cost_score_decrease[Tedarikci])
  * dt
```

```
INIT Cost_Score[5] = NORMAL(0.84, 0.1)

INFLOWS:

cost_score_increase[Tedarikci] = (investment_of_cost_reduction * (1
  - Cost_Score) ) / cost_reduction_delay

OUTFLOWS:

cost_score_decrease[Tedarikci] = Cost_Score * RANDOM(0.001,0.005)

Delivery_Score[1](t) = Delivery_Score[1](t - dt) +
  (delivery_score_increase[Tedarikci] -
  delivery_score_decrease[Tedarikci]) * dt

INIT Delivery_Score[1] = NORMAL(0.75, 0.11)

Delivery_Score[2](t) = Delivery_Score[2](t - dt) +
  (delivery_score_increase[Tedarikci] -
  delivery_score_decrease[Tedarikci]) * dt

INIT Delivery_Score[2] = NORMAL(0.82, 0.12)

Delivery_Score[3](t) = Delivery_Score[3](t - dt) +
  (delivery_score_increase[Tedarikci] -
  delivery_score_decrease[Tedarikci]) * dt

INIT Delivery_Score[3] = NORMAL(0.71, 0.1)

Delivery_Score[4](t) = Delivery_Score[4](t - dt) +
  (delivery_score_increase[Tedarikci] -
  delivery_score_decrease[Tedarikci]) * dt

INIT Delivery_Score[4] = NORMAL(0.81, 0.13)

Delivery_Score[5](t) = Delivery_Score[5](t - dt) +
  (delivery_score_increase[Tedarikci] -
  delivery_score_decrease[Tedarikci]) * dt

INIT Delivery_Score[5] = NORMAL(0.74, 0.13)

INFLOWS:

delivery_score_increase[Tedarikci] = (investment_of_delivery * (1 -
  Delivery_Score )) / delivery_investment_delay
```

```
OUTFLOWS:

delivery_score_decrease[Tedarikci] = Delivery_Score *
  RANDOM(0.001,0.005)

Environmental_Score[1](t) = Environmental_Score[1](t - dt) +
  (environmental_score_increase[Tedarikci] -
  environmental_score_decrease[Tedarikci]) * dt

INIT Environmental_Score[1] = NORMAL(0.76, 0.11)

Environmental_Score[2](t) = Environmental_Score[2](t - dt) +
  (environmental_score_increase[Tedarikci] -
  environmental_score_decrease[Tedarikci]) * dt

INIT Environmental_Score[2] = NORMAL(0.78, 0.1)

Environmental_Score[3](t) = Environmental_Score[3](t - dt) +
  (environmental_score_increase[Tedarikci] -
  environmental_score_decrease[Tedarikci]) * dt

INIT Environmental_Score[3] = NORMAL(0.70, 0.1)

Environmental_Score[4](t) = Environmental_Score[4](t - dt) +
  (environmental_score_increase[Tedarikci] -
  environmental_score_decrease[Tedarikci]) * dt

INIT Environmental_Score[4] = NORMAL(0.81, 0.13)

Environmental_Score[5](t) = Environmental_Score[5](t - dt) +
  (environmental_score_increase[Tedarikci] -
  environmental_score_decrease[Tedarikci]) * dt

INIT Environmental_Score[5] = NORMAL(0.75, 0.11)

INFLOWS:

environmental_score_increase[Tedarikci] = ( environmental_investment
  * (1-Environmental_Score) ) /environmental_investment_delay

OUTFLOWS:

environmental_score_decrease[Tedarikci] = Environmental_Score *
  RANDOM(0.001,0.005)
```

```
Quality_Score[1](t) = Quality_Score[1](t - dt) +
  (quality_score_inceease[Tedarikci] -
  quality_score_decrease[Tedarikci]) * dt

INIT Quality_Score[1] = NORMAL(0.72,0.10)

Quality_Score[2](t) = Quality_Score[2](t - dt) +
  (quality_score_inceease[Tedarikci] -
  quality_score_decrease[Tedarikci]) * dt

INIT Quality_Score[2] = NORMAL(0.80,0.15)

Quality_Score[3](t) = Quality_Score[3](t - dt) +
  (quality_score_inceease[Tedarikci] -
  quality_score_decrease[Tedarikci]) * dt

INIT Quality_Score[3] = NORMAL(0.62,0.12)

Quality_Score[4](t) = Quality_Score[4](t - dt) +
  (quality_score_inceease[Tedarikci] -
  quality_score_decrease[Tedarikci]) * dt

INIT Quality_Score[4] = NORMAL(0.75, 0.13)

Quality_Score[5](t) = Quality_Score[5](t - dt) +
  (quality_score_inceease[Tedarikci] -
  quality_score_decrease[Tedarikci]) * dt

INIT Quality_Score[5] = NORMAL(0.80, 0.14)

INFLOWS:

quality_score_inceease[Tedarikci] = (investment_of_quality * (1 -
  Quality_Score) ) / quality_investment_delay

OUTFLOWS:

quality_score_decrease[Tedarikci] = Quality_Score *
  RANDOM(0.001,0.005)

average_total_score =
  quality_score__average+cost_score_average+delivery_score_average+
  environmental_score__average

cost_importance = (1-cost_score_average)/average_total_score
```

```
cost_reduction_delay = RANDOM(2, 4)

cost_score_average =
   (Cost_Score[1]+Cost_Score[2]+Cost_Score[3]+Cost_Score[4]+Cost_Scor
   e[5])/5

cost__performance_effect[Tedarikci] = Cost_Score *
   weight_of_cost__criteria

delivery_importance = (1-delivery_score_average)/average_total_score

delivery_investment_delay = RANDOM(2, 4)

delivery_performance_effect[Tedarikci] = Delivery_Score *
   weight_of_delivery_criteria

delivery_score_average =
   (Delivery_Score[1]+Delivery_Score[2]+Delivery_Score[3]+Delivery_Sc
   ore[4]+Delivery_Score[5])/5

environmental_importance =
   (1-environmental_score__average)/average_total_score

environmental_investment[Tedarikci] = investment_rate_of_supplier *
   weight_of_environment_criteria *RANDOM(0.2, 0.6)

environmental_investment_delay = RANDOM(2, 4)

environmental_performance_effect[Tedarikci] =
   Environmental_Score*weight_of_environment_criteria

environmental_score__average =
   (Environmental_Score[1]+Environmental_Score[2]+Environmental_Score
   [3]+Environmental_Score[4]+Environmental_Score[5])/5

importance_total = quality_importance+cost_importance+
   delivery_importance+ environmental_importance

investment_of_cost_reduction[Tedarikci] = weight_of_cost__criteria *
   investment_rate_of_supplier *RANDOM(0.2, 0.6)

investment_of_delivery[Tedarikci] = weight_of_delivery_criteria *
   investment_rate_of_supplier *RANDOM(0.2, 0.6)

investment_of_quality[Tedarikci] = weight_of_quality_criteria *
   investment_rate_of_supplier *RANDOM(0.2, 0.6)
```

```
investment_rate_of_supplier[Tedarikci] = supplier's_income_level

long_term_relationship[Tedarikci] = order_quantity

long_term_relationship_effect[Tedarikci] =
  weight_of_long_term__relationship_criteria *
  long_term_relationship

order_quantity[1] = Supplier_Per_Score[1] / (Supplier_Per_Score[1]
  +Supplier_Per_Score[2] +Supplier_Per_Score[3]
  +Supplier_Per_Score[4] +Supplier_Per_Score[5])

order_quantity[2] = Supplier_Per_Score[2] / (Supplier_Per_Score[1]
  +Supplier_Per_Score[2] +Supplier_Per_Score[3]
  +Supplier_Per_Score[4] +Supplier_Per_Score[5])

order_quantity[3] = Supplier_Per_Score[3] / (Supplier_Per_Score[1]
  +Supplier_Per_Score[2] +Supplier_Per_Score[3]
  +Supplier_Per_Score[4] +Supplier_Per_Score[5])

order_quantity[4] = Supplier_Per_Score[4] / (Supplier_Per_Score[1]
  +Supplier_Per_Score[2] +Supplier_Per_Score[3]
  +Supplier_Per_Score[4] +Supplier_Per_Score[5])

order_quantity[5] = Supplier_Per_Score[5] / (Supplier_Per_Score[1] +
  Supplier_Per_Score[2] +Supplier_Per_Score[3]
  +Supplier_Per_Score[4] +Supplier_Per_Score[5])

past_performance_effect[Tedarikci] = weight_of__past_performance *
  Supplier_Per_Score

quality_importance = (1-quality_score__average)/ average_total_score

quality_investment_delay = RANDOM(2, 4)

quality_performance_effect[Tedarikci] =
  Quality_Score*weight_of_quality_criteria

quality_score__average =
  (Quality_Score[1]+Quality_Score[2]+Quality_Score[3]+Quality_Score[
  4 +Quality_Score[5])/5

supplier's_income_level[Tedarikci] = order_quantity

weight_of_cost__criteria = cost_importance/importance_total*0.89
```

```
weight_of_delivery_criteria =
  delivery_importance/importance_total*0.89

weight_of_environment_criteria =
  environmental_importance/importance_total*0.89

weight_of_long_term__relationship_criteria = 0.04

weight_of_quality_criteria =
  quality_importance/importance_total*0.89

weight_of__past_performance = 0.07
```

APPENDIX 9

Table A.2 Simulation results for dynamic weights of criteria

1 st run		2 nd run		3 rd run		4 th run		5 th run		6 th run		7 th run		8 th run		9 th run		10 th run	
S4	0.72	S2	0.73	S4	0.73	S2	0.77	S5	0.76	S1	0.71	S4	0.74	S2	0.74	S4	0.73	S5	0.73
S5	0.70	S5	0.72	S5	0.70	S4	0.73	S4	0.72	S5	0.70	S5	0.71	S4	0.71	S2	0.72	S1	0.69
S1	0.67	S4	0.69	S2	0.68	S5	0.67	S2	0.71	S3	0.68	S2	0.68	S5	0.68	S5	0.67	S4	0.67
S3	0.66	S3	0.67	S1	0.66	S1	0.66	S3	0.62	S4	0.66	S1	0.67	S3	0.67	S3	0.66	S2	0.65
S2	0.65	S1	0.65	S3	0.65	S3	0.62	S1	0.59	S2	0.65	S3	0.63	S1	0.62	S1	0.65	S3	0.63
11 th run		12 th run		13 th run		14 th run		15 th run		16 th run		17 th run		18 th run		19 th run		20 th run	
S5	0.79	S4	0.75	S4	0.73	S5	0.75	S4	0.76	S2	0.79	S5	0.72	S2	0.72	S2	0.74	S4	0.73
S2	0.72	S2	0.69	S5	0.70	S4	0.71	S5	0.72	S5	0.71	S4	0.71	S4	0.71	S4	0.71	S2	0.71
S4	0.68	S1	0.66	S2	0.68	S2	0.70	S2	0.68	S4	0.66	S1	0.70	S5	0.69	S1	0.69	S5	0.69
S1	0.67	S5	0.65	S1	0.67	S3	0.65	S1	0.65	S1	0.65	S2	0.67	S1	0.63	S5	0.68	S3	0.66
S3	0.64	S3	0.63	S3	0.60	S1	0.64	S3	0.62	S3	0.64	S3	0.65	S3	0.62	S3	0.63	S1	0.65
21 st run		22 nd run		23 rd run		24 th run		25 th run		26 th run		27 th run		28 th run		29 th run		30 th run	
S2	0.81	S4	0.76	S4	0.74	S2	0.73	S5	0.74	S4	0.74	S4	0.73	S5	0.75	S4	0.74	S4	0.72
S4	0.71	S2	0.70	S5	0.72	S5	0.72	S4	0.72	S2	0.68	S2	0.68	S2	0.71	S5	0.71	S2	0.69
S5	0.70	S5	0.67	S2	0.70	S4	0.71	S2	0.68	S5	0.66	S1	0.65	S4	0.66	S2	0.70	S5	0.68
S1	0.66	S1	0.65	S1	0.68	S3	0.67	S3	0.66	S3	0.65	S5	0.63	S3	0.64	S1	0.68	S1	0.66
S3	0.60	S3	0.64	S3	0.63	S1	0.62	S1	0.62	S1	0.64	S3	0.61	S1	0.61	S3	0.64	S3	0.62
31 st run		32 nd run		33 rd run		34 th run		35 th run		36 th run		37 th run		38 th run		39 th run		40 th run	
S4	0.74	S2	0.71	S2	0.75	S2	0.72	S5	0.72	S4	0.72	S5	0.77	S2	0.76	S5	0.74	S4	0.79
S5	0.71	S5	0.69	S5	0.72	S4	0.69	S2	0.70	S2	0.71	S2	0.71	S5	0.71	S4	0.71	S5	0.72
S2	0.67	S1	0.68	S4	0.70	S5	0.66	S4	0.68	S5	0.70	S1	0.70	S3	0.69	S2	0.69	S2	0.68
S1	0.64	S4	0.67	S1	0.67	S3	0.65	S3	0.65	S1	0.67	S4	0.68	S4	0.67	S3	0.65	S1	0.67
S3	0.63	S3	0.61	S3	0.62	S1	0.62	S1	0.63	S3	0.65	S3	0.57	S1	0.64	S1	0.63	S3	0.63

Table A.2 continues

41 st run		42 nd run		43 rd run		44 th run		45 th run		46 th run		47 th run		48 th run		49 th run		50 th run	
S4	0.77	S5	0.71	S4	0.73	S2	0.75	S4	0.74	S2	0.76	S2	0.75	S2	0.73	S5	0.75	S5	0.73
S1	0.68	S4	0.70	S1	0.71	S4	0.71	S2	0.72	S4	0.72	S4	0.73	S5	0.72	S4	0.70	S4	0.71
S5	0.66	S2	0.66	S5	0.69	S5	0.68	S5	0.71	S5	0.70	S5	0.71	S4	0.70	S1	0.68	S2	0.70
S2	0.65	S3	0.64	S2	0.66	S1	0.66	S3	0.68	S3	0.66	S1	0.64	S1	0.63	S2	0.67	S1	0.67
S3	0.64	S1	0.63	S3	0.63	S3	0.63	S1	0.64	S1	0.64	S3	0.62	S3	0.59	S3	0.61	S3	0.61
51 st run		52 nd run		53 rd run		54 th run		55 th run		56 th run		57 th run		58 th run		59 th run		60 th run	
S4	0.71	S5	0.74	S4	0.72	S5	0.71	S2	0.73	S4	0.73	S2	0.78	S5	0.73	S4	0.74	S4	0.74
S5	0.69	S4	0.71	S2	0.71	S4	0.70	S4	0.72	S5	0.71	S5	0.75	S2	0.71	S5	0.72	S2	0.72
S2	0.68	S2	0.70	S5	0.70	S2	0.68	S5	0.68	S2	0.69	S4	0.70	S4	0.69	S2	0.69	S5	0.69
S1	0.66	S3	0.66	S1	0.66	S1	0.65	S1	0.64	S1	0.65	S1	0.62	S1	0.67	S1	0.66	S3	0.65
S3	0.65	S1	0.66	S3	0.54	S3	0.61	S3	0.62	S3	0.59	S3	0.61	S3	0.65	S3	0.64	S1	0.61
61 st run		62 nd run		63 rd run		64 th run		65 th run		66 th run		67 th run		68 th run		69 th run		70 th run	
S5	0.76	S4	0.73	S2	0.73	S4	0.74	S2	0.75	S5	0.74	S4	0.74	S4	0.74	S4	0.78	S4	0.74
S2	0.73	S5	0.71	S4	0.71	S5	0.72	S4	0.72	S4	0.70	S2	0.73	S2	0.72	S2	0.75	S5	0.71
S4	0.69	S2	0.70	S1	0.69	S1	0.71	S5	0.70	S2	0.68	S1	0.69	S1	0.67	S5	0.74	S2	0.69
S1	0.67	S3	0.68	S3	0.68	S2	0.69	S1	0.66	S1	0.65	S5	0.68	S5	0.66	S1	0.65	S1	0.65
S3	0.60	S1	0.61	S5	0.66	S3	0.66	S3	0.63	S3	0.61	S3	0.63	S3	0.63	S3	0.61	S3	0.64
71 st run		72 nd run		73 rd run		74 th run		75 th run		76 th run		77 th run		78 th run		79 th run		80 th run	
S2	0.75	S2	0.74	S4	0.74	S5	0.73	S5	0.73	S4	0.76	S4	0.74	S5	0.74	S4	0.75	S5	0.71
S4	0.73	S4	0.72	S2	0.71	S1	0.69	S2	0.72	S2	0.74	S2	0.73	S4	0.69	S5	0.70	S2	0.70
S1	0.70	S5	0.71	S5	0.69	S2	0.67	S4	0.67	S5	0.70	S5	0.72	S2	0.67	S2	0.69	S4	0.67
S5	0.68	S3	0.67	S1	0.68	S4	0.65	S1	0.65	S3	0.67	S3	0.63	S1	0.63	S1	0.68	S1	0.66
S3	0.65	S1	0.66	S3	0.59	S3	0.60	S3	0.63	S1	0.66	S1	0.61	S3	0.61	S3	0.65	S3	0.64

Table A.2 continues

81 st run		82 nd run		83 rd run		84 th run		85 th run		86 th run		87 th run		88 th run		89 th run		90 th run	
S5	0.74	S4	0.73	S2	0.72	S5	0.74	S4	0.74	S4	0.74	S5	0.75	S2	0.73	S2	0.75	S5	0.73
S4	0.69	S1	0.70	S1	0.70	S4	0.71	S5	0.71	S2	0.72	S4	0.72	S5	0.72	S5	0.71	S2	0.71
S2	0.67	S2	0.68	S5	0.68	S1	0.69	S1	0.69	S3	0.68	S1	0.69	S4	0.69	S4	0.70	S1	0.70
S3	0.62	S5	0.67	S4	0.66	S3	0.68	S2	0.68	S5	0.66	S3	0.68	S1	0.64	S1	0.65	S3	0.66
S1	0.61	S3	0.63	S3	0.64	S2	0.66	S3	0.63	S1	0.65	S2	0.62	S3	0.62	S3	0.58	S4	0.63
91 st run		92 nd run		93 rd run		94 th run		95 th run		96 th run		97 th run		98 th run		99 th run		100 th run	
S5	0.73	S5	0.72	S5	0.75	S2	0.74	S2	0.74	S5	0.76	S2	0.74	S2	0.76	S5	0.75	S5	0.74
S4	0.71	S2	0.70	S2	0.69	S5	0.71	S4	0.72	S2	0.72	S4	0.71	S4	0.74	S1	0.72	S4	0.71
S1	0.70	S4	0.67	S4	0.68	S4	0.70	S5	0.68	S4	0.68	S3	0.67	S5	0.67	S2	0.71	S1	0.68
S2	0.69	S1	0.65	S1	0.67	S1	0.68	S1	0.65	S1	0.66	S5	0.64	S3	0.65	S4	0.69	S3	0.64
S3	0.63	S3	0.62	S3	0.64	S3	0.59	S3	0.58	S3	0.64	S1	0.63	S1	0.62	S3	0.62	S2	0.63