AN EVOLUTIONARY BASIC DESIGN TOOL

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DOCTOR OF PHILOSOPHY
IN ART, DESIGN AND ARCHITECTURE

by
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June, 2010

I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

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ABSTRACT

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As a creative act, design aims at achieving innovative solutions to fulfill the requirements provided in the problem definition. In recent years, computational methods began to be used not only in design presentation but also in solution generation. The study proposes a design methodology for a particular basic design problem on the concept of emphasis. The developed methodology generates solution alternatives by carrying out genetic operations used in evolutionary design. The generated alternatives are evaluated by an objective function comprising an artificial neural network. The creative potential of the methodology is appraised by comparing the outputs of test runs with the student works for the same design task. In doing so, three different groups of students with diverse backgrounds are used.

Keywords: Evolutionary Design, Creativity, Basic Design Education, Emphasis, Genetic Algorithms, Artificial Neural Networks.

ÖZET

EVRİMSEL BİR TEMEL TASARIM ARACI

Dilek Akbulut

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Danışman: Prof. Dr. Bülent Özgüç

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Yaratıcı bir süreç olarak tasarım, problem tanımında belirlenen gereksinimleri yerine getirecek yenilikçi çözümler bulmayı hedefler. Yakın zamanda sayısal yöntemler, tasarım sunumunun yanısıra tasarım çözümleri üretiminde de kullanılmaya başlanmıştır. Bu çalışma, vurgu kavramı üzerine yapılan bir temel tasarım problemi için bir tasarım yöntemi önerir. Geliştirilen yöntem, evrimsel tasarımda kullanılan genetik işlemleri yürüterek çözüm önerileri üretir. Üretilen çözümler, bir yapay sinir ağından oluşan hedef fonksiyonu tarafından değerlendirilir. Yöntemin yaratıcı potansiyeli, ortaya çıkan sonuçlarla aynı tasarım problemine üç farklı öğrenci grubundan alınan sonuçların karşılaştırılması ile değerlendirilmiştir.

Anahtar Sözcükler: Evrimsel Tasarım, Yaratıcılık, Temel Tasarım Eğitimi, Vurgu, Genetik Algoritmalar, Yapay Sinir Ağları.

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CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

Design is a creative act which leads an iterative process. The goal of this creative act is creating and representing forms which fulfill the requirements provided in the problem definition.

Before industrial revolution, design act was mainly carried out by craftsmen. Those designed through making by using traditional production methods and forms. With the introduction of new production techniques, the definition of design act changed. Designer became the one who is responsible for creating and presenting the artifact, rather than making and producing it. For many years, designers have used paper based techniques to carry out such a design act. However, with the introduction of the computers, the designers left paper-based methods and began to use them as a presentation tool.

A similar shift in design education has been witnessed right from the beginning of 20th century as well. The current form of design education has its roots in Ecole Des Beaux Arts model which is based on the "ateliers" system depending on the pedagogical method of "learning by doing." Beginning from 1919, the design studio concept was strengthened by the Bauhaus model which aimed combine art with craft and technology. For most of the design institutes, Bauhaus is regarded as the pioneer of modern design education. However, about a century after Bauhaus, the changing market and technological conditions necessitates restructuring of the design curriculum. The utilization of the computers as a design tool not only changes the needs of the market but also forces the institutions to integrate CAD with education either within or beside design studios.

Until recent years, computers were used as mainly a tool of presentation. Their ability to easily manipulate and simulate helped the creation process. However, "evolutionary design" appeared as a recent and an efficient tool with computer implementation which reduced time and energy spent by the designers on construction and evaluation of design alternatives.

In fact, the concept of evolutionary design is based on the idea of generative systems, which is first introduced by Aristotle. As will be mentioned in the following chapter, Aristotle applies the generative logic for animals. Both in his 'Generation of Animals' and 'Politics,' he talks about reproduction and anatomy of animals with a generative point of view. Later on, generative systems seem to be used in literature and philosophy. Even in 'Gulliver's Travels' Jonathan Swift tells a story of a book writing machine, which operates on a system of combining words of a language. In 17th century, Leibnitz, who was both a philosopher and a mathematician, thought of using generative logic in machinery design. His approach may be regarded as the ancestor of the morphological method in engineering design, which was raised in 20th century.

Mainly evolutionary design act consists of three phases as representation, generation and evaluation. In representation, the problem is defined with the data set necessary for form generation. After representation, generation phase is carried out solely by the system itself with the criterion and samples provided beforehand. In last phase, which is evaluation, among the generated items the most proper ones are selected according to the criterion provided before. Until the system reaches the proper results, the generation and evaluation phases are repeated. In case of a change in data set, the process is repeated from representation phase.

It can be said that evolutionary design act has mainly two separate abilities of generating and evaluating any form of design item. Since in representation phase the problem and the criterion are identified out from the system, this phase highly depends on human act. Human mental effort can also be applied upon evaluation phase since the system is able to suggest the most proper items generated. The designers select one among the suggested items.

If design is regarded as mainly a problem-solving process, a definition of problem should be done. Problems arise when there is a goal, and problem-solving act is all about attaining that goal. As Mitchell states, “the goal sought by a problem-solver is often some real or abstract object. In some circumstances, rather then seeking an object or a state, a problem solver may want to find path or sequence of operations that leads to some specified point such as the center of a maze, or a check-mate in chess.” (1977) Problem definitions usually include the goal description, conditions to be met, tools, operations and resources to be used.

In any problem definition, the data provided may be less or more then the goals. In such a case, open ended solutions which serve like alternative pathways to the goals are achieved. Reaching a solution by a certain data set may serve like switching one of those pathways. Problem definition act in design is under construction continuously even after production period. As the needs change, data set for any problem changes. However, design act can benefit from above mentioned pathway model in such a case.

In architecture for example; modifications are done on buildings according to changing needs even after construction. Design brief may change during and after construction period. An open air auditorium may turn out to be a closed one, or windows can be added to a façade. Moreover, the function of the buildings can change. A jailhouse may be utilized as a hotel or a factory can serve as an exhibition hall many years after its construction. In a way, buildings are reusable since the forms and functions of a building may be similar with one another.

However, change of design brief does not always result in modifications on the artifact which is readily in hand all the time. In industrial design, for example, any change in brief results in modifications on further generations of the artifact. Since mass production is done in quantities and it is hardly possible to do modifications on the produced artifact, change in design may be reflected to the masses produced afterwards. While form and function similarities result in reusability of buildings, such an issue is generally a coincidence in objects; scissors may be used for cutting nails where there are no nail scissors. However multi-functional objects also exist; the engines of some tractors are used as water pumps at the same time. But generally modifications in an already produced generation of object are done in the form of additions to that object. Or similarities of several objects results in combining such a set of objects under one concept.

The idea of reusability in design seems to work with architecture more then industrial design. However, keeping alternative pathways does not only deal with the concept of reusability, but also with altering the further generations of the design objects. Moreover if any error in design is detected during simulations, such alternative pathways can also be inserted to correct and improve the artifact. Evolutionary design enables the designer to use alternative pathways as the design brief changes. The iterative character of the process makes it possible to modify the data again and again.

The concept of form and function similarities in design can be regarded as gene resemblance. Such an approach of identifying objects with their genes makes us closer to evolutionary design method. While evolutionary design aims at getting new forms by combining varieties, it benefits from an approach of identifying objects according to their forms and functions. On the other hand, using evolutionary design method while dealing with artifacts having resembling gene, reduces time spent on the process.

Evolutionary design has another advantage of preventing biases and prejudices which may be existent on designers' mind. Designers generally depend on their past experiences during designing. They may be unable to improve possible solutions with respect to their prejudices or unawareness. As a totally automated process, evolutionary method is free of such prejudices and is able to raise surprising results that were not thought before.

As a method following a generative technique carried out by computers, the creative capacity of evolutionary design is not limited to straightforward solutions. On the contrary, it is capable of raising surprising solutions. The earliest command about creative capacity of computers was done by Lady Lovelace during mid 1800's on Analytical Engine which is regarded as the ancestor of modern computers. When Lady Lovelace was stating that Analytical Engine has no pretentious to originate anything, most probably she was thinking of using the device with well-defined limits. However, as in the case of evolutionary design, the more complex the solution criteria and the more the number of identified samples, the more the computer tends to be creative.

However, the samples and the criteria identified to the genetic algorithm are utilized by a process which randomly operates on a cut-and-combine base. In contrast, the design act carried out by human designers is a more conscious process which is supported by a learning phase. In general, learning process makes the designer be aware of the general concepts and principles applied to the specific area of design.

Apart from humans, the act of learning is able to be simulated by artificial neural networks in the virtual environment to some extend. The learning act in human brain is carried out by the neurons and the connections or synapses between them. Likewise, the units in the artificial neural networks act as neurons and the weights connecting them serve as the synapses. While connections between neurons determine the level of learning in the human brain, the ability of learning in an artificial neural network is provided by adjusting the weights between the units.

In general, neural networks are used to extract patterns and predict further behaviors of a system which is hard to be defined mathematically. Unlike evolutionary design, they do not lead an algorithmic process operating on a rule-based approach. The way they function is more regarded as a case-based process since the network is first trained by examples and use this trained data in the prediction of the forthcoming step of the system. Today, neural networks are being used in diverse areas from medicine to psychology, meteorology, pattern and speech recognition, economic forecasting etc.

1.2 The Scope and the Aim

The aim of the study is to develop an evolutionary design methodology with an addition of the use of neural networks and examine its potential to generate and identify creative solutions. Fundamentally the study stems on the use of a neural network as the objective function of the genetic algorithm. Without the use of neural network, the process carried out by the genetic algorithm simply operates on randomly mutating the identified samples or dividing them into pieces and combining these pieces to obtain new forms. By such an approach, the sample items are not only identified to the system, but the system is trained with these items as well. As a result, the system becomes aware of the aimed design criteria.

Computers are often utilized in design process as a presentation tool. Far from being a means of presentation, the developed tool is expected to learn about the evaluation criteria in a design problem and generate creative solutions. Much of the design practice depends on the utilization of existing elements and concepts. Although the methodology leads combination or mutation process similar to the mainstream design practice, it is expected to bring out surprising solutions with an unexpected approach.

The case study is based on the concept of “emphasis” which is one of the principles of design. Emphasis is chosen as the scope of the design problem since it could be achieved and evaluated in a composition within a rule-based approach. After the training phase, the system is asked to generate its own solutions. As a result, the system is expected to become aware of the concept of “emphasis,” and generate more intelligent solutions. In order to evaluate the creativity of the process, the outputs are compared with the responses of three groups of basic design students to the same problem.

In spite of the fact that evolutionary design depends on previous solutions while generating a new solution to a problem, the method is able to raise surprising items, which were not met before. On the other hand, the introduction of the neural network is expected to provide the system consistency in form generation.

1.3 Outline of Thesis

The thesis is formed out of six chapters. The second chapter elaborates the automation in design in a broad sense. The third chapter is on the evolutionary design and the concept of creativity which is associated with evolutionary process within the framework of the thesis. The subject of the forth chapter is human learning process and artificial neural networks. In the fifth chapter the case study will be presented. Finally, the sixth chapter will be the conclusion.

CHAPTER 2

AUTOMATION IN DESIGN

Since the study suggested within the thesis offers an iterative and systemized approach to design, this chapter will deal with the attempts in design automation beginning with generative systems.

2.1. Generative Systems

A generative system operates in such a way that it produces a number of potential solutions to a problem. In this section, the attempts to systemize and automate a generative process will be introduced beginning from Aristotle, who is regarded as the father of the concept.

2.1.1 Historical Background

The concept of generative systems dates back to Aristotle. In “Generation of Animals,” he mentions male and female as the chief principles of generation:

> “The male and the female are the principles of generation. By a ‘male’ animal we mean one which generates in another, by ‘female’ one which generates in itself. This is why in cosmology

> too they speak of the nature of the Earth as something female and call it 'mother', while they give to the heaven and the sun and anything else of that kind the title of 'generator' and 'father'. Now male and female differ in respect of their *logos*, in that the power of faculty possessed by the one differs from that possessed by the other; but they differ also to bodily sense, in respect of certain physical parts." (Book I, I-II, pp.11-13)

In his discussions about the design of a city in "Politics", he uses an analogy made with different species of animals. He states that after determining the organs that are indispensable to every animal, varieties can be obtained by making different combinations of them. Following such logic, he offers to generate potential cities by first analyzing the constituent parts, and making combinations of these.

> "For we agree that every state possesses not one part but several. Therefore just as, in case we intend to obtain a classification of animals, we should first define the properties necessarily belonging to every animal (for instance some of the sense organs, and the machinery for masticating and for receiving food, such as mouth and a stomach, and in addition to these the locomotive organs of the various species), and if there were only so many necessary parts, but there were different varieties of these (I mean for instance certain various kinds of mouth and stomach and sensory organs, and also of the locomotive parts as well), the number of possible combinations of these variations will necessarily produce a variety of kinds of animals (for it is not possible for the same animal to have several different sorts of mouth, nor similarly of ears either), so that when all the possible combinations of these are taken they will all produce animal species, and there will be as many species of the animal as there are combinations of the necessary parts:-so in the same way also we shall classify the varieties of the constitutions that have been mentioned. For states also are composed not of one but of several parts, as has been said often." (Book IV. III. 8-11, pp. 293-294)

Since Aristotle, the idea of generative systems was used in many fields such as philosophy, music, engineering and architecture. In 13th century, Spanish scholar Lull developed a system consisting of concentric discs or cards mounted on a central axis. Each disc contained words or symbols which could be combined in different ways by rotating the discs. For example, sentences like "I love mice," "You hate cats," "They eat frogs" could be obtained by turning the discs (Ramon

Lull's Ars Magna, 2005). With machines containing at least two of such discs, Lull aimed to obtain the possible knowledge by making different combinations of words and symbols (Mitchell, 1977). Although nearly forgotten today, Lull's ideas had a great influence during that time. Later Leibniz named Lull's approach as "arte combinatorial."

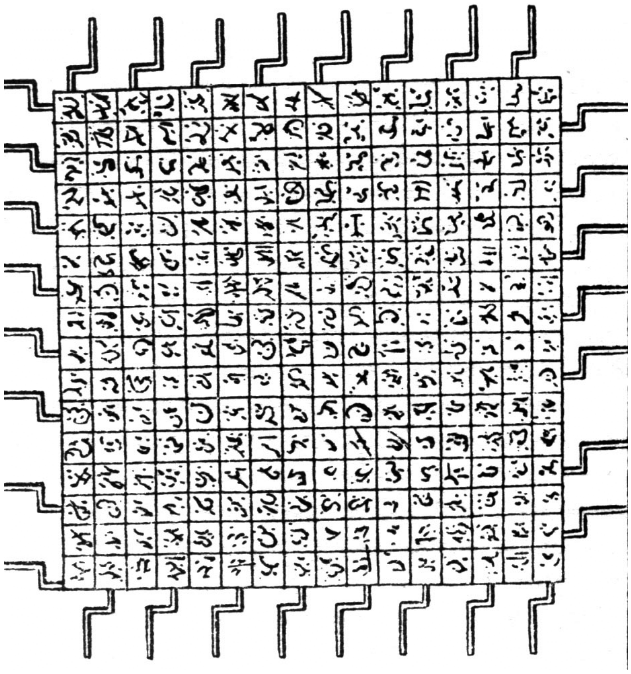


Figure 2.1: The book writing machine in "Gulliver's Travels" (Swift, 1994, p.202)

In Jonathan Swift's famous book "Gulliver's Travels" (1994), a similar system of Lull's is encountered. First published in 1726, this fantasy book is about the travels of Gulliver made to Lilliput and Lagado, two fictional places. While Gulliver visits the academy of Lagado, he meets a professor who is working on a book writing machine (figure 2.1) consisting of a frame in which randomly spinning wheels determine the words. Just like the system of Lull, this fantastic machine aimed to improve speculative knowledge by practical and mechanical operations. By this machine, even the most ignorant person was capable of writing books on philosophy, poetry, politics, law, mathematics, and theology without the least assistance of genius or study. The machine was constructed out of wooden bits as dice which were connected to each other within a frame by slander wires. On each face of the wooden bits, words written on paper were attached. On the edges of the frame, there were forty iron handles which were used to turn the dice and change the whole disposition of the words. Each time the handles were turned, the professor was seeking for a combination of few words which might be meaningful and take part of a sentence. By creating such a character of a crazy professor with the fantastic machine, Swift seems to be mocking with the 13th century Lullian combinatorial art (Jonathan Swift writes Gulliver's Travels, 2005).

Leibniz, the philosopher also appears as one of the important figures who thought of using generative logic. Leibniz was not only a philosopher, but a mathematician of that time. His fascination for the 'Aristotelian division of concepts into fixed "categories"' (Davis, 2000), led him to invent a special alphabet whose elements are not sounds, but concepts. On the other hand, Aristotelian metaphysics was the main theme of his bachelor's degree thesis. In 1673, Leibniz designed a calculating machine that can do ordinary mathematic. Until that time, Pascal was the one who invented a machine which was capable of making addition and subtraction. However, the device which was named as "Leibniz Wheel" later, could perform four basic operations of arithmetic. As a figure working both on philosophy and mathematics, Leibniz first thought using generation of combinations in design of machinery as well. As Mitchell states (1977), he claims to apply the generative method in design of a variety of machines such as pumps, telescopes, or submarines in a letter he has written to Duke Johann Fritz in 1671. His approach may be regarded as the foreshadowing of the morphological method in engineering design introduced by Fritz Zwicky in 20^{th} century which will be mentioned later.

2.1.2 The emergence of Computers

Leibniz's calculating machine with his inventions in calculus and attempts in forming a new language are regarded to be important milestones in the development of the computer. However, Charles Babbage's 'Analytical Engine' is regarded as the father of computer. Until 19^{th} century there had been lots of attempts to build up mechanical calculators. Babbage's 'Difference Engine' (figure 2.2), which was completed in 1832, opened the way to generate the idea for his 'Analytical Engine.' Mainly the Difference Engine was based on a straightforward logic which was 'designed to compute tables of numbers according to the method of finite differences, and then automatically to print the tables as they were computed' (Hyman, 1982). On the other hand, Analytical Engines were thought to be versatile, programmable automatic calculators. The device is also said to employ several features of modern computers such as sequential control, branching and looping (Charles's Babbage's Analytical Engine, 2005). As Hyman states, four functional units familiar in the modern computer could be distinguished in Analytical engine as input-output system, mill, store and control (1982). Having been born between the French Revolution and the English Industrial Revolution, Babbage appears as an important figure trying to approach both social and engineering aspects of production with a scientific touch. Although he was regarded as a mathematician, he also acted as an engineer since during the time there was no strict difference between pure sciences and applied sciences. In 1835, he released "On the Economy of Machinery and Manufactures." In this book, nearly all the aspects of mass production like power, material, price, division of labor, machinery, and legal restrictions are elaborated with a scientific approach. According to Hyman (1982), even Marx was influenced by this book when writing his "Capital."

Although 'Analytical Engine' was never completed, Lady Ada Lovelace's commands written on this device stands as one of the most famous early ideas about the creative capacity of computers. As the daughter of the poet Lord Byron, Lady Lovelace was one of the few female figures of her time who was interested in science and engineering. After meeting Babbage in 1833, Lady Lovelace began to play an important role in his life. She married with Lord Lovelace in 1835, who was also an engineer. Beginning from 1849, Lady Lovelace worked for the documentation and translation procedures of Babbage's works. Since she had sufficient mathematical knowledge to understand the projects, and enough time to devote for such a work, this seemed to be a useful way to outlet her talents. She was probably one of the first persons in the world to write programs for Analytical Engine, and years later a major programming language has been named Ada in her honor. Her commands on the Babbage's Analytical Engine were precious, and fanciful at the same time. For example she used analogies as;

> "We may say most aptly that the analytical engine weaves algebraic patterns just as the Jacquard-loom weaves flowers and leaves."(Davis, 2000, p.178)

Here, she refers to a weaving device called "Jacquard Loom," which was invented by Joseph-Marie Jacquard. The device operated with punched cards which were also thought to be used in Analytical Engine of Charles Babbage. Another critical

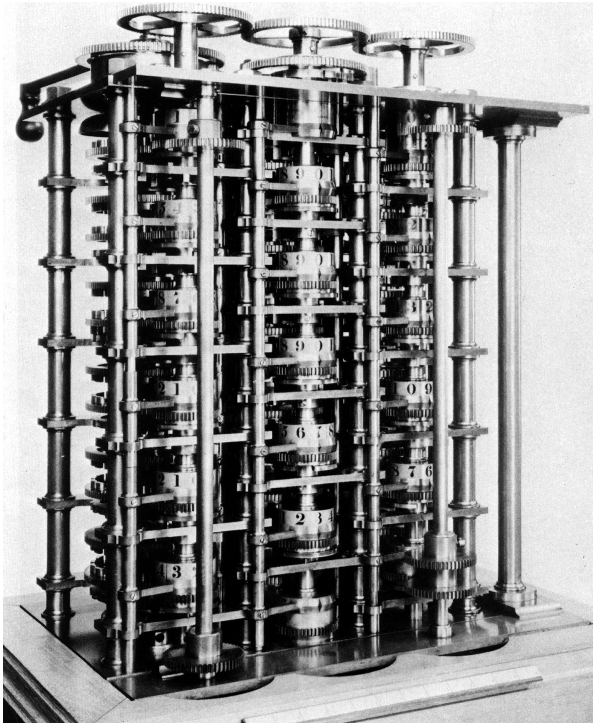


Figure 2.2: Babbage's Difference Engine completed in 1832. (Hyman, 1982, between pages 48-49)

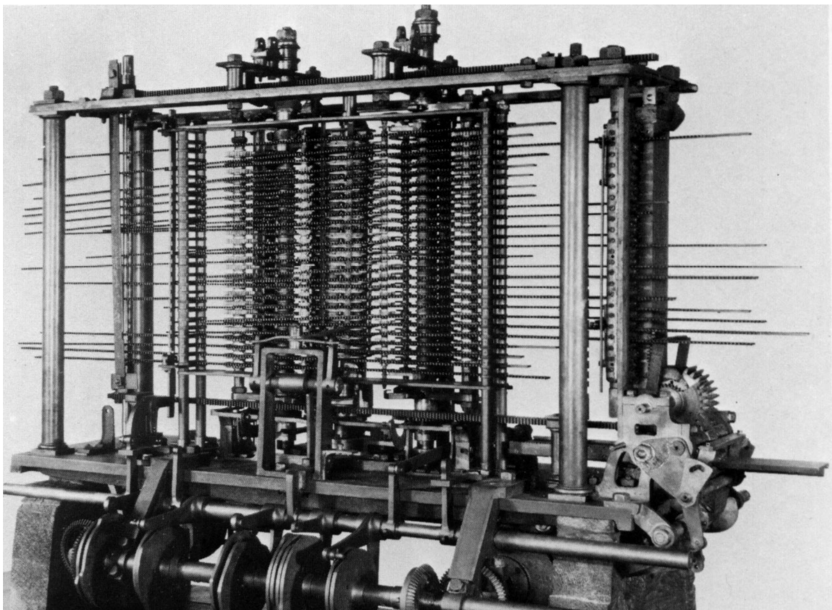


Figure 2.3: The mill of minimal analytical engine under construction when Babbage died. (Hyman, 1982, between pages 176-177)

command of Lady Lovelace, as quoted by Hyman (1982) , seems to fit exactly to the creative capacity of generative systems;

> "Supposing, for instance, that the fundamental relations of pitched sounds in the science of the harmony and musical composition were susceptible of such expression and adaptations, the engine might compose elaborate and scientific pieces of music of any degree of complexity and extent."(p.198)

However years later Lady Lovelace's argument was criticized for basing on the assumption that, "as soon as a fact is presented to a mind, all consequences of that fact spring into the mind simultaneously with it". As Mitchell states (1977), knowledge of a generative system on a procedure do not guarantee that the result generated by the procedure will execute will not be original or surprising. The more complex the solution criteria, the more sophisticated the solution generation process is, and the more surprising solutions it will bring, as in the case of evolutionary design.

2.2. Generative Systems in Design

Although design seems to be a mysterious act, which does not follow steps strictly defined, generative logic is somehow applied to it. Leonardo da Vinci is regarded to be one of the first to use the generative approach. Though Leonardo did not participate in a project as an architect throughout his life, he left hundreds of drawings of centralized church plans and bird's eye views. Architecture appears to be just one of the areas of interest of Leonardo. Following a systematic logic, he seems to produce "endless variations on circular, octagonal, or other polygonal plans. This suggests that he was interested not in planning real churches, but rather in the application of ideal patterns to such structures" (Schofield, 1999).

Basically there are two kinds of the centralized church plan: simple or complex. Simple plans are formed out of only one space-circular, polygonal or square surrounded by a peristyle (Guillaume, 1999). However Leonardo was interested more in complex plans which has two types as "radiating plans" and "cross-shaped plans." Radiating plans are formed out of a central polygonal space (usually octagonal) surrounded by peripheral elements. On the other hand, cross shaped plans, as the name suggests, are based on two perpendicular axes crossing in the central square space with peripheral elements forming the arms of the cross (figure 2.4). However, Leonardo's approach did not follow such a categorization; rather he led a systematic logic in producing the centralized church plans. According to Frankl, as cited by Mitchell (1977), Leonardo had a way of beginning with the simple forms as square, circle, octagon or dodecagon and reaching at any geometrical form of central plan church. Frankl's sample matrix-like scheme (figure 2.5) describes how Leonardo tried to reach various plans by alternating the elements.

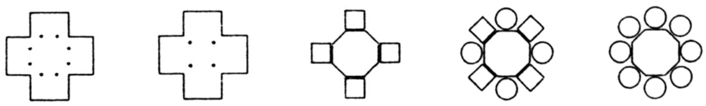


Figure2. 4: The types of centralised church plans (Guillaume, 1999, p.450)

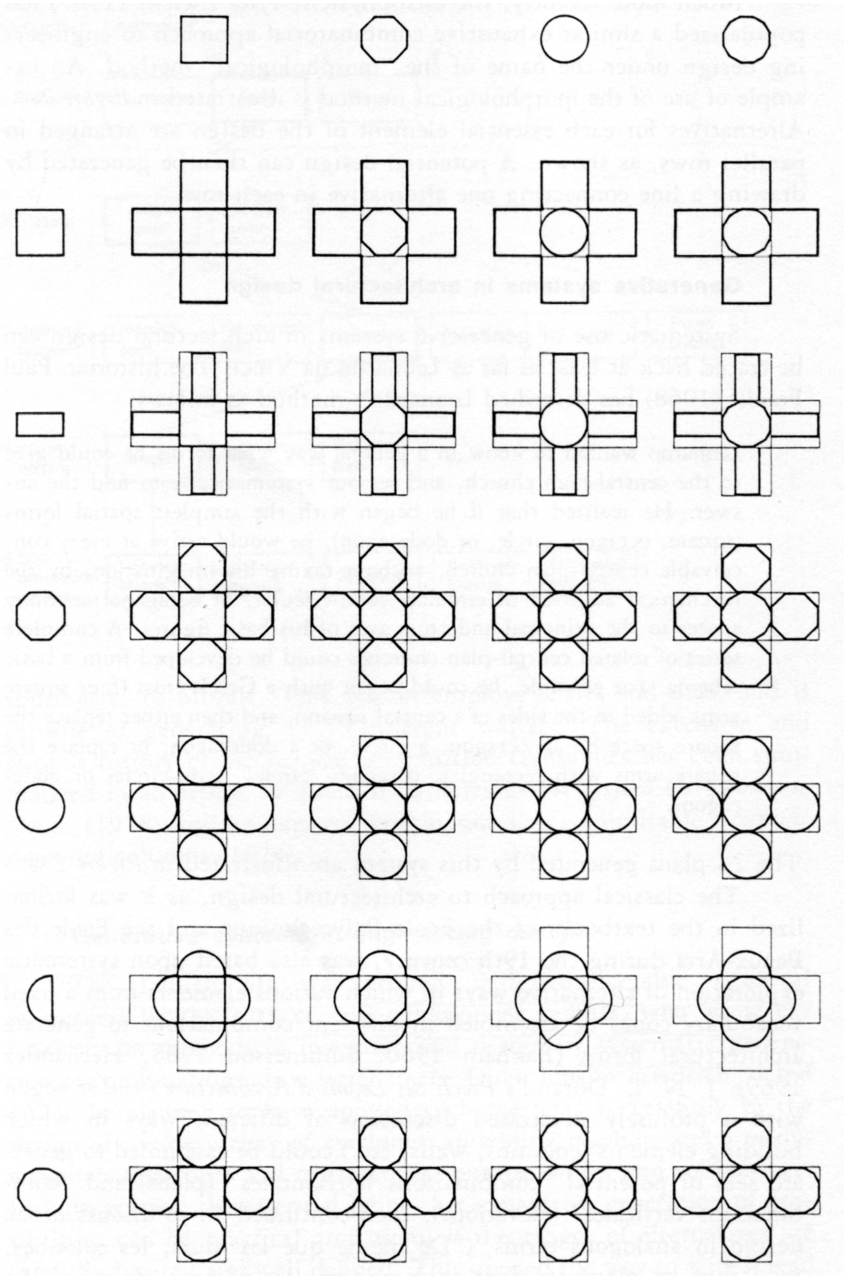


Figure 2.5: Frankl's scheme for Leonardo's generation of church plans (Mitchell, 1977, p.36)

It can be said that every geometric shape acts as an element in forming the plan as words are the elements of sentences. By just mechanically adding or alternating an element, various plans are achieved in this approach.

The traces of generative systems are also seen in engineering design. As mentioned before, Leibniz was the first to propose using generative logic in machinery design. In 20^{th} century, astrophysicist Fritz Zwicky proposed a new method following a similar approach. In his article "The Morphological Method of Analysis and Construction" (1948), Zwicky in a way offered a schematized version of Leibniz's generative approach. Mainly the method aims at identifying the total set of possibilities which can be applied during design of a product. In this method, first of all a matrix for the product to be designed is identified which consists of any variables like material, color, parts or design elements. These attributes determine the columns of the matrix. On the other hand the rows of the matrix are filled with varieties of the attributes. The design process is accomplished by making combinations of variables. A sample matrix for the design of a lamp is put forward in table 2.1.

Table 2.1: The morphological matrix for a lamp design.
(http://www.mindtools.com/pages/article/newCT_03.htm)

Power Supply	Bulb Type	Light Intensity	Size	Style	Finish	Material
Battery	Halogen	Low	Very Large	Modern	Black	Metal
Mains	Bulb	Medium	Large	Antique	White	Ceramic
Solar	Daylight	High	Medium	Roman	Metallic	Concrete
Generator	Colored	Variable	Small	Art Nouveau	Terracotta	Bone
Crank			Hand held	Industrial	Enamel	Glass
Gas				Ethnic	Natural	Wood
Oil/Petrol					Fabric	Stone
Flame						Plastic

A recent example of such an automated process of product design is proposed by Wallace and Jakiela. While morphological method stands as a method of engineering design, this approach aims at combining conceptual engineering design and industrial design to reach "useful and beautiful" (Wallace, Jakiela, 1993) designs. The system may be regarded as a follower of morphological method, since it contains computer catalogues of the components of products. The whole process is computer driven. Besides making selections from component catalogs, the system is also able to locate the components within the product according to identified specifications of use (for example on desktop, or in one's hands), physical qualities (thin, small, wide, etc.) and orientation (vertical or horizontal) of the product. In the end, the system generates items that it finds acceptable according to ergonomic, aesthetic and manufacturing rules. The system also involves a library of style prototypes. After generation of the surface housings, designer is also able to apply styles from this library. Moreover, designer can create new styles and expand the library by adding those.

In summary, the system utilizes three kinds of data as;

1. User inputs involving product traits, product use and style type.
2. Libraries of standard components and style prototypes.
3. Product rules of ergonomics, aesthetics and manufacturing.

The process of form design led by the system is described in four stages;

1. Product Organization: locating the components in three dimensional space relative to molding.
2. Surface Design: enclosing the components in an appropriate surface (housing)
3. Surface Detailing: adding style-specific details to the surface such as speaker grills, buttons, grills or vents.
4. Graphics: applying graphical elements such as color or logos.

(Wallace, Jakiela; 1993)

Recently there are commercial examples of such computer programs which aim at automating design process. One of such programs is the thinkID released by think3. Similar to the system proposed by Wallace and Jakiela, thinkID operates with standard libraries, user inputs and rules specific to aesthetics, production, ergonomics etc. The company suggests that product design is a three step process out of conceptual design, modification and product engineering. Between each of these steps, data necessary for design is said to be lost or skipped. In order to avoid the problem of loosing data between these steps and to shorten the time spent for the overall design process, such a program is developed. The program is capable of not only visualization, but also with making critical aesthetic, functional and engineering decisions by making optimization (think3, 2005).

In fact, the use of computers in design optimization process, especially in architecture, is not a new concept. Beginning from 1960's, designers were involved with automating the design process by computers. One of the earliest examples of such attempts was URBAN5, which was developed by Negroponte and Grossier in 1965. As Negroponte states, URBAN5's original goal was to "study the desirability and feasibility of conversing with a machine about an environmental design project … using the computer with an objective mirror of the user's own design criteria and form decisions; reflecting responses formed from a larger information base than the user's personal experience" (1970). Since during the time computers were not widely used and the architects were not familiar with these machines, URBAN5 suggested two languages to communicate: English (entered from a typewriter), and a graphic language (using a cathode-ray tube and light pen). The basic spatial concept of the program was based on the manipulation of ten foot cubic spaces graphically (Olsten, 1971). The program was not only able to display the layout of the design with respect to conditions of light, material etc., but also calculate and perform simulations of circulation, panic mode etc. Moreover the designer is able to qualify activities and make the computer perform those. URBAN5 was intended to perform as a design partner. It had one central "attention" mechanism that either listens or hears from the designer, always giving him the opportunity to change his mind or restate a situation at any time (Negroponte, 1970). This user-friendly program offered an instruction manual for each button in the program for it was designed to be a self-teaching system. At the beginning, the program was asking the user if it was his first encounter with the program or not. If not, a tutorial page was introduced to the user. Besides using a fixed language, the program was also able to learn words as far as the designer states a criterion properly. Since verbal communication was available with the computer, the designer was able to make conversations, teach the program words and record them in the computer. While the system is stored on a disc, the designer's personal system or archive is recorded on a magnetic tape. When a designer enters a display terminal, the system asks his name and after identifying the designer, loads his tape.

Another early system used in design automation is BOP (Building Optimization Program) used by Skidmore, Owings and Merrill (SOM). The program was first developed in 1967 by Neil Harper and David Sides in order to be used in design of building complex to be built in O'Hare Airport. In order to operate the program, the designers first defined the design factors for high-rise office buildings in English language statements, and receive sufficient geometrical output along with estimated costs (Sides, 1975). BOP was found to be helpful in early phases of design since the architect can produce alternative solutions and examine alternative proportions and cost changes (Teague, 1975). Later programs like PLUS (Planning and Land Use System) was developed on the basis of BOP by SOM.

Although computers are generally used in design automation with their visualizing abilities, these examples show us that they take part in decision making and evaluation processes. In carrying out such operations, the computer uses methods of minimization, maximization and optimization. Therefore it can be said that computers act as the tools for the management of design information. The following chapter will deal with the attitudes and tools in minimizing, maximizing, and optimizing design information.

CHAPTER 3

EVOLUTIONARY DESIGN
AS A CREATIVE DESIGN METHOD

Within this chapter the nature of design process and the process of evolutionary design as a design method will be introduced together with the concept of creativity. The creative potential of evolutionary design will be elaborated with respect to several studies done before.

3.1 The Nature of Design

The design process is identified in various ways. In general, design is a goal oriented, constrained decision making process which requires exploration and learning (Gero, 1990). The aim of the mentioned process is to find sustainable and creative solutions that fulfill the requirements defined in the problem definition (Giaccardi, Fischer, 2008).

Design process tends to initiate change in the man-made things (Jones, 1992). Until the appearence of design as a profession, the act of initiating change was carried out by craftsmen. With the emergence of design profession, idea generation and craftsmanship became separate labor items and the craftsmen who "made" the objects were replaced by the designers who "planned" the objects by drawing (Akbulut, 2009). The craftsman's major act is to grasp the item by carrying out a hand operated process. Equipped with a technical and intellectual background, the designer handles the same process by visualizing the designed item in different media. While the craftsman participates in nearly all of the production steps, the designer plans the item and the production process on paper collaborating with certain other occupational groups. Though, the craft tradition depends on a process of trial-and-error over the product for many centuries, the paper based techniques uses scale drawings as the medium for experiment and change (Jones, 1992).

Over the past years, a considerable change in the handling of design process has been witnessed. Until the introduction of computers, designers had used paper based techniques to carry out the design act. For establishing shapes, designers used a sketchpad, a practiced hand and a selection of pencils and markers, and perhaps cardboard, clay, and other physical media (Graham, Case, Wood, 2001). However, these techniques are limited to the correct and systematic transfer and documentation of design information. This information is usually imprecise, uncertain, and incomplete which makes design problems hard to be solved by general problem solving methods (Liu, Tang, Fraser, 2004).

The attempts to provide models for the design process resulted in defining descriptive and prescriptive models. While descriptive models usually emphasize the importance of generating a solution concept early in the process, prescriptive models point out for more analytical work to precede the generation of solution concepts. Descriptive models are solution based and the solution generated at the very beginning of the process is then subjected to analysis, evaluation, refinement and development. The process is heuristic; using previous experiences and general guidelines with no guarantee of success. A heuristic is a "best guess" or "rule of thumb" solution to a problem (Klein, 1991). On the other hand, prescriptive models offer a more algorithmic, systematic procedure and provide a particular design methodology (Cross, 1989).

The descriptive design process is basically carried out in three steps as generation, evaluation and communication. French (1985) developed a more detailed model consisting mainly of four steps as analysis of the problem, conceptual design, embodiment of schemes, and detailing (Figure 3.1). In the conceptual design phase, broad solutions to the problem statement are formed in the form of schemes. In this phase engineering science, practical knowledge, production methods and commercial aspects are brought together to take important decisions. In embodiment of the schemes phase the generated schemes are worked in greater detail and a final choice among the alternatives is made. In detailing phase small but essential points are fixed with good quality work to avoid delay and failure in final design. Though the process is visualized in flow diagram, there are feedback loops between each step showing the iterative returns to earlier stages where necessary.

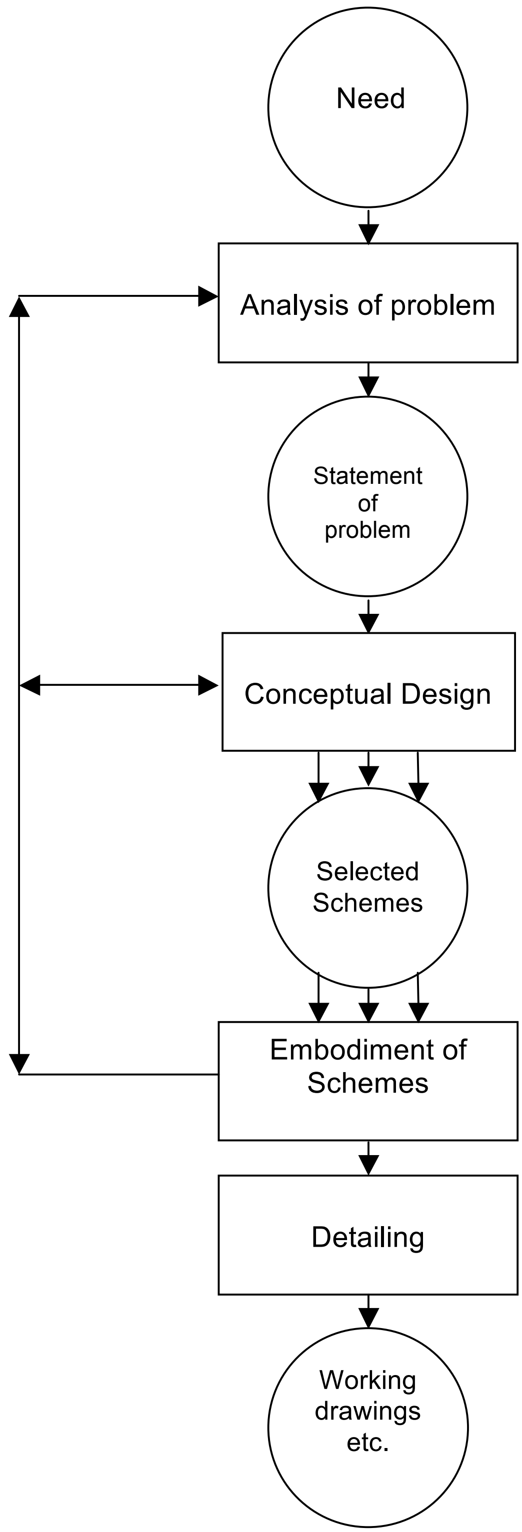


Figure 3.1: French's model of the design process (Cross, 1989, p.21)

On the other hand the prescriptive model offers more improved ways of working with algorithms, providing systematic procedures with a particular design methodology. An algorithm is simply defined as every kind of systematic calculation method in mathematics (Beyazıt, 1994). It is a precise set of rules to a particular type of problem (Klein, 1991). The prescriptive approach requires more analytical work to precede the generation of solution concepts. It needs to ensure that the real design problem is identified and no important elements of the problem are overlooked (Cross, 1989).

The formal view of prescriptive design process is accepted as a three phase sequence comprising of analysis, synthesis and evaluation. Jones (1992) describes these three stages as “breaking the problem into pieces,” “putting the pieces together in a new way,” and “testing to discover the consequences of putting the new arrangement into practice.” Analysis is the stage where the formulations are made for the final design. It provides the context for all that follows. In synthesis stage, a considerable work is carried out in developing formal models and possible solutions. In evaluation stage the alternative designs are assessed on the basis of fulfilling performance requirements such as operation, manufacture and sales. Evaluation phase is usually carried out by making simulations, numerical and ordinal analysis.

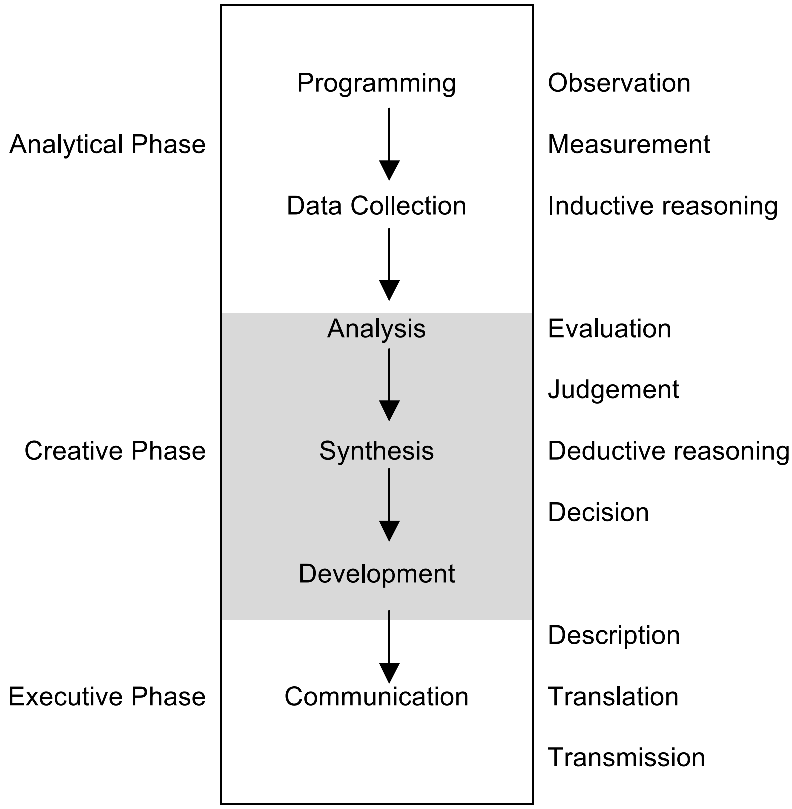


Figure 3.2: Archer's model of the design process (Cross, 1989, p.25)

A more detailed prescriptive model developed by Archer includes interactions with the world outside of the design process itself, such as inputs from the client, the designer's training and experience, other sources of information etc. (Cross, 1989). Archer (1984) defines six types of activity as programming, data collection, analysis, synthesis, development and communication (Figure 3.2). In programming stage crucial issues about the problem are established. Required data is collected, classified and stored in data collection stage. In analysis stage sub-problems and design specifications are identified. Design proposals are prepared in synthesis while prototype designs are build up in development stage. Communication is the stage where manufacturing documentation such as drawings are prepared. However these six types of activities are summed up in three broad phases as analytical (programming and data collection), creative (analysis, synthesis and development) and executive (communication) phases.

Archer's model offers a rough process frame to the design process. Though more complex models have been proposed later on, they were criticized for being too intricate to swamp the problem in fine details. A more comprehensive and clear model for design process offered by Pahl and Beitz (Figure 3.3) remains effective today. The process is decomposed into four main stages as clarification of the task, where necessary information is collected; conceptual design, where suitable solution principles are combined into concept variants; embodiment design, where the determined layout is developed into a technical product with technical and economic considerations, and detail design where all drawings and other production documents are produced after arrangement and determination of form, dimension, surface, and material properties.

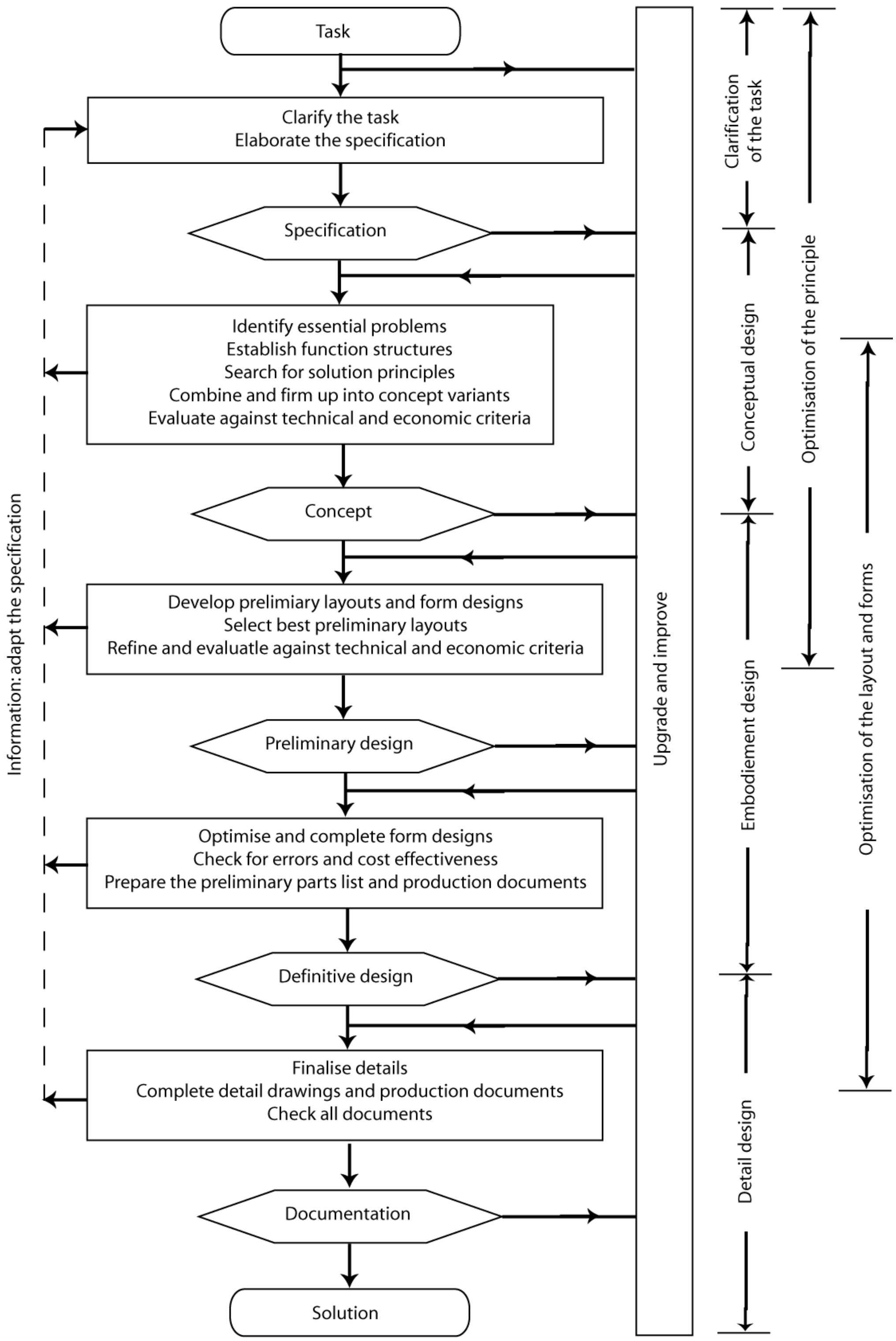


Figure 3.3: The model of Pahl and Beitz (http://www.wikid.eu/index.php/Phase_model)

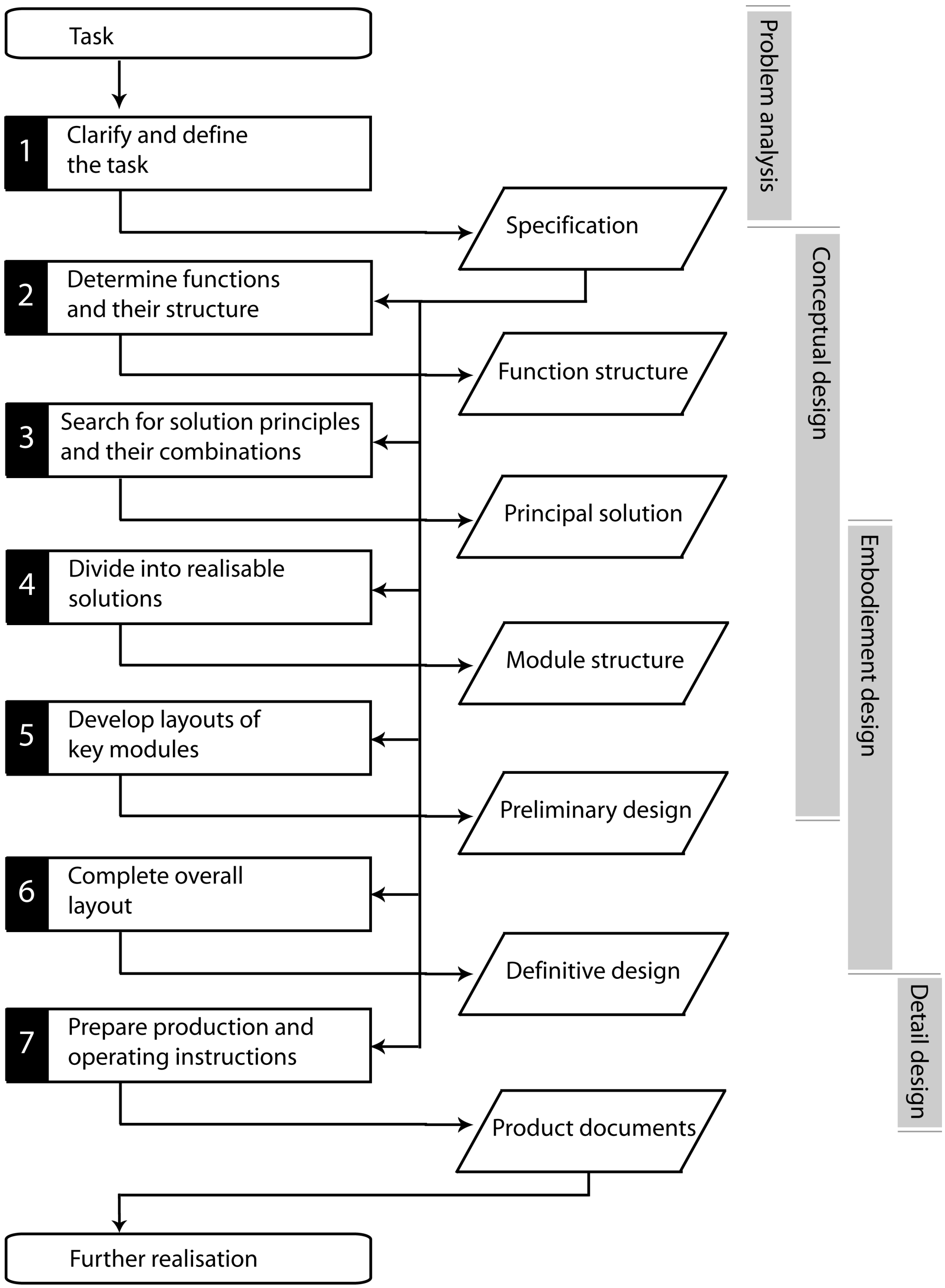


Figure 3.4: VDI model of design (http://www.wikid.eu/index.php/Phase_model)

The German professional engineers' body, Verein Deutcher Ingenieure (VDI) has produced a guideline in this area including the VDI 2221 "Systematic Approach to the Design of Technical Systems and Products" which offers a systematic approach to design (Figure 3.4). The system follows a systematic procedure of first analyzing and understanding the problem, breaking it into sub-problems, finding suitable sub-solutions and combining these into an overall solution. However the system is criticized for being problem-based rather then having a solution-based approach.

3.2 Creativity and the Design Act

Design is a purposeful act which creates an artificial world. The aim of this creative process is to generate products that fulfill the predefined needs in a problem. The process is categorized as routine and non-routine that points to the emergence of either known, expected and ordinary structures or unexpected, surprising structures which are called as "creative solutions" answering the needs.

3.2.1. The Concept of Creativity

Creativity has been defined in many different ways. According to Gotz (1981), creativity is a form of making and is thus a public activity as distinct from private mental activities. It is not about the thoughts, feelings and mental processes of the creator but about concretization. It is about the act of making, rather then the capacity to act. Creativity is often understood as a person's ability to produce something new, novel, unexpected and surprising (Takala, 1992; Fischer, 1992). According to Boden (1991), creative ideas are brought into being by unusual and surprising combinations of ideas.

Likewise Hebb and Donderi (1987) suggest that creativity, or insight, is a function of mediating processes that lead to the recombination of ideas to produce new ideas. It is defined as the improbability of combination, which brings novelty. However, every surprising or unpredictable idea cannot be identified as creative either it is useful, illuminating or challenging. Therefore, rather then being opposed to creativity, constraints act as the criteria of judgment which make creativity possible. Without them, random processes alone can result only first time curiosities, but not radical surprises. A creative idea need to be as simple as possible. Otherwise a complex solution may easily be misidentified as creative due to its improbable nature.

Since creativity is an act, the outcome of this act is expected to be creative products which are expected to be new, original and unique. Mc Laughlin (1992) categorizes creative products in three groups as new scientific theories, works of art and inventions. Although creativity is accepted as an act that manifests itself in a wide spectrum from science to art, the relation between design and creativity is respected to be special as a result of the nature of design. Though science and art are regarded to proceed with either convergent or divergent ways of thinking, design process needs both ways in equal proportions. Designers must solve externally imposed problems to satisfy the needs of others in a visually pleasing way (Lawson, 1997), so they need to approach the problem both from scientists' and artists' perspectives. This uneasy relationship forces the designer to generate functional, usable, and visually pleasing answers to problems simultaneously.

Creativity has long been regarded as a black box process (Mc Laughlin, 1992). However, based on the mathematician Henri Poincare's conception of the creative process, Kneller (1965) offered a five step model of creative process consisting of "first insight," "preparation," "incubation," "illumination," and "verification." "First insight" simply involves the recognition of the problem. It is followed by "preparation" which involves considerable conscious effort in the search for a solution to the problem. In this phase, the problem may be reformulated or completely redefined as the range of possible solutions is explored. The following phase which is named as "incubation" is relatively a relaxing period where the ideas are waited to precipitate and be crystallized in mind without applying any conscious effort. During the incubation period the mind continues to reorganize and re-examine all the data which was acquired in the former stages. During "illumination" the creative idea suddenly emerges and in the last phase "verification" the idea is tested, elaborated and developed (Lawson, 1997). However creativity is not a straightforward process. Just like the design process, it leads a recursive nature and the problem definition is identified again and again as the process continues. It requires the ability to change the direction of thinking and generating more ideas.

McLaughlin (1992) categorizes creative process into four groups: mechanical and random generation, selection, reminding, and merging of retrieved ideas and experiences. Mechanical and random generation is basically production of elements by some predefined procedure. As ideas are generated, the decision to identify the final product gains importance. Selection is the category where the proper creative solution is set apart. Reminding may be characterized as retrieval of information and lastly the retrieved information and experiences are merged to come up with creative solutions.

Although creativity is regarded as a black box process, attempts to develop computational models of creativity critically need a selection and evaluation stage that facilitates the system to set aside the worthless items. The process of exhaustively generating all possible presentations cannot be regarded as a creative process since mechanical generation can yield both creative and useless items at the same time.

3.2.2 Creativity in Design

Although design employs creative thinking, creative thinking and creative design are not identical concepts. "Creative design" is concerned with the creation of the new structures since design needs the form of an artifact, or the description of the structure of the artifact. Finding new applications for an existing product may be an example of creative thinking whereas finding new products and structures to perform the same application is an example of creative design. (Rosenman, Gero, 1992).

Design produces new structures in response to certain requirements. These requirements determine the function of the object. The function depicts what the product is for. On the other hand, the product has certain behavioral attributes that make it capable of carrying out particular functions. The behavior of a product describes what the product does defining the potential functions. Thus, behavioral attributes are the key to matching structure to function (Rosenman, Gero; 1992). Recognizing the potential functions and employing those behaviours on a certain product is creative thinking while creating completely new structures to perform a defined function is creative design.

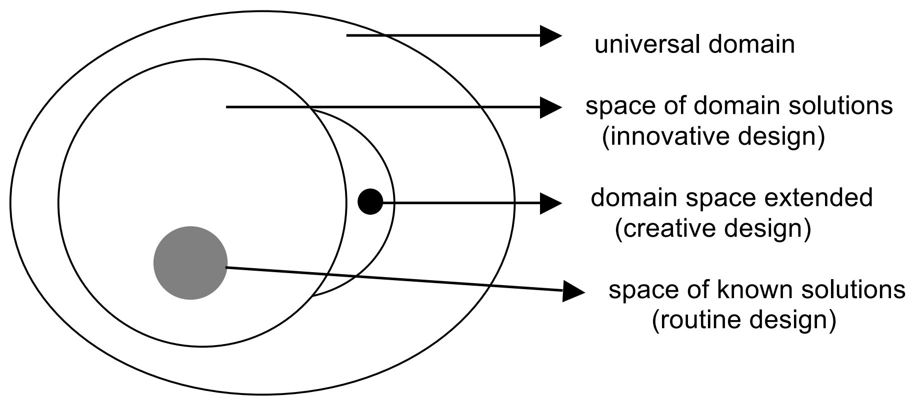


Figure 3.5: The Domains of Routine, Innovative and Creative Design (Rosenman, Gero, 1992, p.115)

In general design is categorized as routine, innovative and creative design (Figure 3.5). Routine design can be defined as the design process which proceeds within a well-defined environment where all the variables and their ranges are known. Much of the design practice lead is routine and depends on existing prototypes. On the other hand, innovative design proceeds by manipulating the applicable ranges of values. What results, is a design with a familiar structure but novel appearance because the values of the defining variables are unfamiliar (Gero, 1990). Apart from those, creative design uses new variables, reaches entirely new structures since it extends the space of potential variables. It incorporates innovative design but involves the creation of products that have little obvious relationships to existing products. Whereas, routine design involves the instantiation of a given type and innovative design involves the generation of new subtypes, creative design involves the generation of entirely new types (Rosenman, Gero; 1992).

In order to generate new structures, there are basically two methods; to start from existing elements and to modify them, or to reach new structures from basic building blocks. Starting from existing elemets includes combinatorial design, analogical design and design through mutation. The approach of starting from basic building blocks is called as “design from first principles.” The designers employ either one of the methods or a combination of several to obtain creative structures.

Combinatorial design involves importing parts from various designs and combining them into a new design. The combined cases can either be from relevant or an irrelevant domain. Mutation, on the other hand, just involves the modification to a structural element without importing elements from outside. The mutation act can either be carried out randomly or controlled. Though random mutation creates suprising results, often they are meaningless. Design by analogy involves making associations to generalizations outside the current domain. It requires the recognition of a structure in another context to match the required behavioral properties. Without relying existent structures, design from first principles operates on more abstract level. By decomposing a problem, it tries to reach a primitive level where the relation between function, structure and behaviour is obvious. The operational objectives are reformulated and the requirements are investigated to form new structures. These new structures are generally independent from the existing designs.

3.3 Evolutionary Design

In the last decade, the process of design manifested considerable changes. While the designers tried to turn the design knowledge into form with the help of traditional techniques, today they try to automate the design process to an extend (Akbulut, 2008). Often designers' interaction with computers is limited to utilization of visualization software. However, generative techniques in which genetic algorithms are applied to design tasks are utilized as a new tool in design today. Those techniques, which are mentioned as "interactive evolutionary design" or "aesthetic selection," are regarded as a new style of human-computer interaction for creative tasks (Lund, 2000). The act of evolutionary design namely operates on the basis of genetic algorithms. Below, evolutionary design will be introduced following genetic algorithms.

Evolutionary computation concerns with search. Any point or position in the search space defines a particular solution and search process is some kind of a task of navigating that space (Bentley, Corne, 2002). There are many search algorithms, however what distinguishes evolutionary algorithms from other search methods is its inspiration upon the mechanism of evolution in nature.

There are four main families of evolutionary algorithm in use today as genetic algorithms, evolutionary programming, evolution strategies and genetic programming. Among these, the genetic algorithm is the most well known and popularized of all and often the term is used to denote each of the four main families of methods.

3.3.1 Genetic Algorithms

The principles of genetic algorithms are formed in Michigan University during 1970's by John Holland who tried to simulate the genetic process in living organisms in computers (İşçi, Korukoğlu, 2003). Genetic algorithms are based on the Darwinian concept of natural evolution where certain methodology on reproduction and survival of the fittest is employed. Basically genetic algorithms are search algorithms used for optimization. In order for this methodology to work,

- There should be a certain population among whose members reproduction is available.
- There should also be constraints determined in order to select the fittest individuals to survive.

Genetic algorithms work on evolutionary mechanisms of reproduction, crossover and mutation. In biological systems, every individual has a genetic code which consists of four nucleotides as adenine, guanine, cytosine and thymine. The sequence of these nucleotides forms the genetic code or "genome" which is unique for every individual. All specifications of an individual are encoded in these chromosomes. Any variety in chromosomes results in structural or behavioral differences between individuals. While reproduction is the exact duplication of an individual, crossover and mutation are the processes that can produce new individuals. Crossover may be defined as the chromosome exchange between parents (genotypes) during reproduction while mutation is the variation on the chromosome of an individual. However crossover and mutation are not able to produce individuals which can survive all the time. As a result of natural selection, the offspring (phenotypes) which are fit to the environment are able to survive, while the rest are eliminated.

Genetic algorithms make use of the search space, which involves the coded solutions or genotypes to the problem, and the solution space, which consists of actual solutions or phenotypes. In genetic algorithms the representation of the chromosomes differs from human chromosomes. First of all, the units of the human chromosome are defined (adenine, guanine, cytosine and thymine) while in genetic algorithms a representation scheme for every problem is required. Representation scheme is used to obtain coding of parameters and identify individuals. Every individual is attributed a gene where every parameter is coded. The representation of a gene may be in string, or tree form.

Genetic algorithms operate on reproduction among the members of a population in order to obtain robust individuals. The search is directed by the "survival of the fittest" principle of evolution. During reproduction processes, whether a random crossover or mutation is made and the process continues until the population obtains the fittest individuals. This provides the search the ability to generate better solutions. The basic principle is; a population of solutions, evolving according to the survival of the fittest principle, and new candidate solutions are produced by mutation and/or crossover operators.

Koza (1992) summarizes the steps of genetic algorithms as follows:

1. Completion of the genetic algorithm
    - Determine the representation scheme.

A scheme with a string length L and alphabet size K is selected. This scheme should cover all possible solutions of the problem in the search space.

- Determine the fitness measure.

It should be capable of evaluating all possible alternatives represented by the scheme.

- Determine the parameters and variables controlling the algorithm.

The primary parameters of a genetic algorithm are the population size (M) and the maximum number of generations to be run (G). Secondary parameters are pr, pc, pm; they control the frequency of reproduction, crossover and mutation respectively.

- Determine the way of designating the result and the criterion for terminating run.

Run of a genetic algorithm is terminated in two ways; first, if the fitness of the best individual in the run is close to the optimal solution with an acceptable predefined error value, operation of the algorithm is terminated. Genetic algorithm cannot always find the exact solution of the problem; it generally finds solutions which give the results approximate to the exact solution in the defined variable range. The second way of termination is the execution of the maximum number of generation predefined at the third step. Although an acceptable solution cannot be found, operation is terminated when the maximum number of generation to be run is reached.

2. Operation of genetic algorithm:
    - Create an initial population randomly according to accepted representation scheme.

      Size of the population is determined in the preparation step.
    - Perform the following sub steps on the population iteratively until the termination criterion has been satisfied.
        1. Evaluate the fitness of each individual in the population.
        2. Create a new population of strings by applying at least the first two of the following three operations. The operations are applied to

individual string(s) in the population chosen with a probability based on fitness.

    i. Copy the existing individual string to the new population. (reproduction)
    ii. Create two new strings by genetically recombining randomly chosen substrings from two existing strings. (crossover)
    iii. Create a new string from an existing string by randomly mutating the character at one position in the string. (mutation)

3. The best individual string that appeared in any generation (i.e. the best so far individual) is designated as the result of the genetic algorithm for the run. This result may represent a solution (or an approximate solution) to the problem.

A simpler description of genetic algorithm of Bentley and Corne (2002) is as follows:

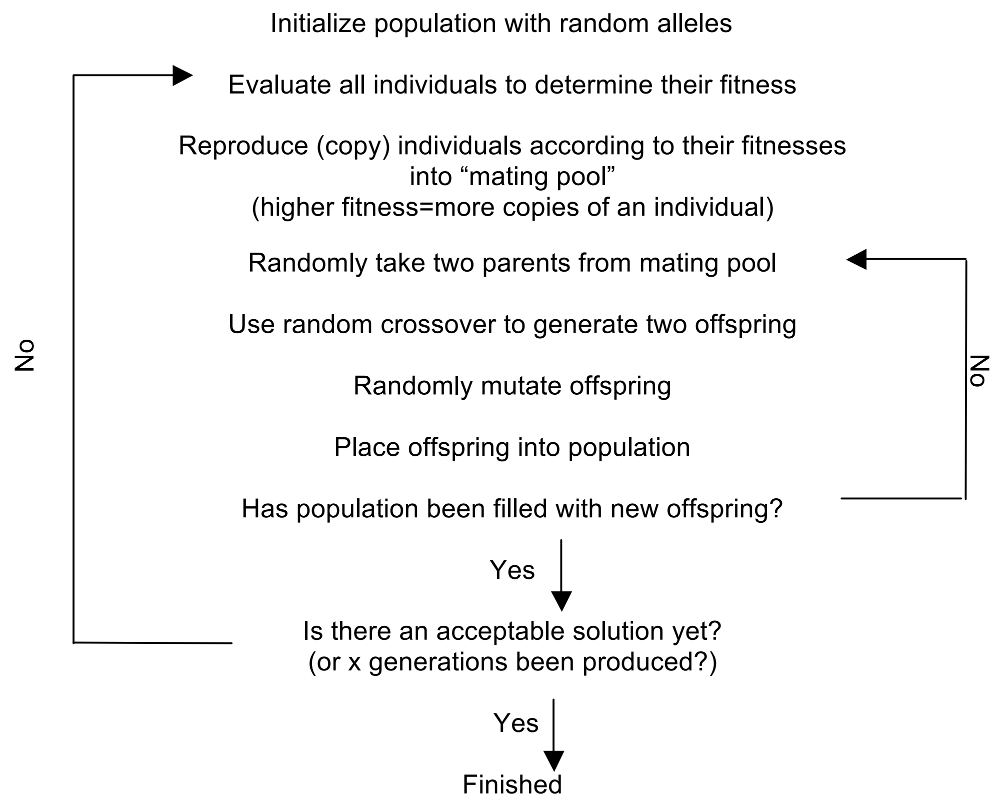


Figure 3.6: The simple genetic algorithm (Bentley, Corne, 2002, p.26)

3.3.2 The Process of Evolutionary Design

Genetic algorithms are utilized as an optimization tool in evolutionary design process. Bentley identifies four main reasons why the choice of evolutionary algorithms is appropriate for design problems (1999.) The first reason is that evolution is a good and general purpose problem solver. The second one claims that evolutionary algorithms have been used successfully in every type of evolutionary design. The third reason is that evolution and human design process share many similar characteristics. According to the fourth and the last reason, the most successful and remarkable designs known to mankind were created by natural evolution, the inspiration for evolutionary algorithms.

Basically evolutionary design applies a generative logic in finding answers to design problems. The concept of "generative system" which is raised by Aristotle, operates to raise a number of potential solutions by putting together various different combinations of alternatives.

The idea of putting together is also basic for evolution. According to Dawkins (1986), evolution is like a blind watchmaker who puts together the parts without seeing. Since it is blind, it does not have logic, it is random and unconscious. Likewise, evolutionary design by computers does not involve conscious design at all. Evolutionary design is simply a process capable of generating designs (Bentley, 1999). However, this unconscious nature of the process rather makes it capable of raising innovative solutions. What makes the process conscious is the human designer.

Bentley (1999) makes a categorization for evolutionary design where he divides those design activities into four parts as evolutionary design optimization, creative evolutionary design, evolutionary art, and evolutionary artificial life forms. "Evolutionary design optimization" is not mentioned to be a generative or creative process at all. It is simply characterized as the application of evolved parameter values to existing designs. On the other hand, "creative evolutionary design" aims to generate entirely new designs starting from little or nothing. These have the ability to generate surprising solutions and vary the number of decision variables. Two approaches are mentioned in this category as "conceptual evolutionary design" which deals with the production of high-level conceptual frameworks for designs and "generative evolutionary designs" or "genetic design" which is involved with generation of form of designs directly. As the name suggests, "evolutionary art" is an art form and tends to new forms and images with very small population sizes where human evaluator sets fitness for each member of the population. It is regarded as commercially the most successful type of evolutionary design. Lastly and briefly, "evolutionary artificial life forms" emerges as a new field of computer science known as artificial life. It deals topics such as artificial brains, behavior strategies, methods of communication.

Design is known as a problem solving act. A problem exists if something is desired but the actions necessary to obtain it are not immediately obvious. The goal sought by a problem solver is often some real or abstract object. Then problem solving involves obtaining an appropriate candidate object, and verifying if the object satisfies the goal description (Mitchell, 1977.)

A problem statement is expected to include conditions to be satisfied by the object, tools and operations that can be used, and limits on resources to be used. Such information may be in verbal, graphic or numerical form (Mitchell, 1977.) In the case of evolutionary design by computers, all of the problem statement is expected to be in numerical form. Also, the generated items are also identified in numerical form.

The design concept is required to be described in a genetic code in the evolutionary model (Frazer, Frazer, Liu, Tang, Janssen, 2002). This genetic code which is named as representation scheme, is then subjected to genetic operations for generation of design alternatives. Evolutionary algorithms (e.g. genetic algorithms GA, genetic programming

GP) differs in representation scheme (i.e. string based, tree based schemes respectively). The representation must provide the computer with ways to create, manipulate and modify the solution alternatives. (Funes, Pollack 1999). Evolutionary design begins with the description of the representation scheme which must be capable of defining all possible solutions of the design problem. In the conducted case study, the string based representation scheme is employed. In another application, other representation schemes easing the genetic operations and/or evaluation process may also be preferred.

Evolutionary design starts with the creation of an initial population. The individuals constituting the initial population may be constructed randomly or a predetermined set of individuals may also be given as an initial population. Although a randomly generated initial population encourages the diversity, the source of creativity, it may also include vast amount of undesirable or uninteresting solutions. Such a population will decrease the probability of success and increase the operation time. Therefore, a well prepared initial population can perfectly keep the diversity and decrease the operation time. The process is illustrated in figure 3.7.

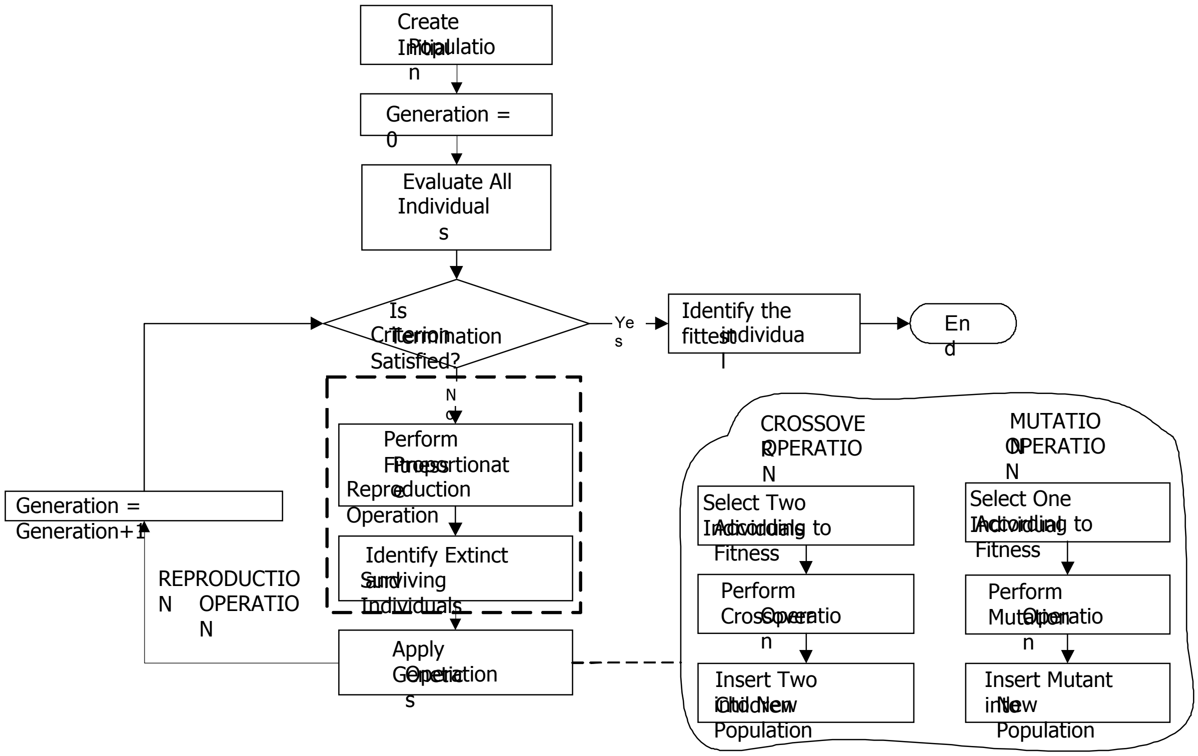


Figure 3.7: Evolutionary Design Process

A sample Generative Design System (GDS) consisting of four elements; the design representation, a generation engine, an expression engine, and a mechanism for evaluation and selection of newly generated design specifications, is offered by Gatarski and Pontecorvo (1999). (Figure 3.8)

“Representation” is the element in which set of parameters and constraints are identified for the design problem. While the “parameter-set” forms the “genetic” elements of design as form and structural aspects; the “constraint-set” controls the aesthetic and fabrication aspects of design. Apart from these, a prototype-set, which can be regarded as the pool of future parent genes, is also an element of representation.

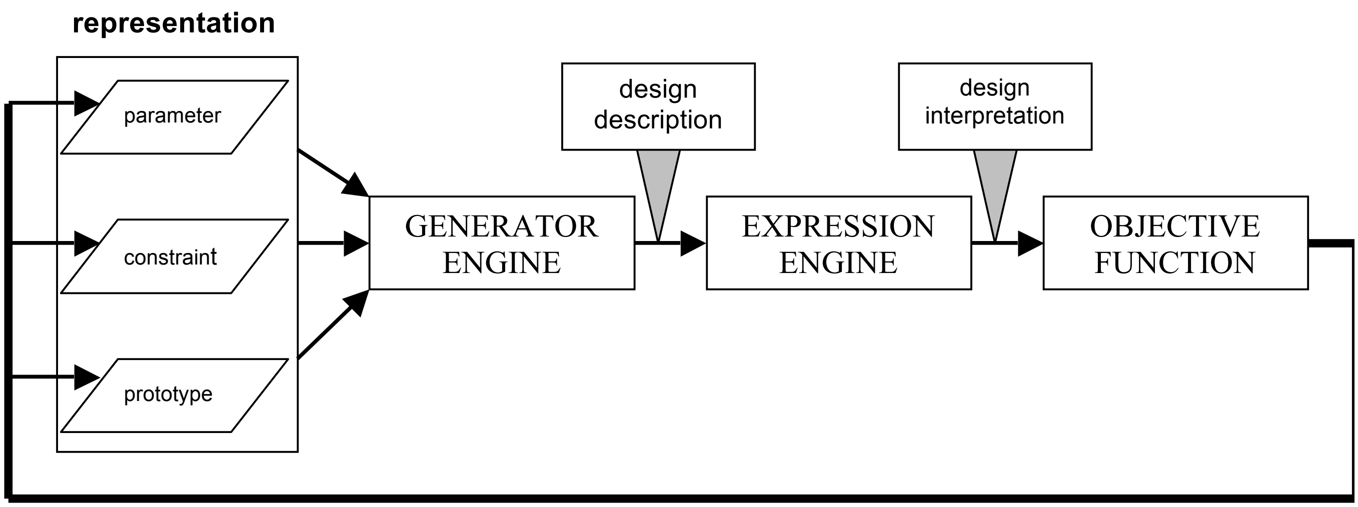


Figure 3.8: Generative Design System Tool (GDS) Flow Diagram by Gatarski and Pontecorvo (1999)

New design descriptions are offered by the “Generation Engine.” Basically genetic algorithms are utilized by generation engines; parent prototype design descriptions are taken and processed under the concepts of crossover and mutation.

“Expression Engine” serves as a translator which renders the new design descriptions into a visible structure.

The fitness of the results is measured by “Evaluation and Selection Mechanism.” However, as Gatarski and Pontecorvo (1999) mention, this mechanism is carried out by human-designer since it offers a more robust, intelligent, and subtle analytic capability then computed functions.

The part identified as “representation” in GDS which includes parameter set, constraints and prototype set, can be regarded as the analysis stage. Synthesis stage seems to be carried out by the generative system, in which design description appears. Finally, evaluation is made by the human designer which also serves as a feedback to later analysis. Generative Design is also recursive by both means of the system's behavior to reach out the fittest individual, and by means of the cycling structure of the whole process.

Evolutionary design is mated with several other techniques to breed hybrid design methods. Some of the examples to these adaptations are presented as follows.

i. Case-Based Design

A method which is already adapted to evolutionary design is "case based reasoning." It provides a methodology for directly using previous designs in a new design problem. Basically the provided methodology works on analogical reasoning from a set of already existing solutions. For designing, combination and adaptation are the ways of analogical reasoning. Since designers very often reuse features of a previous design, case adaptation is simply making changes on a recalled design to fit into a new situation. The things to be changed and the way to make these changes are the major considerations in case-based design. However case-based reasoning differs from knowledge based design systems like "design by prototypes" which will be mentioned later. As Gero, Kazakov and Schnier mentions, the expert knowledge in case-based design is not compiled and stored, but is available only implicitly in a database of previous design cases (1997).

Gomez de Silva Garza and Maher introduce a design process model GENCAD (GENetic Case Adaptation) which combines case based reasoning and genetic algorithms. The process model seen in figure 3.9 provides a method for the overall process of case selection and adaptation. This is strength of GENCAD over genetic algorithms since GA does not require any knowledge in order to select and adapt features, for selection and adaptation is done at random.

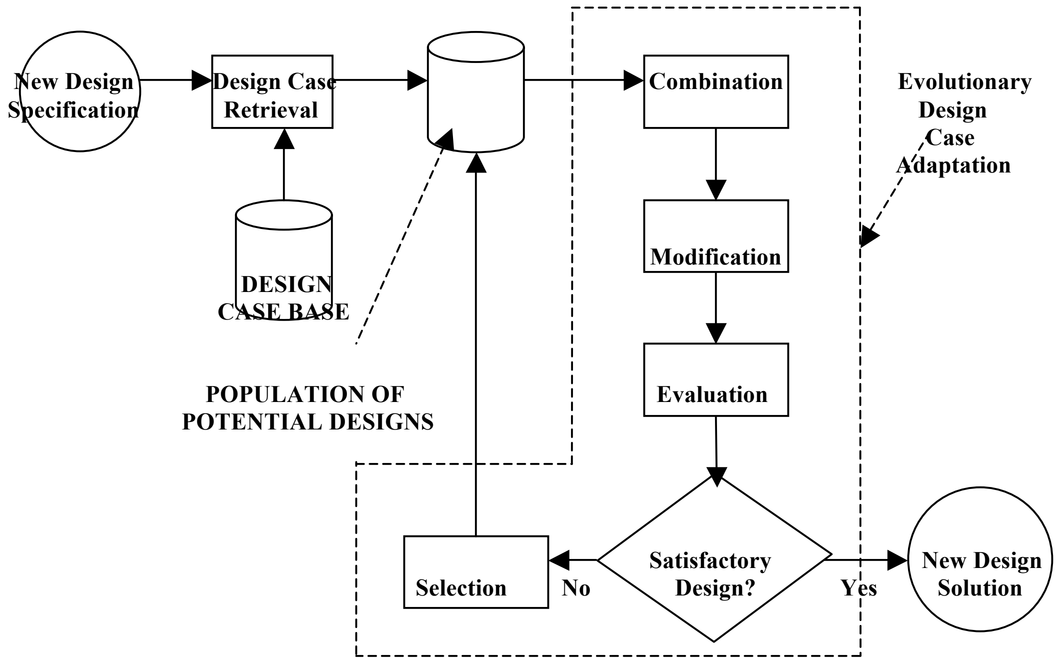


Figure 3.9: Process model for case-based design with evolutionary case adaptation by Gomez de Silva Garza and Maher (2001, p.182)

For the process, the case memory where precedents are retrieved serve as the starting point. The first step in the process is to determine the close cases from the case base. This is done by comparing the descriptions of the new problem and the retrieved solutions. By this way, the precedents which contain information that might be useful in solving the problem are retrieved. After then, case adaptation is carried out by combination and modification. Basically combination is "crossover" which produces two offspring, and modification is "mutation" producing one offspring. Also evaluation and selection are added to this Evolutionary Design Case Adaptation process since the results they give define the paths for the solution of the problem.

In GENCAD a case representation does not only include the description of the designed artifact. The representation may include such descriptions:

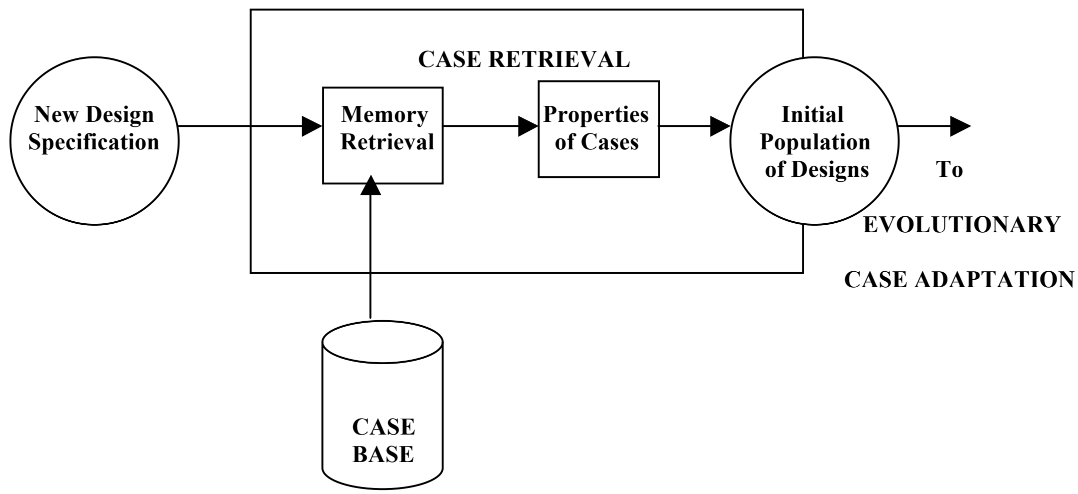


Figure 3.10: An expanded view of case retrieval by Gomez de Silva Garza and Maher (2001, p.183)

- the problem that was solved by the solution,
- the problem-solving steps that were taken to reach the solution,
- annotations, explanations or justifications of aspects of the solution and/or
- annotations, explanations or justifications of the problem-solving steps that were taken in generating the solution. (Gomez de Silva Garza, Maher, 2001)

Also some contextual and support information such as the environment the artifact operates can be included. All these information may or may not be used during the adaptation process. Therefore it is possible for the cases to pass through a preparation step before the adaptation begins so that they become the initial population. Figure 3.10 shows the expanded view of such a case retrieval process.

In short the process deals with two problems:

1. deciding which features are characteristic for a design and are to be kept, and which features have to be changed; and
2. producing new designs, fulfilling the new requirements, reusing features that have been identified as characteristic, and adapting these features (Gero, Kazakov, Schnier, 1997.)

ii. Designing by Prototypes

Another method which is found to be crucial for genetic design is "using design prototypes." While case-based design is regarded to depend on unstructured data, design prototypes are mentioned to be a model for knowledge-based design.

In broad sense, types are means to make classifications. An "archetype" is the first and often the singular example of a type. Tac Mahal or Eiffel Tower may be the examples for the term archetype. A stereotype is a copy without change. Mass production manufactures stereotypes. And finally a prototype is the first on which others are modeled.

Gero offers the term "design prototypes" as a conceptual schema for representing a class of generalized groupings of elements, derived from like design cases which provide the basis for the commencement and the continuation of a design. Design prototypes do this by bringing together in one schema all the requisite knowledge appropriate to that design situation (Gero, 1990). Usually a designer's mind operates by making connections with similar design cases to find a solution. Design prototype provides the necessary knowledge for such a design solution. A design prototype is a class of design elements (Rosenman, Gero, 1992.) In a way, design prototypes provide the means for generalization to produce an example for the type.

According to the design process formulation of Gero, there are three main groups as function, structure and behavior. Gero also defines these three as the variable groups used to interpret an artifact. Function, structure and behavior (expected behavior and actual behavior) and relations between them includes processes for selecting and obtaining values for variables. These three abstract notions are also regarded as the representation of the design knowledge such that ;

1. The function of a design object is defined as its teleology.
2. The behavior of a design object is defined as the attributes that are derived or expected from its structure
3. The structure of a design object is defined as its elements and their relationships. (Gero, Kannengiesser, 2003)

Apart from these three, relational knowledge, qualitative knowledge, computational knowledge, constraints and context knowledge are added as the components of prototypes.

Relational knowledge identifies the relevant variables between function, structure and behavior. In a way, it constructs a dependency network. On the other hand, qualitative knowledge provides information on the effects of modifying values of structure variables on behavior and function. However the values of the variables are modified in normal ranges. Computational knowledge is the quantitative counterpart of qualitative knowledge and is used to determine values of variables. Constraints appear in both qualitative and quantitative knowledge. Although it seems to be a part of expected behavior, it is applied on function and structure. Constraint on function is the expected behavior, whereas constraint on structure is the reduced range of possibilities. And lastly, context knowledge identifies exogenous variables for a design situation.

Design prototypes provide generalized knowledge about an artifact. These generalizations are valuable in establishing commonalities in especially big scale design projects. Gero and Kannengiesser (2003) identify two kinds of structure as “static structure” and “constructed structure.” While static structure refers to the parts that are visible to the observer, constructed structure is about the internal representations that the structure can associate with. These internal representations are commonly interpreted as the observer’s knowledge, belief and goals. Constructed structure refers to the subjective approach with different views and knowledge. Since different views and different knowledge prevent smooth interaction in a design team, design prototypes can act as a base for construction of common sense.

3.3 Creativity in Evolutionary Approach

Natural evolution is constrained to the creation of life. All its designs are capable of self replication and nearly all grow from a single cell (Dawkins, 1986). Evolution certainly exhibits some of the properties of creativity. It simply is a special kind of unconscious search algorithm where the parameter constraints are not strictly defined.

Likewise, evolutionary computation can become creative unless it leads to a strictly defined search process. Traditional implementation of evolutionary search relies on good parameterization to find a good solution. However this hinders the search to come up with creative solutions at the beginning. The essence of evolution is improvement over time (Bentley, Corne, 2002). It generates qualitatively better solutions then the previous generations that are able to survive. By each generation, the solutions are improved.

In natural evolution, no information about the fundamental nature of solutions is provided. The fittest simply survives. On the other hand, evolutionary design requires considerable knowledge about the parameters embedded within the representation. This can limit the search space and result in uncreative solutions.

Evolutionary design appears to be a kind of routine design act which depends on well-defined state space with identified parameters and constraints. A given type is achieved by employing mutation and crossover on existing prototypes. However, as a routine design act, evolutionary design can be forced to become "creative." Since in creative design space of domain solutions are extended, making slight modifications in the parameter and constraint codes can be regarded as an attempt to extend the space of solutions. The parameter set can be contracted, search space can be enhanced or changes, or useful information from other domains can be transferred. Innovation involves discovery within a discipline while creativity requires transfer of knowledge from without (Goldberg, 1999). So knowledge in one area applied to different search space can be regarded as a way to enhance creativity in evolutionary design.

Conventional methods and evolutionary design can be compared in sense of control. Since randomness appears as a critical element in genetic design, and the role of the designer is limited, designers' sense of control and surprise differ then conventional methods. Evolutionary design supports lower degree of control, but provides a sense of surprise and convergence. As Lund (2000) mentions, evolutionary design has a potential to actually change the user's and designer's intentions and pre-conceptions of that which is being designed and, in doing so, adds an important factor to the creative process.

Evolutionary design appears as a method which raises fast and easy solutions to complex and hard design problems. Design process needs a considerable documentation of the information gathered from diverse areas. If this information is not systematically classified and stored, a part of it can be overlooked during the design process. Evolutionary design provides the exact usage of this information without being ignored (Akbulut, 2008).

The evaluation of a design by quantitative methods is not always easy. When evaluating criteria such as aesthetics, usability etc. designers very often conceive their personal experiences. This results in the solutions' restraint with subjective criteria. The process of evolutionary design aims at releasing the generated solutions from such subjective traits (Akbulut, 2008). In fact, the evolutionary process can be designed in such a way that the evaluation stage is totally led by human designers in order to enhance creativity. Especially in evolutionary art forms, the process is just used as a generator where the final outcome is selected by human designer. So the creative capacity of evolutionary methods is under human control at any rate.

CHAPTER 4

HUMAN LEARNING PROCESS AND ARTIFICIAL NEURAL NETWORKS

Design is an iterative act which requires continuous learning, evaluation and reformulation of the criteria and the solution space. Learning, which is peculiar to design act, is a cognitive process carried out in brain as an electrochemical reaction in synapses between neurons. Recently, computers have made it possible to model the activity of neurons and to simulate complex brain functions such as learning. Cellular properties of neurons besides the circuitry of the systems and the cognitive processes are analyzed and modeled by artificial neural networks. The following chapter will focus on the subject which will also be used within the case study.

4.1 A Brief History of Learning Theory

Until the nineteenth century, the study of mental activity was a branch of philosophy and the chief method of understanding mental activity was introspection. By the mid of nineteenth century, the method of introspection helped empirical study of the mind to emerge which then became an independent discipline concerning primarily with the study of sensation; called as “experimental psychology.” By the end of nineteenth century, psychologists turned to analyzing subjective experiences such as learning, memory, attention, perception and voluntary action by means of experiments carried out both on animals and humans. This extended the quantitative approach of experimental psychology to higher mental processes and culminated in a rigorous empirical tradition called “behaviorism.” However, behaviorist tradition’s concern with measuring observable responses to controlled stimuli neglected all processes between stimulus input and behavioral output, as well as the constructive brain processes that underlie perception, action, planning, thinking, attention and complex forms of memory. This narrowness of behaviorism resulted in the emergence of cognitive psychology in 1960’s, which tended to analyze the brain processes that intervene between stimulus and behavior. Early studies of the cognitive psychology indicate that perception shapes behavior and that perception itself is a constructive process that depends not only on the information inherent in the stimulus but also on the mental structure of the perceiver. In cognitive psychology, each perceptual or motor act is correlated with a characteristic pattern of activity in a specific set of interconnected cells. The pattern of connections also stores information about the perception and the motor act (Kandel, Kupfermann, 1995).

Learning participated in both the behavioral and cognitive theories as one of the basic mental activities. Ivan Pavlov and Edgar Thorndike's studies on conditioning are regarded as one of the first examinations of behaviorism and learning. Later, the cognitive theory approached learning as a cellular mechanism taking place in diverse locations in brain. However in 1980's a number of researchers stressed that the heart of learning lies in the way individuals process experience and their critical reflection of experience (Kelly, 1997; Rogers, 1999). This resulted in the emergence of experiential learning theory which regards learning more as an internal and experience-based process. In brief, experiential learning is considered as a cycle that begins with experience, continues with reflection and later leads to action that becomes a concrete experience for reflection (Demirbaş, 2001). Besides behavioral and cognitive theories, experiential learning theory suggests a holistic integrative perspective that combines experience (concrete experience), perception (observations and reflections), cognition (formation of abstract concepts and generalizations) and behavior (testing implications of concepts in new situations) (Figure 4.1). According to experiential learning theory, learning is the process whereby knowledge is continuously created and recreated through the transformation of experience (Kolb, 1984). Although the experiential learning cycle uses different terms, it is remarkably similar to the problem solving, decision making and creative processes conceptually. The concrete experience coincides with incorporation while reflective observation is paired with incubation, abstract conceptualization with insight and active experimentation or testing in new situations with verification.

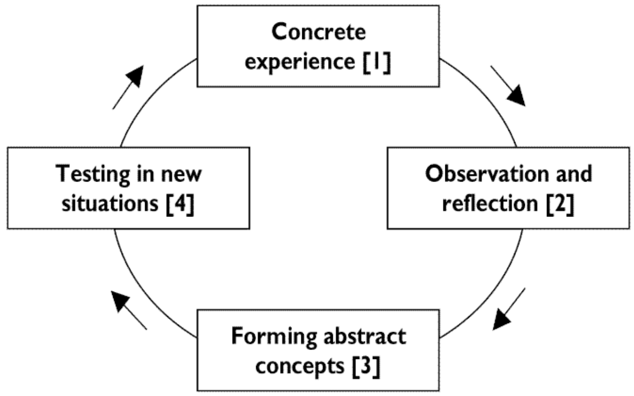


Figure 4.1: Experiential learning cycle
(http://chat.carleton.ca/~tblouin/Kolb%27s%20Leaning%20Styles%20Model/more%20info%20kolb1_files/explrn.gif)

4.2 Learning and Memory

In brief, learning is the process by which humans and other animals acquire knowledge about the world (Kupfermann, Kandel, 1995). A broad definition of the term is stated to be an adaptive change in behavior caused by experience. Adaptive indicates that the change must have some meaning for the behavior of the animal and the survival of the species while change points out a measurable difference between the behavior before and after some identifiable and imposed event (Shepherd, 1988).

Closely allied to learning is memory. Memory may be defined as the storage and recall of previous experiences. It is the retention of learned information (Bear, Connors, Paradiso, 2007). Memory is necessary for learning; it is the mechanism whereby an experience is incorporated into the organism, so that it can later cause the adaptive change in behavior (Shepherd, 1988). We learn what the world is about – acquiring knowledge of people, places and things that are available to consciousness- using a form of memory that is commonly called as “explicit.” Or we learn how to do things – acquiring motor or perceptual skills that are unavailable to consciousness – using “implicit” memory. Many learning experiences have elements of both implicit and explicit learning. Constant repetition of an experience can transform explicit memory into the implicit type (Kupfermann, Kandel, 1995).

The act of learning is examined in two main categories as procedural learning and complex learning. Procedural learning involves learning a motor response (procedure) in reaction to a sensory input and is broken into two categories as nonassociative learning and associative learning. Nonassociative learning is the change in the behavioral response that occurs over time in return to a single type of stimulus. It has two sub categories as habituation and sensitization. Habituation is simply learning to ignore a stimulus that lacks meaning (Bear et. al. 2007). It is the decrease in behavioral response that occurs during repeated presentation of a stimulus (Shepherd, 1988). On the contrary, sensitization is learning to intensify a response to all stimuli, even ones that previously evoked little or no reaction (Bear et. al., 2007). The second category, associative learning is basically forming associations between events. In associative learning, an animal makes a connection through its behavioral response between a neutral stimulus and a second stimulus that is either a reward or punishment (Shepherd, 1988). It is elaborated under three sub-categories. The first is classical conditioning, which is discovered by Ivan Pavlov at the beginning of century. The essence of classical conditioning is the pairing of two stimuli (Kupfermann, Kandel, 1995). The first stimulus which is unconditional evokes a measurable response to a second stimulus, called conditional stimulus. In Pavlov’s experiments, the unconditional stimulus was the sight of a meat and the response was salivation by the dog. The second category is operant or instrumental conditioning, studied by Edward Thorndike, in which an individual learns to associate a response with a meaningful stimulus, typically a reward (Bear et. al, 2007). In classical conditioning, the subject or the animal is a passive participant in learning. By contrast, the animal is asked to solve a problem and get the reward (or avoid punishment) by operating on its environment and actively participate in the experiment in operant conditioning (Shepherd, 1988).

The mentioned types of learning have received the greatest attention from behaviorists and that have been most amenable to experimental analysis by neurobiologists. However there are several other types of learning grouped under complex learning. For example imprinting, is the process of forming a behavioral attachment to a parent. Latent learning is about the speed of learning in an environment after being exposed to it. An animal learns an operant task in an experimental environment after being exposed to it much faster then the ones unfamiliar to the same environment. Observational learning, on the other hand, is the rapidity in learning a task after observing another subject performing the same task (Shepherd, 1988).

4.3 The Structure of a Biological Neuron

A neuron is the key to understanding the processing of the brain. In brain, learning and any other process is conceived by synaptic transmission of electrochemical substances called neurotransmitters between neurons. In human brain, approximately 100 billion neurons form a network that process throughout lifetime. All these neurons are present at birth though many more are later pruned away during early development and no new neurons are formed later on (Harth, 1993). Although neurons are interconnected to each other, there exists other neurons that are directly connected to muscles.

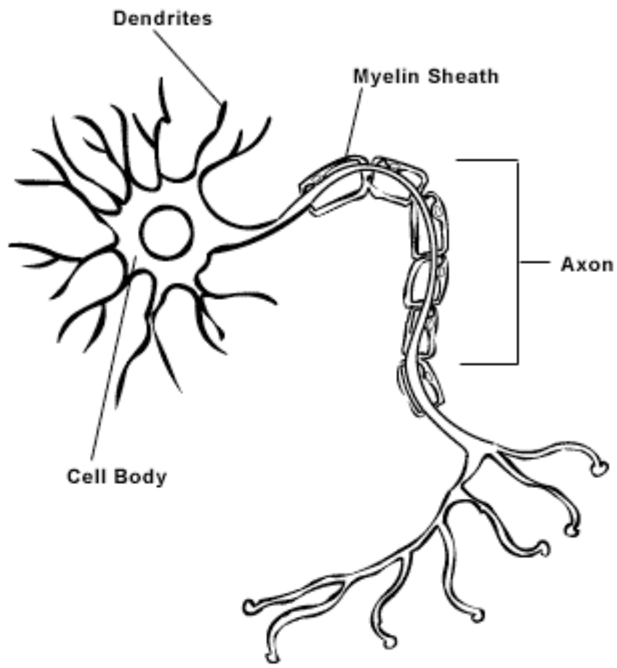


Figure 4.2: The structure of a neuron
(http://www.brandonpaton.com/wp-content/uploads/2009/NEURON2.gif)

Basically a biological neuron is a living cell consisting of a cell body containing usual subcellular components as nucleus, mitochondria etc. and lengthy protrusions branching out different directions. What differentiate neurons from other cells allowing the neuron to function as a signal processing device are these fibers through which messages are sent and received (Figure 4.2) (Gurney, 1997; Harth, 1993). There appear two types of fibers: the dendrites, like branches stemming out the cell body and the single axon which then branches into axon terminals. Dendrites and the axon provide the signal transmission between the neurons. The neuron receives a signal by dendrites and transmits that signal via its axon. The dendrites are connected to the neighboring neuron's axon terminals in order to provide this message transmission and this connecting junction is called "synapse."

The process of signal transmission is carried out with the help of the reaction and transmission of electrochemical substances called "neurotranmitters" between neurons. These neurotranmitters raise or lower the electrical potential of the cell body. When the electrical potential of the neuron reaches a threshold level, an electrical pulse which is also called "action potential" is sent down the axon. Thus, the neuron fires and the signals are propagated from neuron to neuron passing through synapses. The firing of a neuron occupies about one thousandth of a second. The synapses that increase the potential are called "excitatory," whereas those which decrease it are called "inhibitory." On the other hand, synaptic connections exhibit plasticity; that is, with respect to long-term stimulation, the strength of connections may change (Russel, Norvig, 1995.) This special feature is essential for the activity of learning since learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes (Stergiou, Siganus, 2005.)

4.4 The Nature of Artificial Neural Networks:

It can be argued that the idea of neural networks emerged with the questions "how does the brain work?" and "can we make a machine think?" In fact, the first studies on machine thinking can be regarded as the attempts to rise rule-based or case-based systems. Parallel to the works on machine thinking, other researchers were trying to investigate the structure of brain and the properties of biological neurones.

Works on artificial neural networks (ANNs) emerged as a discipline, which combined these different areas of work such as neuroscience and computation. By processing information in a similar way the human brain does, neural networks have the ability to derive meaning from complicated or imprecise data as in economic forecasting, human behavior, image and speech recognition etc. Since these complex data are hard to be analyzed and solved by mathematical tools, neural networks are used to detect patterns and investigate the trends. One way to describe this complicated knowledge is to state rules describing the behavior of a system. This rule-based approach can be formulated by algorithms. Another way which leads to knowledge description is mapping significant states of the system into some more compact internal representation so that later occurrences of these states can be recognized. This approach is used in teaching by example, or by artificial neural systems (ANS) (Works 1992). The natures of the problems appropriate for rule-based systems and ANS are stated in figure 4.3.

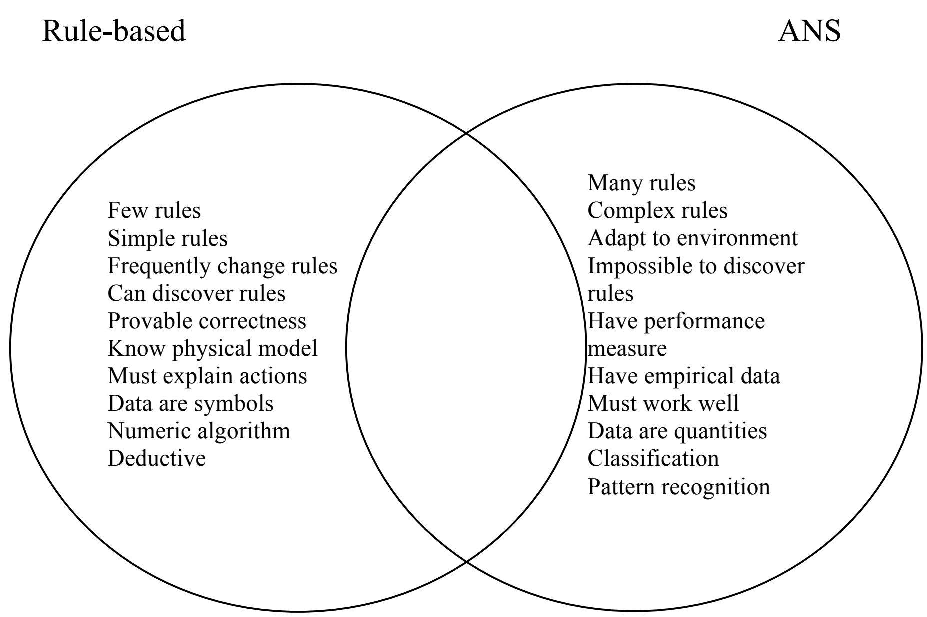


Figure 4.3: Work's scheme on the nature of rule-based and case-based problems (1992, p.28)

Neural networks can be regarded as experts in the area it has been given to analyze. Instead of leading an algorithmic approach, that is processing by following a set of instructions like computers programs do, they “learn by example” and use this trained data in prediction of the forthcoming step. They cannot be programmed to perform a specific task; on the contrary, the network finds the way to solve the problem by itself with an unpredictable and ambiguous operation. Although conventional computers’ use of cognitive approach to problem solving seems to contradict with artificial neural networks, both the computers and ANNs are complement of each other. There are tasks which suit one of them or which require the combination of both (Stergiou, Siganus 2005).

Employing artificial neural networks in defining complex relationships between input and outputs for highly non-linear problems is common. “ANNs have also been used to learn design relationships from previous designs by generating the appropriate mapping functions.” (Gunaratnam, Degroff, Gero, 2003, p.284) They are black-box modeling tools having a learning ability. In this particular application, after completion of a supervised learning process, an ANN is used to mimic a human designer’s decision mechanism.

A typical ANN is composed of large number of highly interconnected processing elements (i.e. neurons). These elements are analogous to biological neurons and are tied together with weighted connections that are analogous to synapses. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons, and learning algorithms for ANNs draw a similar analogy. The process of learning typically occurs by examples. In other words, a set of input/output data is subjected to network to iteratively adjust the connection weights (synapses). These connection weights store the knowledge necessary to solve specific problems (Güroğlu, Çetin, Erden, 2001).

4.5 Units of an Artificial Neural Network:

Just like the human brain, an artificial neural network consists of processing elements called "units" which perform the functions that real neurons do. The connection between units is provided by links associated with numeric weights similar to the synapse. The unit receives input signals and produces an output. The most commonly used model of a unit is shown in figure 4.4. Inputs reaching at the unit are collected by a summing node, or an input function of $\sum$, processed by an activation function, and an output is distributed. The unit has two modes of operation: the training mode and the using mode. In the training mode, the unit is trained to fire or not according to particular input patterns. On the other hand, in the using mode, when a thought pattern is detected by the unit, its associative output is released as the output.

There are three main ingredients to a neural network such as;

a) the disposition of the nodes and links between them;

b) an algorithm for the first mode of operation of the network, the training phase;

a method of interpreting the network's response during its second mode of operation, the recall phase. The useful properties of the network usually involve non-linearities, which help the stability and robustness properties of the network, but also make it difficult to treat analytically (Lisboa, 1992).

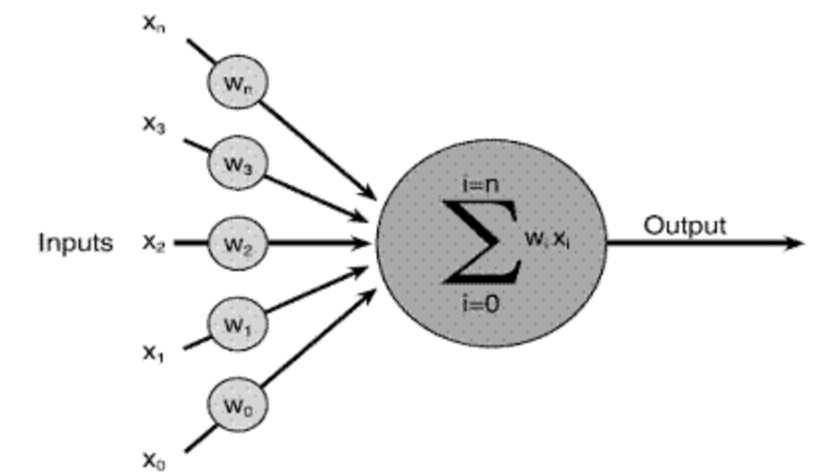


Figure 4.4: The unit of an artificial neural network.
(http://www.hevi.info/wp-content/image014.gif)

4.6 Network Structures

The structure or the topology of the network is called "disposition." The classifications of the network structures vary. A distinction can be made between feedforward, partially recurrent, and fully recurrent nets. Also it is possible to distinguish single-layered and multi-layered networks. Apart from these architectures, there also exists different interconnection topologies having specific characteristics that make them useful for particular applications.

4.6.1 Feedforward and Recurrent Networks

In a feedforward network, the links are unidirectional and does not lead a cyclic character (figure 4.5). Signals travel from input to output without making a feedback loop. In a multi-layered feedforward net, each unit is connected with units in the next layer. On the contrary, a recurrent network, as in figure 4.6 and figure 4.7, is a feedback system with an internal state. So the output at any instant depends also to that internal state of the system. The recurrent or feedback networks are very powerful and can become very complicated. These networks are dynamic, that is they can become unstable, they can oscillate or exhibit chaotic behavior (Russell, Norvig, 1995.) Their state changes continuously until they reach at an equilibrium. This equilibrium is conserved as long as the input changes and a new equilibrium is reached. The human brain is regarded to be a recurrent network; otherwise humans would not have short-term memory.

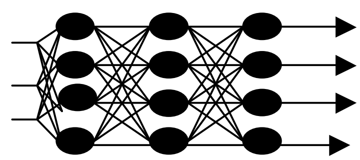


Figure 4.5: feed-forward network (Works, 1992, p.39)

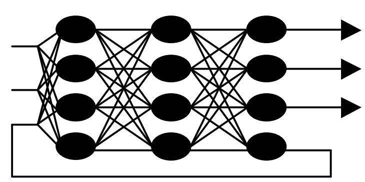


Figure 4.6: Partially recurrent network (Works, 1992, p.39)

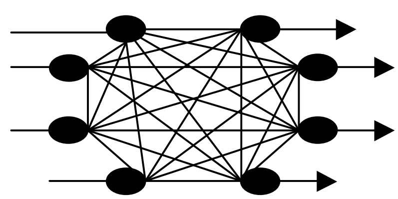


Figure 4.7: Fully recurrent network (Works, 1992, p.39)

4.6.2 Single-layered and Multi-layered Networks

The essence of the distinction between single layered and multi layered networks lies on the number of layers of units. A single layered network has simply two layers of units, namely input and output layers. The input layer receives the raw information that is fed to the network from the environment, whereas the output layer represents the processed information that is to be released from the network. Sometimes between input and output layers there appears hidden units. These units form hidden layers that is connected only with the input and output layers, but not with the outside world. Such networks with one or more layers of hidden units are called multi layered networks. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections to the hidden unit. These hidden units cannot be observed by the input-output behavior of the network. The examples on figures 4 and 5 can also be regarded as a multilayered net with one hidden layer.

4.6.3 Some Special Architectures

As mentioned before, apart from the above distinctions, there are special architectures of artificial neural networks which are appropriate for specific tasks. Among them, Hopfield Network, Boltzman machine and Kohonen network will be mentioned. These three architectures are used generally in pattern recognition tasks.

i. Hopfield Network

Hopfield network is a special example of a recurrent net which uses bidirectional connections with symmetric weights. All the units are connected to each other, thus serve both as input and output units. An example which consists of four units is illustrated in figure 4.8. Hopfield network functions as an associative memory; that is after training with a set of examples, a new stimulus is processed in such a way that it is corresponded to the example in the training set that most closely resembles to the stimulus. In short, Hopfield network serves as an optimization tool.

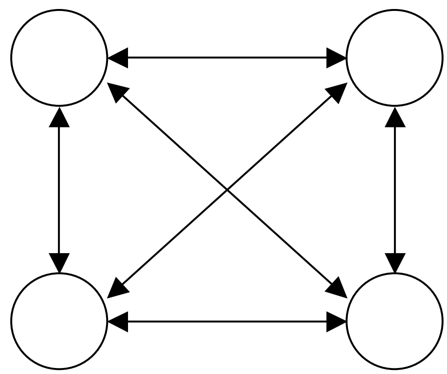


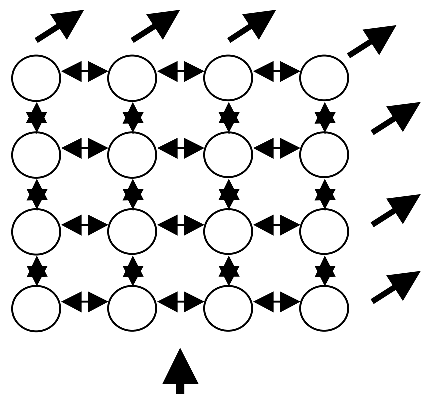
Figure 4.8: Hopfield Architecture (Lisboa, 1992, p.12)

ii. Boltzman Machine

Another kind of special network which also uses symmetric weights is Boltzman machines. In contrast with Hopfield networks, the units in Boltzman machines are neither input nor output nodes. However, these also try to approximate the input to the training set.

iii. Kohonen Networks

Unlike Hopfield and Boltzman, Kohonen networks are self-organizing architectures which use asymmetric weights. The main difference of the network is the presence of the lateral connections which link nodes in the same layer. Such topology is said to mimic similar connectivities found in the cerebral cortex. Kohonen networks leads the process of unsupervised learning and the main function is said to be data coding.



Input

Figure 4.9: Sample Kohonen Network (Lisboa, 1992, p.21)

4.7 Training Neural Networks

The main function of the neural networks which is pattern detection and trend investigation is based on a training phase where the network learns. There are two categories of training;

- Associative mapping: the network learns how to produce a particular pattern depending on the set of input units.
- Regularity detection: the units of the network learn how to respond to some particular properties of the input patterns. Whereas in associative mapping the network stores the relationships among patterns, in regularity detection the response of each unit has a meaning.

In neural networks, the knowledge is stored in the weights binding the units. So learning mechanism is basically the determination of weights. According to the weight determination function, there are two kinds of networks as

- Fixed Networks: where the weights are fixed
- Adaptive Networks: in which the weights are changeable.

For adaptive networks there are two categories of learning;

- Supervised Learning: This method requires an external teacher by whom the network is thought how to respond to particular input signals.
- Unsupervised Learning: As the name suggests, no external teacher is needed. It is self-organizing.

CHAPTER 5

CASE STUDY:

THE COMPUTER IMPLEMENTATION

AND THE STUDENT RESPONSE

ON THE BASIC DESIGN PROBLEM ON EMPHASIS

The case study proposes a design automation methodology for a particular design problem. It aims to develop and to explore the creative potential of an evolutionary design methodology which is able to "learn" the evaluation criteria of the problem. For this purpose, a system which combined genetic operations with artificial neural networks is proposed. The computer implementation has been done in MATLAB® environment. The system is operated for a basic design problem on the concept of "emphasis." The same problem is also given to a group of basic design students. The creative potential of developed methodology is evaluated by comparing the outputs of the test runs with the student works for the same design task.

5.1. The Original Study

The case study stems on the computer implementation of a design problem given to students of basic design. The problem aimed at making the students aware of the concept of emphasis, which is regarded as a design principle.

5.1.1. Basic Design Education

The aim of educational practice is to provide knowledge, skills and sensitivity on certain subjects (Saranlı, 1998). Correspondingly, design education curriculum, in general, involves courses that develop design knowledge, artistic skills and technical background (Demirbaş, Demirkan, 2003; Uluoğlu, 2000), which supports the backbone of the curriculum, the design studio courses,. The design studio courses are in a sense the simulation ground for the students where the outcomes of the other courses are combined and utilized within the studio projects carried out (Akbulut, 2010).

Among the design courses, basic design stands crucial since the freshman design students encounter with the phenomenon of design first in basic design course (Denel, 1998). In first year's curriculum of every university art and design department, regardless of the fields of specialization, there is always a course called basic design which deals with the grammar of visual language. This visual language is the basis of design creation and a designer must be equipped with the knowledge of principles, rules and concepts of visual organization in order to enhance his capability in visual organization (Wong, 1993).

In general, the course curriculum includes topics such as:

1. Elements of design: point, line, direction, size, shape, value, texture, color
2. Visual perception: organization principles, proximity relationship, similarity, shape properties, figure-ground relationship.
3. Principles of Design: repetition, harmony, contrast, concept, balance, unity, hegemony, emphasis.
4. Space, form and geometry: two and three dimensional concepts (Gürer, 1998).

5.1.2. The Concept of Emphasis

Emphasis, which is regarded as one of the principles of design, determines the visual weight of a composition. It is about "creating a single focal point, the area towards which the viewer's eye is most compellingly drawn" (Zelanski, Fischer, 1996.) By emphasis, designers are able to control the attention of the viewer since emphasis resolves where the eye goes first.

There are three stages of emphasis relating with the visual weight of an object within a composition:

- Dominant: The object which is emphasized most; the one which is given the most visual weight.
- Sub-dominant: The objects of secondary emphasis, the object which stand in the middle ground of the composition.
- Subordinate: The elements which are emphasized least, which recede to the background of the composition.

(McClurg-Genevese, 2005)

There are several techniques for achieving emphasis. Three major methods for controlling emphasis is identified as follows:

1. Emphasis by Contrast: By contrast, maximum visibility is aimed to be achieved. “As a general rule, a focal point results when one element differs from the others.” (Lauer, Pentak, 2000) The differing element interrupts overall feeling and automatically attracts attention. Contrast can be achieved by almost endless possibilities.

Color and value can be used as a tool to obtain contrast. A light form between dark elements or a bright color among dull colors is emphasized by color-value contrast.

Size can be regarded as another tool of contrast; an unexpectedly smaller or bigger element among many elements about the same size attracts attention.

Likewise, an unexpected, unusual shape like a vertical line among horizontal lines, a round shape among rectilinear shapes becomes a focal point immediately by making emphasis by contrast.

The technique of achieving emphasis by contrast can be extended to direction, texture, style, etc.

2. Emphasis by Placement: The elements in a design create emphasis if a focal point is obtained by the placement of these elements. Firstly emphasis is achieved by the proper placement in relation to the format. An object placed to the center of the format is often perceived as the focal point. However, emphasis can

also be achieved if many of the elements point to one item, like the perspective lines in a landscape painting. Radial design is also a good example of such, in which forms radiate around a central point of attention.

Basically, the most important place in the format is the center (Saw, 2003) That is where the viewer looks at first. As the forms go away from the center, they loose their visibility. On the other hand they become slightly more noticeable as they touch the edges of the format or as they overlap with the edge and are cropped. However this works well unless it is overdone. The secondary element in a composition is perceived with respect to the primary point of interest. An object which is overlapping, touching or approaching to the focal point is secondary object by proximity. The object which is of the same color, size, or shape of the primary object is secondary by similarity. And the object which is pointed out by the primary is secondary by continuance.

3. Emphasis by Isolation: This is about grouping the elements and putting one element apart from the group. In fact, isolation can be regarded as a kind of placement, or a “contrast of placement” (Lauer, Pentak, 2000.) An item which stands apart from its surrounding is expected to be the primary point of focus.

5.1.3. The Exercise on the Concept of Emphasis

The exercise which is applied to basic design students is based on achieving emphasis on a single element in a composition. The students are asked to emphasize one among seven black squares in any dimension which are supposed to be placed on A4 format paper. The students' success on the project is evaluated on the basis of the number of examples generated with different approaches. At the beginning, the students are neither shown examples, nor given a lecture on the concepts and techniques of achieving emphasis as summarized in the previous section. On the other hand, the instructors tend to make the students aware of the concept of emphasis on the basis of the given problem by shortly telling how to emphasize a single square.

5.2. Computer Implementation: Evolutionary Design Methodology

The basic design task presented above served as the source of inspiration for the study. A certain methodology which combined artificial neural networks with genetic algorithms is built up to explore the creative potential of evolutionary design process with respect to human designers. The developed methodology generates solution alternatives by carrying out genetic operations (i.e. reproduction by crossover and mutation). Then, the generated alternatives are evaluated by an objective function comprising an artificial neural network. It is an iterative process searching for the best solution alternative. These stages are carried out in MATLAB® environment.

The design concept is required to be described in a genetic code in the evolutionary model (Frazer et. al. 2002). This genetic code which is named as representation scheme, is then subjected to genetic operations for generation of design alternatives. Evolutionary algorithms (e.g. genetic algorithms GA, genetic programming GP) differs in representation scheme (i.e. string based, tree based schemes). The representation must provide the computer with ways to create, manipulate and modify the solution alternatives. (Funes, Pollack 1999). Evolutionary design starts with the description of the representation scheme which must be capable of defining all possible solutions of the design problem. In the conducted case study, the string based representation scheme is employed.

5.2.1. The Initial Population

In the conducted case study, both of the evolutionary process and the neural network require a sample set at the beginning. While the sample set is involved to the evolution as an initial population, neural network employs the sample set for training. The preparation of initial sample sets requires special attention. A well composed initial population guarantees the generation of interesting solutions, decreases the time required for operation and keeps the process away from getting stuck in a feasible but inefficient solution. Similarly, the generalization ability of the neural networks highly depends on the patterns used in training. A well prepared training set does not have to include large number of samples. On the contrary, use of vast amount of similar samples may cause the net to memorize the samples rather than to have generalization ability. Therefore, a set including a few but specific samples is used for training. Such a set decreases the time required for training as well.

The representative samples of emphasis have been achieved by placing one dominant square among seven squares placed on an A4 format paper. In the same way, an initial population is formed out of samples containing seven squares one of them whether emphasized or not. The samples not including emphasis inside provides diversity in evolution process. Moreover, these samples are involved in the training process to teach the concept of emphasis.

Since issues like color, texture, cropping or craft are hard to be traced in digital medium, emphasis is achieved by only applying contrast of size, contrast of placement, and contrast of orientation. Apart from the items, which employ one of the techniques of achieving emphasis, there also exist examples employing two or three techniques together (e.g. contrast of size and placement, contrast of size and orientation, contrast of placement and orientation, or contrast of size, placement and orientation).

Emphasis due contrast of placement is a matter of isolation concept and is achieved by grouping the 6 squares and putting the seventh square out of the group. The group of squares may be formed;

- by keeping the squares in equal distance or close to each other
- by overlapping the squares or making them touch to each other, or
- by putting them on the same direction (as if a line), or around a shape (a circle for example)

Emphasis due contrast of orientation basically refers to the direction of the square. The principle for making emphasis with orientation is to tilt one of the squares while the others are placed with the same angle to the format. If one of the squares is tilted, it is regarded to be emphasized since it points out a different direction from the rest. So it can be regarded as a contrast of direction of the placement

Emphasis due contrast of size is simply made by enlarging or reducing the regular size of one of the squares which is agreed to be 2.5cm x 2.5cm.

In the sample set, some types of layouts are repeated with different approaches of emphasis each time. Within the framework of the study, these layouts are regarded as "typologies." The sample set contains 8 groups of typologies besides a mixed group of samples which do not belong to any of them. These typologies are linear, group of two rows, circular, V shape, T shape, H shape, diagonal and checkered.

Each sample contains 7 black squares among which one of them is supposed to be emphasized. However conscious preparation of the initial set must result in a correct and unbiased initial population including both emphasized and non-emphasized samples. Therefore, conscious preparation requires an expert designer to a certain extent. Among the samples, the ones in which one of the squares is emphasized are graded to be 1, whereas the others not having emphasis or ambiguous emphasis are graded to be 0.

The samples which do not have emphasis, (i.e. having 0 grade) consist of the compositions in which squares are located;

- symmetric across an axis.
- within groups having at least 2 squares. The squares may be equal in size, unless one of them is the smallest or the biggest.
- in such a way that they form a closed shape (a circle for example).
- in such a way that with the same orientation they make a sequence even by overlapping, touching, or following each other with the same distance.
- in such a way that they make two or more sequences pointing out (emphasizing) two or more squares.
- with the same angle, while two or more of them are tilted (emphasis due

orientation), or

- where all of the squares are the same size or two or more of the squares are bigger and smaller then the regular size (emphasis by size).

According to the representation scheme, the squares are defined by the coordinates of lower left corner, angle of orientation, and the size of the square (i.e. 4 entries for each square). Therefore, each sample including 7 squares in the A4 format is represented by 28 entries, which can be regarded as the genes of genetic representation scheme. The sequence of the so called 4 coordinates with respect to the bottom left corner of the square are;

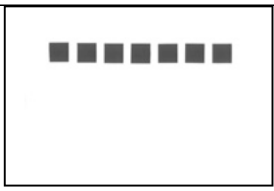
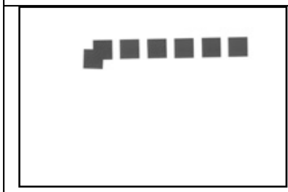
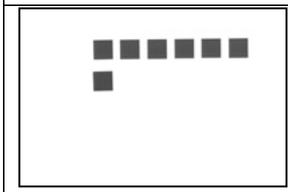
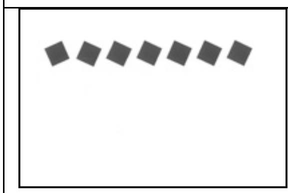
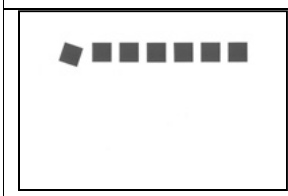
1. the distance of the corner to the x coordinate of the A4 format; x
2. the distance of the corner to the y coordinate of the A4 format; y
3. the angle of rotation of the square; Θ
4. the size of the edge of the square; d

So, the string of each sample can be formulated as:

[(x1, y1, Θ1, d1), (x2, y2, Θ2, d2), …..(x7, y7, Θ7, d7)]

The initial population is formed out of 56 samples. Below in Table 5.1, linear typology samples, is presented with the coordinates and grades while the rest of the initial population are available in Appendix section.

Table 5.1: Samples of linear typology

Type	Sample	Coordinates	Grade
Linear		[35 65 0 25 70 65 0 25 105 65 0 25 140 65 0 25 175 65 0 25 210 65 0 25 245 65 0 25]	**0**
		[60 70 355 25 72 60 0 25 107 60 0 25 143 60 0 25 178 60 0 25 213 60 0 25 246 60 0 25]	**1**
		[73 60 0 25 107 60 0 25 143 60 0 25 177 60 0 25 213 60 0 25 247 60 0 25 73 100 0 25]	**1**
		[20 67 25 25 51 57 330 25 89 57 330 25 128 57 330 25 167 57 330 25 206 57 330 25 245 57 330 25]	**1**
		[15 58 0 25 70 58 0 25 105 58 0 25 140 58 0 25 175 58 0 25 210 58 0 25 245 58 0 25]	**1**
		[20 59 0 25 55 59 0 25 90 66 0 40 142 59 0 25 177 59 0 25 212 59 0 25 247 59 0 25]	**1**
		[30 57 345 25 70 60 0 25 105 60 0 25 140 60 0 25 175 60 0 25 210 60 0 25 245 60 0 25]	**1**

Some typology samples with grades is illustrated in Figure 5.1.

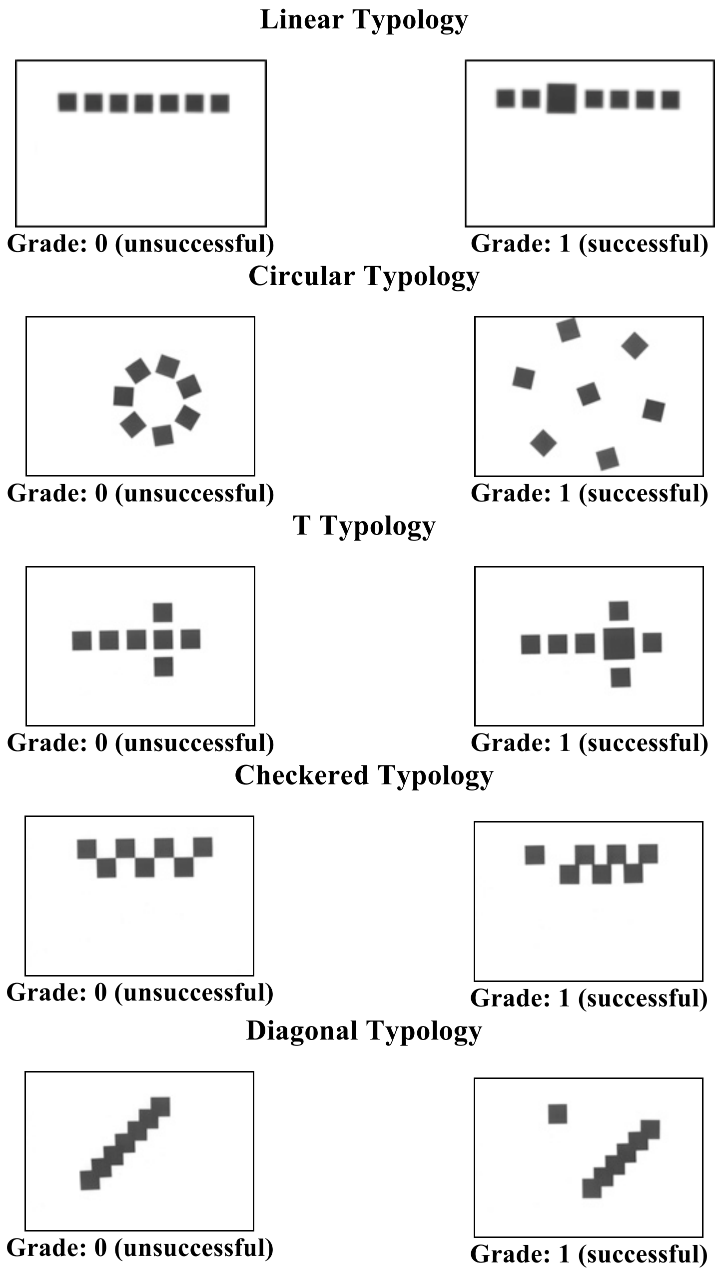


Figure 5.1. Representation of the individuals belongs to various typology groups.

5.2.2. An Artificial Neural Network as the Objective Function

In order to achieve automatic evaluation of the generated design alternatives, an evaluation metric is required. This evaluation metric must express the designer's intent and have the ability to guide evolution process to generate feasible alternatives. Although, the designer's intent, design goals, principles and constraints can easily be defined verbally, many times finding analytical definitions for them is quite difficult. Therefore there are some interactive evolutionary design applications in literature (Bezirtsiz, Lewis, Christeson 2007). In those applications, while genetic operations generate new solutions, evaluation of them is left to the human designer. However, people can not interactively examine hundreds of design alternatives in a short time. Therefore, interactive approach is only applicable to small solution populations for a limited number of iterations. This causes the process not to be a complete automation but randomness in generation of solutions is still able to reduce the restrictive effect of inexperienced/prejudiced designer to a certain extent.

In the conducted case study, backpropagation is employed as a learning algorithm. Since it has the highest generalization ability, it is the most common supervised learning method for the feed forward neural networks. This algorithm uses a group of input and output vectors of the pre-selected examples to train the network. The net is constructed by initially selecting small random weights and biases. When the network is subjected to the input vector, the error (i.e. mean square error) is calculated by comparing the network's output and the desired output. Then, the error is propagated backwards from the output nodes to the inner nodes by calculating the local errors for each of the inner neurons. The weights and biases are adjusted to decrease the local error. The whole process repeats until the error is minimized. After the completion of training, the network approximates the correct outputs closer to the designer defined error value.

A typical way (e.g. gradient descent method) for the calculation of the error and the readjustment of the weights are presented in Equation I and II. Where the E, d_i and η represent the error, the desired output and the learning rate respectively:

$$E = \frac{1}{2} \cdot \sum_{i=1}^{n} (d_i - y_i)^2 = \frac{1}{2} \cdot \sum_{i=1}^{n} \left[di - a\left[\sum_{q=1}^{l} \omega_{iq} \cdot a\left[\sum_{j=1}^{m} \upsilon_{qj} x_j \right]\right]\right] \quad \text{[Eq.I]}$$

$$\Delta\omega_{iq} = -\eta \frac{\partial E}{\partial \omega_{iq}} \quad \text{and} \quad \Delta\upsilon_{qj} = -\eta \frac{\partial E}{\partial \upsilon_{qj}} \quad \text{[Eq.II]}$$

The learning rate determining the speed of learning is defined by the designer at the beginning. The partial derivatives in the above definitions can easily be calculated by the derivative chain rule; the details are given in numerous references (Gao 1999; Lippman 1987).

The performance function for backpropagation learning algorithm of the neural network is mean square error function. In mean square error function, the network output is compared to a target while each input is applied to the network. The error is calculated as the difference between the target output and the network output. Since the average of the sum of these errors is desired to be minimized, the backpropagation algorithm adjusts the weights and biases of the network each time it propagates backwards. The function is as follows:

$$\text{Mean square error} = \frac{1}{N} \sum_{k=1}^{N} e(k)^2 = \frac{1}{N} \sum_{k=1}^{N} \left[t(k) - y(k) \right]^2$$

t(k): output of the k^{th} training sample
y(k): output of the network to the input of k^{th} training sample
N: number of training samples

The function of the neural network is as follows:

$y = f(I, W, B)$

y:	output of neural network
f:	nonlinear function combination of layers of activation functions representing the neural network
I:	Inputs to the neural network
W:	Weight parameters of the network that are adjusted during training
B:	Bias parameters of the network that are adjusted during training

The network is a single layered structure which consists of 11 neurons in the hidden layer and a single output neuron. Each of the 11 neurons in the hidden layer receives 28 weights for the so called 28 coordinates from each training sample. Therefore, the weight vector received by a single neuron in the hidden layer in figure 5.2 denotes the summation of 28 weights received by the same neuron. The total input received by a single neuron is the summation of the multiplication of each weight with each input.

$$I = (i_1 w_{1i} + i_2 w_{2i} + i_3 w_{3i} + \ldots + i_{28} w_{28i}) + b_i$$

$$I = \sum \text{ input of a neuron}$$

i = input

w = weight

b = bias

The output of a neuron in the hidden layer is obtained by a tan sigmoid transfer function which is as follows:

$$a = \frac{2}{1 + e^{-2n}} - 1$$

On the other hand, the function of the output neuron is

$$a = n$$

A typical training process is illustrated in Figure 5.2.

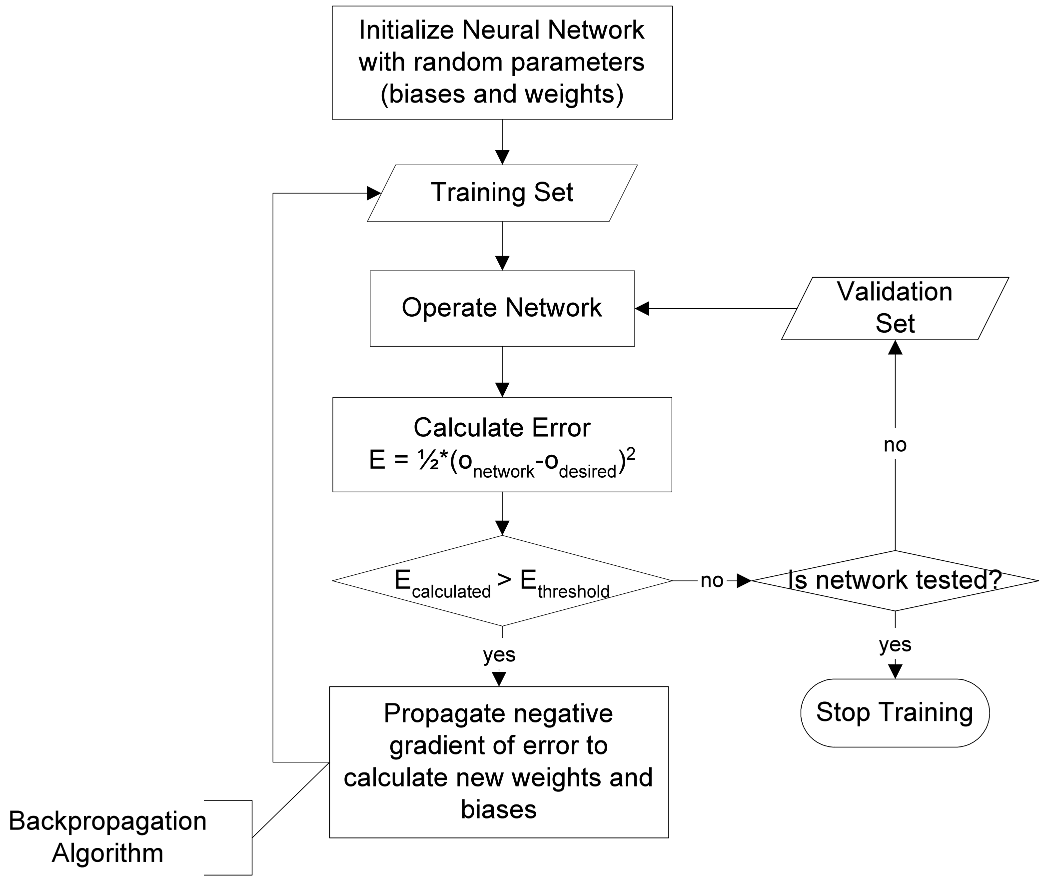


Figure 5.2. A typical backpropagation training process for ANN.

Then the trained network is employed as the objective function in evolutionary process. For some other cases including constraints besides design goals, a penalty value may be applied to the objective function. For a successful evaluation, the penalty must also consider the amount of constraint violation.

The proposed strategy is a two step process. Before running evolution process, an artificial neural network is constructed and trained for our specific problem. Therefore, a feed-forward neural network structure is formed out of one hidden layer, connected to a single output neuron. The network output manifests the degree of emphasis in a sample. Since there is no proven analytical method in literature, both the number of samples in the training set and the number of hidden neurons in the network architecture are decided by trial and error. The number of individuals in the training set is found to be sufficient when the system responds to the training and the validation data well, and generates meaningful outputs. The other parameter for training, the number of neurons in the architecture, adjusts the mean square error of the learning algorithm. The target mean square error value (i.e. the termination criteria for the training process) is also defined by performing several tests. This value has a significant effect on the generalization ability of the network. The network is observed to be unable to be trained and generate when the mean square error is a big number, while the network is inclined to memorize the training set and repeat the same samples during generation phase when the mean square error is a small number.

In these tests, the sample set is divided into two as training set and validation set. The network successfully completing the training is subjected to the validation set. The most successful network presenting the best approximation in the validation set is selected as the objective function of evolution process as shown in Figure 5.2.

5.2.3. The Generation Process

Genetic algorithms are known for the three aspects of generation as reproduction, crossover and mutation. In reproduction the algorithm repeats an individual in the initial population whereas in crossover two individuals are selected and combined in order to raise an offspring. On the other hand, mutation is the process where random changes to a gene of a single individual are applied.

As a genetic operation, the system generates new individuals by even combining two samples, or by repeating a sample which it finds powerful with slight differences in dimensions, distances or orientations of the squares, or either by changing the orientation of the whole composition.

The parents participating in crossover operation are selected regarding their fitness values. They are divided at random points and obtained parts are crossed with each other. Both single and multi point crossover operations are possible to be employed. A sample crossover operation is given in Figure 5.3.

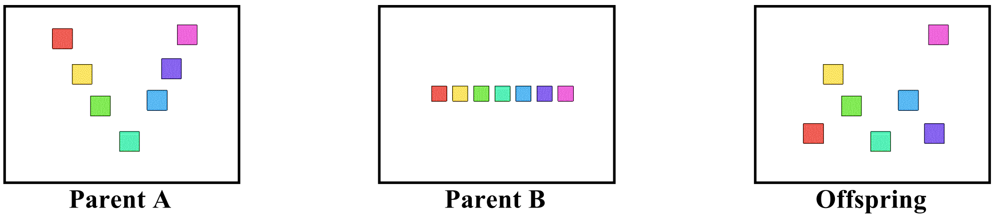


Figure 5.3 A sample crossover operation.

Mutation is generally a secondary operation in evolutionary algorithms; it is especially employed to restore the lost diversity in the population at previous generations (Koza 1992). However, in this particular application mutation can also be an effective tool in achieving emphasis in generated compositions. Mutation is an asexual operation, which is operated on a single individual. Again, an individual represented by a string is selected regarding its fitness value. Then, a value at a random point of the string is modified. A typical mutation operation is given in Figure 5.4. Mutation can be seen in the configurations of the bottom and top squares.

a. Before mutation **b. After mutation**

Figure 5.4. A typical mutation operation

Besides generating slight modifications in typologies given in initial population, the process also produces totally new results. Some samples of these modifications are given in Figure 5.5. The modification on an individual not including emphasis is also illustrated in the last row.

Reference Sample **Computer Generated Output**

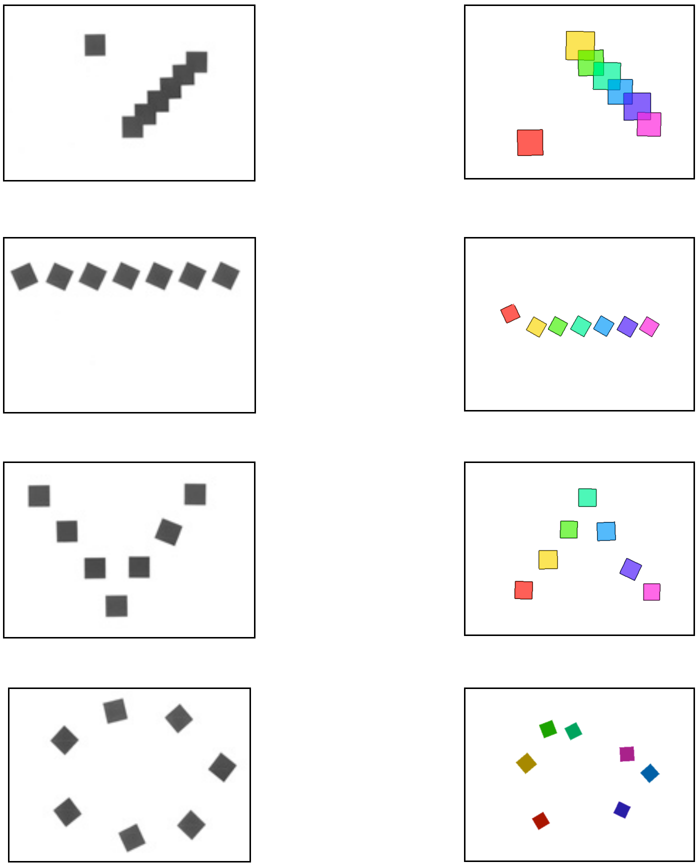


Figure 5.5. Outputs produced by modifications in the test runs with designer prepared initial population.

Some examples of the totally new productions are presented in Figure 5.6. These individuals are generated by effectively employing crossover and mutation operations. All approaches for achieving emphasis are applied in these individuals.

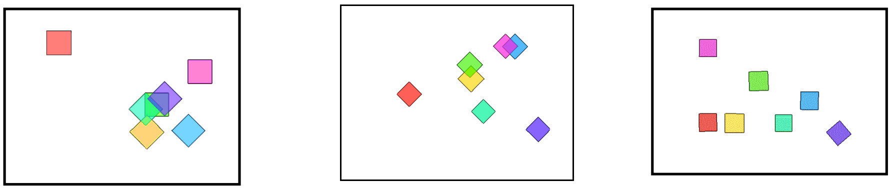
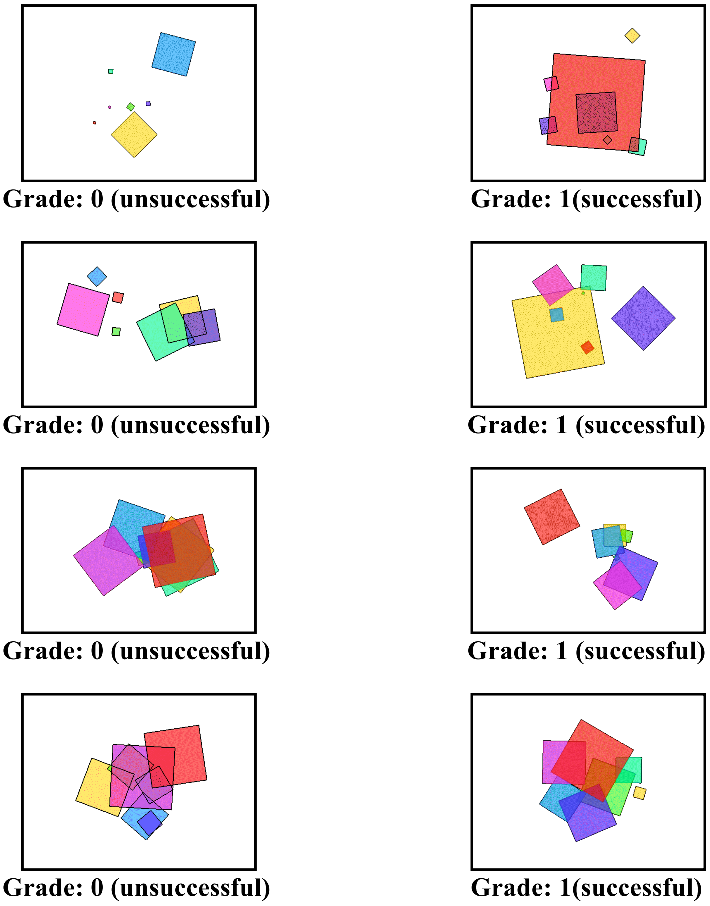


Figure 5.6. Totally new outputs produced by effectively employing crossover and mutation operations.

Apart from crossover and mutation operations, the system is able to be run on random basis. When randomly run, the system generates offspring without taking initial population into account. In random generation, the coordinates of lower left corner, angle of orientation, and the size of each square are determined randomly. Since the random generation generally may result in over-sized individuals, overlapping is inevitably common in the population. Emphasis is obtained generally by size difference or placing a square solely out of the group. However, it is hardly possible to generate a composition belonging to a specific typology. Some outputs for the test runs with randomly generated initial population are given in Figure 5.7. In order all the squares to be visible; in the table, the individuals are presented with transparent colors. The color information is not considered in the evaluation of the degree of emphasis.



Grade: 0 (unsuccessful)

Grade: 1(successful)

Grade: 0 (unsuccessful)

Grade: 1 (successful)

Grade: 0 (unsuccessful)

Grade: 1 (successful)

Grade: 0 (unsuccessful)

Grade: 1(successful)

Figure 5.7. Some outputs for the test runs with randomly generated initial population.

5.3. The Classwork

The conducted study is also given to the students within the framework of basic design course as a classwork. In order to evaluate the computer outputs with the student responses, three different groups of freshmen basic design students were chosen. The student groups are found specific for the evaluation with respect to their former art education during secondary school level and their method of admission to the university.

5.3.1. Art Education at Secondary School Level

Before enrolling a design department, students generally go through art education at a limited level during secondary education (Akbulut, 2010). Turkish secondary education comprises of mainly two categories of institutions which are general high schools and vocational and technical high schools. While general high schools aim to prepare students for higher education, vocational high schools provide specialized instruction with the aim of training qualified personnel (OSYM, 2006). General high schools have sub branches which are specialized in language education which can either be run by the government, or be owned by private sector. Admission to the mentioned schools is available by showing out an academic success in the selection exam held at the beginning of secondary education. Similarly, apart from vocational and technical high schools, there exist schools specialized in art education, teacher's education and military high schools, which aim to prepare the students for higher education in relevant fields.

The curriculum in secondary education in Turkey covers mainly 40 hours a week. Among the courses offered, art courses only take one hour a week in classical high school education. However the vocational and technical schools specialized in art education offer a curriculum condensed in the field. The vocational schools in graphic design and photography offer a basic art education out of 18, 22 and 28 hours a week during second, third and forth years of secondary education. The courses offered vary from drawing, basic design, photography, illustration, typography, computer aided design, animation, print making etc. (http://talimterbiye.mebnet.net/Ogretim%20Programlari/dersdaglimcizelgeleri/haftal %C4%B1k%20ders%20da% %9F%C4%B1l%C4%B1m%20%C3%A7izelgesi.pdf.)

5.3.2. Student Profile

Turkish education system offers two methods for students who are likely to become designers. The students who want to be enrolled in one of design departments need to take either the student selection examination which is organised once a year by Student Selection and Placement Centre, or aptitude exam which is independently organised by the higher education institution giving bachelor's degree in art and design. Student selection examination score needed to be enrolled in a design department such as architecture, landscape architecture, city planning, industrial design and interior architecture is based on the evaluation of qualitative and quantitative reasoning abilities. On the other hand departments of fine arts, graphic design, and visual communication design accept students by aptitude exams. Generally these aptitude exams are based on the evaluation of special skills, such as drawing, and general and academic knowledge.

The exercises were carried out by three separate groups of freshmen basic design students. The first group consisted of first year Graphic Design students of Bilkent University Faculty of Art, Design and Architecture in 2006-2007 fall semester. The second and the third groups were Gazi University Faculty of Fine Arts in 2009-2010 fall semester freshmen basic design students of Industrial Design and Visual Communication Design. The student groups will be mentioned as GRA, ID and VCD respectively in the following tables.

The second group was admitted to the university by student selection and placement examination quantitative part while the first and the third groups were placed in the departments with aptitude exams. Although the first and the third groups are both admitted with aptitude exam, the backgrounds of the students demonstrate a considerable divergence. The majority of the first group is graduate of private schools specialized in language education while the third group consists of graduates of vocational high schools specialized in art and graphic design.

Table 5.2: The Participant Profile

		1^{st} Group (GRA)	**2^{nd} Group (ID)**	**3^{rd} Group (VCD)**
	Male	16	1	8
	Female	25	16	5
	Average Age	18.65	18.35	19.23
graduation	State High Schools specialized in language education	3	15	2
	Private High Schools specialized in language education	27	1	1
	General High School	5	-	2
	Fine Arts High School	2	-	-
	Vocational High School	2	-	7
	Technical High School	-	-	-
	Teacher's High School	-	1	-
	Military High School	-	-	1

5.3.3. The Students' Responses

At the beginning of the class practice, the students were made aware of the concept of emphasis by just showing the initial population used in computer implementation without extra verbal explanation. All the members of the initial population were exhibited to the students with + and – signs corresponding "1" and "0" grades respectively. Finally, the students were asked to create compositions including emphasis as many as they can. The classwork had to be executed on A4 format papers with 7 black squares on each. Some examples created by the students are presented in Figure 5.8.

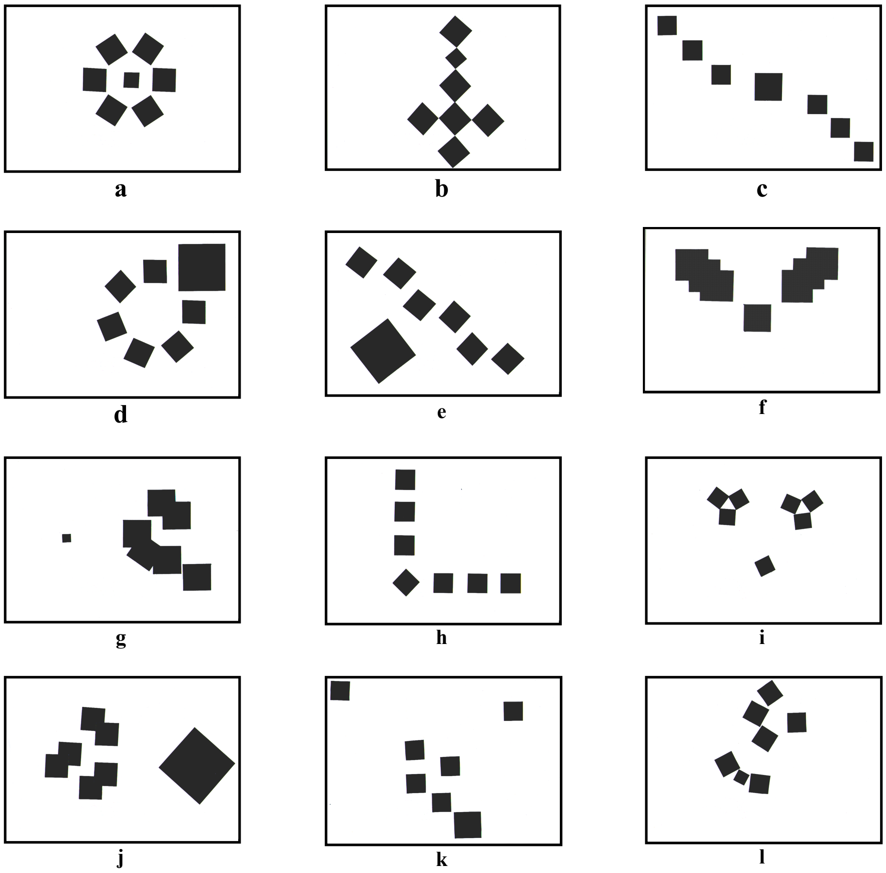


Figure 5.8. Some of the student outputs on emphasis.

At the end of the practice, each student produced examples as many as he/she can. The classwork was evaluated according to two criteria; first the number of approaches being involved by the student, and second, the typologies used and created. Although none of the approaches were verbally identified to the students, they are expected to practice these approaches in their work.

It is observed that the students are generally able to reproduce introduced approaches with small modifications as it is illustrated in the compositions “a”, “b”, “c”, “d”, “e” and “f” in Figure 5.8. Some innovative approaches, not included in the initial population such as “g”, “h”, “i”, and “j” are also employed in compositions. On the other hand, “k” and “l” can be given as examples of unsuccessful student outputs. The concept of emphasis is not strongly handled in these compositions.

5.4. Results

The computer implementation of the evolutionary process has been run for both randomly generated and human prepared initial populations. At the end of test runs beginning with randomly generated initial population, it is not always possible to generate compositions having emphasis. Although randomness is a powerful tool providing diversity, a randomly generated population may cause the search to have a distant start in the solution space. Moreover, the evolution with randomly generated individuals does not have typology information at the beginning. This decreases the probability of success and increases the required computation time. However, even for these kinds of starts, the process always tries to keep the individuals approximating at least one of the approaches to obtain emphasis (e.g. contrast of placement, size or orientation).

According to outputs of the tests with random initial population, no regular typology has been encountered. Moreover overlapping is abundantly preferred to create emphasis. This is the natural result of size diversity in random generations.

Another difference stemmed from randomly generated initial population is observed in creating emphasis by placement. This approach is about grouping the squares and setting one square apart from the group. In the training set, it is achieved by employing only one of three methods; keeping the squares in equal distance, overlapping or touching the squares, and putting them in the same direction. However, the offspring raised by randomly generated initial population uses two or more methods at the same time to group the squares.

Another group of tests are performed by a designer prepared initial population. This population includes some compositions employing different approaches to create emphasis. In general, the process does not have a tendency to repeat a typology employed by a large number of individuals in the initial population. In fact, for each generation, the process regenerates the whole population (i.e. reproduction). The typology, which is repeated most initially, may not be repeated at the next generation unless the typology has a high fitness value.

Two different approaches are observed in the generation of the compositions. First, the fitter compositions are subjected to small modifications by mutation operation. Therefore, emphasis can be achieved by just changing parameters such as angle of orientation or size etc and keeping the typology. In the test runs some outstanding examples of this approach were observed. These compositions are obtained by mirroring, centering or rotating the individuals in the initial population although these techniques are not taught to the process. Second, totally new compositions are obtained by crossing the samples in hand and applying random mutations.

After collecting the result of test runs, the same problem is given to the basic design students. To make a fair and unbiased comparison, the concept of emphasis is thought by the same samples used in training of the network. As a result of classwork, it is observed that the students did not have a tendency to make size variations. They generally prefer to use squares consistent in size with the ones in the samples. Some innovative typologies also appeared. However a significant resemblance was also detected in these innovative typologies. This also proves the rewarding of successful outputs by the students in a similar way with the evolution process.

In order to make a comparison between the student works and the computer outputs, test runs without applying elitism are also carried out. Elitism is a method applied in genetic algorithms which aims "to preserve the best individuals in the population by inserting them into the following population if they are not already there" (Bentley 1999, p.427). It guarantees the survival of the fittest individuals by carrying them to the initial population in the next generation. Genetic algorithms apply elitism to avoid the existence of unsuccessful individuals. However, this may result in the lack of "diversity", which refers to "the amount of different genetic material in the population" (Bentley 1999, p.427). In order to provide diversity in the generated individuals and to enhance creativity respectively, the genetic algorithm is run 500 times without applying elitism. As presented in Table 5.3, among the 500 individuals, 44,4% is found to manifest successful emphasis whereas the same rate is 98,39%, 98,5%, and 92,5% respectively in student works.

Table 5.3: The ratio of successful and unsuccessful outputs

	Computer Outputs (Elite Count)	**Student Works (GRA)**	**Student Works (ID)**	**Student Works (VCD)**
Successful Emphasis	44,4 % (222 individuals)	98,39 % (551 individuals)	98,5% (326 individuals)	92,5% (222 individuals)
Unsuccessful Emphasis	55,6 % (278 individuals)	1,61 % (9 individuals)	1,5% (5 individuals)	7,5% (18 individuals)

The computer implementation does not seem to strictly depend on initial samples while generating new items. Among 500 individuals, only 71 which is 14,2% of the total, were observed to be the slight modifications of the members of the initial sample set. Table 5.4 illustrates the number of the computer outputs which appear to be the variations of sample set and totally new compositions generated. On the other hand, the students were also evaluated on the basis of their success in producing new compositions free from the initial population. The results are presented in table 5.5.

Table 5.4: The results based on slightly modified initial sample set and the results that are independent of the sample set.

Outputs with Successful Emphasis		Outputs with Unsuccessful Emphasis	
Variations of initial sample set (with slight modifications)	New composition	Variations of initial sample set (with slight modifications)	New compositions
53 individuals	169 individuals	18 individuals	260 individuals

Table 5.5: The students' achievement in producing new compositions

	GRA	ID	VCD
Number of total generations	560	331	240
New Compositions	225	162	118
Percentage	40.17%	48.94%	49.16%

Table 5.6: The techniques used to achieve emphasis

Techniques of achieving Emphasis (Contrast created by)	Computer Works (Elite Count)		Student Works					
			GRA		ID		VCD	
	Number of individuals	%	Number of examples	%	Number of examples	%	Number of examples	%
size	15	6,75	107	19,4	70	21,15	56	23,33
position	150	67,56	104	18,8	67	20,24	58	24,16
orientation	11	4,95	35	6,35	12	3,62	5	2,08
size-position	13	5,85	136	24,6	76	22,96	57	23,75
size-orientation	0	0	24	4,35	4	1,20	3	1,25
position-orientation	25	11,26	78	14,1	70	21,75	42	17,5
size-position-orientation	2	0,9	67	12,1	27	8,15	21	8,75

Among the techniques for achieving emphasis, as seen in Table 5.6, the computer used emphasis by contrast of placement most with 67,56% whereas the technique of emphasis by contrast of size and orientation was not used at all (0%). On the other hand, students used each technique of achieving emphasis with close ratios varying between 24,6 % for contrast of size and position, and 4,35 % for contrast of size and orientation. It can be concluded that achieving emphasis by contrast of size and orientation is hard to be learned by both the system and the students.

The outputs of the computer implementation and the students works does not seem to be in accordance. Rather then a system failure, this inaccordance of computer outputs with student works can be related with training since human design act relies on designer's background, personal and cultural preferences. It is understood that the concept of emphasis is better learned by students with respect to the number of successful individuals generated. The students' tendency to use the techniques of achieving emphasis also shows that the process led by human designers does not get stuck on one technique as it is in computer implementation. Computer implementation is seen to be more inclined to reiterate an approach once learned. Although it is able to generate successful individuals with totally new approaches, it does not seem to generate new typologies by repeating or modifying these individuals. On the other hand, students are able to create new typologies. It can be concluded that students perform a more conscious design act in comparison to computer implementation.

CHAPTER 6

CONCLUSION

In the study, an evolutionary design methodology including an artificial neural network as an evaluation tool has been proposed. The tool is used in generating solutions to a basic design problem on emphasis and the creative capacity of it is evaluated by comparing the outputs with the students' responses to the same problem. Emphasis is chosen as the theme of the design problem, since it can be achieved in a composition with a systematic, rule-based approach. Although there are already numerous methods employing evolutionary algorithms in the literature, this study mainly differs at evaluation step. While some of the studies employ analytical and/or rule based approaches to evaluate the generated designs, some others prefer to use interactive approach.

In design problems, the evaluation criteria such as aesthetics, ease of use etc. are not easily measurable or computable as in the case of cost, performance, manufacturability, energy consumption etc. The methods in literature choose interactive approach for evaluation of the mentioned criteria. These methods do not provide the designer with a complete automation tool. Although the generation of ideas is successfully automated and released from the limits of designer's experience, the whole design process is still guided by the designer. For non-expert or prejudiced designers, this may easily cause the generation of biased or uninteresting designs. An inexperienced designer may evaluate a generated alternative as a poor solution at first glance and this causes the alternative to become extinct in the following generations. However, this solution or a part of it may have a potential to be employed by the best solution which is going to be generated by the algorithm. In short, interactive evaluation by an inexperienced designer may result in loosing genetic diversity in the population.

In the developed method, automation of the evaluation step is provided with a well-trained artificial neural network. Although this method also requires an expert designer for the preparation of the training set, once it is successfully trained, the tool is ready to be used by non-expert users. Moreover, it will be able to generate results far beyond the expert designer's experience.

In order to prove the creative capacity of the proposed method, a case study on the concept of emphasis has been conducted and the computer implementation has been carried out in MATLAB® environment. The computer outputs are compared by human designer outputs. For this comparison, the human designers, consisting of freshmen design students, are trained about the concept of emphasis by just showing the same sample set, which is used to train the neural network. After showing the sample set, the students were asked about the differences between the samples and were expected to pronounce the word "emphasis" by themselves. Later on, al of the members of the initial population were shown to the students with + and – signs corresponding to 1 and 0 respectively and the students were then asked to create as many compositions showing out successful emphasis as they can. In the end, the student outputs exhibited a remarkable achievement with respect to computer outputs. Although the results of training proved the ability to correctly detect successful and unsuccessful items, the system was not able to generate successful item as much as human designers. This can be a result of human designers' former familiarity with the concept of emphasis. Although the students were tried to be trained in a similar way as the system has been trained, their concept of emphasis was nurtured by their prior experiences.

The training sample for the neural network must be prepared in such a way that the network will gain inference ability instead of making it memorize all the samples. For instance, in the conducted case study, all training samples employing emphasis by size approach prefer the big square to be emphasized. However, in the outputs of test runs, there exist some compositions where small squares are emphasized. This proves that the network has learned the notion of size.

In the computer implementation, the generation process has been performed with both randomly generated and designer prepared initial population. In the outputs of the randomly generated initial population, the squares appeared to be in diverse sizes and the oversize squares inevitably overlapped.

The test runs performed with designer prepared initial population in general tended to repeat the compositions in the initial population. However, the outputs did not seem to repeat a typology represented with large number of individuals. In raising the offspring, mutation and crossover were used. As mentioned before, mutation is performed by making slight modifications in the representation scheme while crossover is able to generate totally new outputs since it operates on cut and combine basis of representation schemes. In mutation process, besides slight modifications, the tool was able to apply mirroring, centering, or rotating a layout in the initial population.

Although three different groups were used, their response to the emphasis problem did not sharply diverge. The industrial design students which were admitted to the university with quantitative reasoning ability, slightly were more successful then the other two groups in generating successful emphasis with a difference of 0.11 % between Graphic Design and 6% between Visual Communication Design. Although both the Visual Communication Design and Graphic Design students were admitted to the university with similar aptitude exams, most of the Visual Communication Design students were graduated from vocational high schools specialized in graphic design. However this did not result in handling of the concept of emphasis with a better rate. Graphic Design students were more apt to repeat or modify the samples of the initial population since rate of the new composition raised is the lowest in this group. None of the students applied dramatic size variations as in the case of randomly generated computer outputs. On the contrary, most of the squares used in compositions were consistent in size. Another outcome of the classwork appeared to be the repetition of certain new compositions in certain groups. This may be regarded as a result of the interaction between the students.

Computer outputs' success is around 45% in generating successful emphasis while the human designers' success appeared to be around 95%. However the computer implementation is more apt to produce new compositions while the human designers often rely on initial population in generating new items. The human designers' reliance on their former knowledge of the concept resulted in high rate in achieving successful emphasis, low rate in achieving creative solutions.

Among the techniques of achieving emphasis, contrast of orientation appeared to be the hardest technique. The human designers' responded the study with lowest rates in achieving emphasis with contrast of size and orientation followed by contrast of orientation. Likewise, none of the outputs of the test runs reflected contrast of size and orientation technique. On the other hand, contrast of position and size and position appeared to be the most conventional technique of achieving emphasis.

The conducted study can bring out results for teaching in basic design studio. The use of computers in design education is generally limited to utilization as a presentation tool. However, the potentials of computer aided design (CAD) in education are not totally explored yet. The computation attempts in design bring a considerable systematic and analytical approach that is generally defined as a black-box practice. Systematization, different representation of design knowledge and providing collaboration are the main advantages of CAD which should also be utilized in education (Taşlı, 2001). Today, rather then being a black box process, design is becoming more of a knowledge-based business which necessitates knowledge management skills in global market conditions. Such skills needed by the competitive market must be provided by education.

The current tradition of the design studio is shaped under the effect of two models as Ecole Des Beaux Arts and Bauhaus. While the ateliers system offered by Ecole Des Beaux Arts confronted “learning by doing” under the control of a Patron, the concept of design studio offered by Bauhaus aimed to enhance the students with much technical experience by providing a link with professional practice outside the Bauhaus (Farghaly, 2006). Founded at the beginning of 20^{th} century after Industrial Revolution, the Bauhaus tried to integrate art first with craft, then with technology (Balcıoğlu, 2009).

Like the contemporary design education, basic design curriculum has its roots in the foundation course of the Bauhaus called “Vorkurs” which was first taught by Johannes Itten. Vorkurs was designed as a six months course aiming to introduce the students the basic concepts about form and materials (Droste, 1990). The aim of the Bauhaus Vorkurs was to systematically analyze and understand form, regardless of its tectonic, structural or functional qualities (Steinø, 2006).

Both of the revealed educational models intended to cope with the social, economic and cultural circumstances of their time. The curriculum of Bauhaus was designed to answer the needs emerging with industry and mass production. Similarly, Itten’s approach in the Vorkurs was a result of the new craft-industry relationship. After almost a hundred years, basic design education can be restructured to suit the new human-computer interaction and the global market needs such as systematic thinking and knowledge management.

CAD is introduced in the design education curriculum whether as a separate course or within studio teaching. However, inserting CAD in early steps of education can result in student's struggle with the program more than producing design concepts (Taşlı, 2001). So rather than introducing a tool which requires high level control of the user, programs that enhance the students' awareness of the design concepts and help to construct their own value system can be utilized in basic design education.

In the proposed tool, the designer contributes to the process in three steps; in preparation of the initial population, in training and in assessment of the outputs. Preparation of the initial population and training can help to enhance systematic thinking and knowledge management skills while the student's participation in the evaluation step and assessment can help to construct a value system and develop awareness about the design concept.

The student's performance criteria for design are often based on the approval from the master, which is the studio instructor (Taşlı, 2001). The training and evaluation procedures carried out by the studio instructor are attained by the human designer in the proposed method. Teaching, on the hand, is regarded as the reciprocal of learning and the teachers themselves are the beneficiaries of the process rather than their audiences (Chen, Heylighen, 2006). As Schön mentions, the student learns about design and the process of designing at the same time during studio practice (1985). So evaluating or criticizing a work and finding ways to restore it can serve as an alternative way of learning. Such a process can help the student to construct his own value system and enhance an autonomous approach to design.

The proposed tool can be utilized in such a way to familiarize the students both with the systematics of design concepts and the CAD techniques. On the other hand, students' training is another concept to be handled. Within the study, the training of the ANN was tried to be simulated in class practice. For this purpose, the students were not given the title "emphasis" at the beginning and the successful and unsuccessful examples were exhibited on the walls of the studio during the studio hours. On the aspect of arising awareness, letting the students grasp the concept by just comparing the samples can be regarded as an efficient tool. However it can be claimed that displaying the initial population resulted in students' failure to generate outputs dissimilar to each other.

The proposed evolutionary design method can be seen as a promising tool for the automation of the design process. The application area of the tool can be extended by training the neural network for different purposes or employing totally different evaluation instruments. The method at the same time can be designed as an education tool which enables student's participation as the master and evaluator to a certain extend.

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APPENDIX

APPENDIX:

The Initial Population

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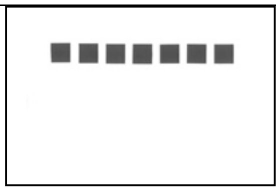
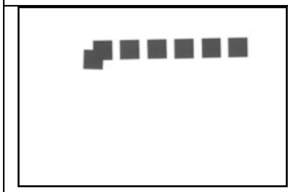
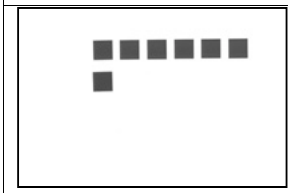
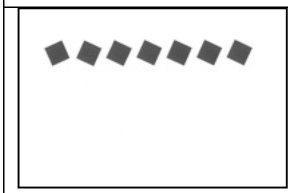
Linear		0
		1
		1
		1
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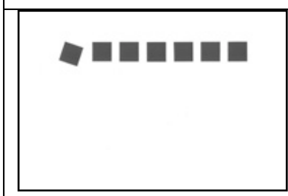
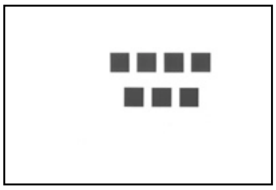
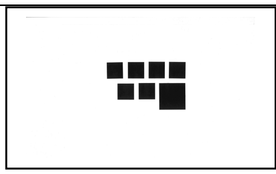
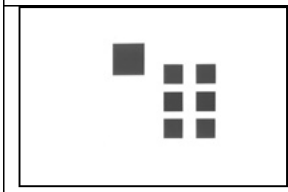
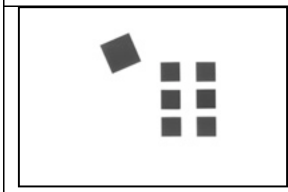
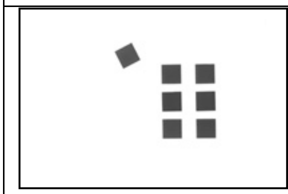
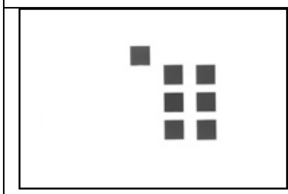
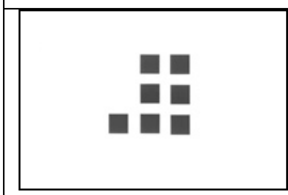
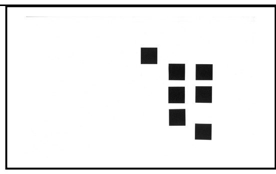
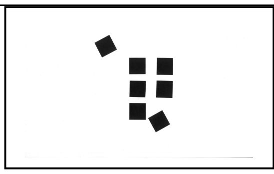
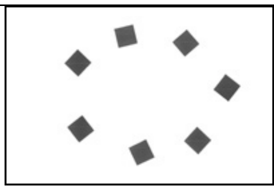
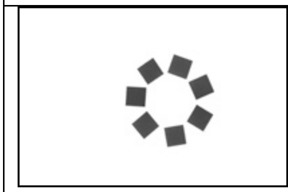
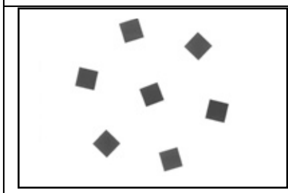
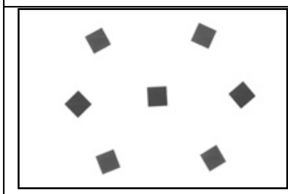
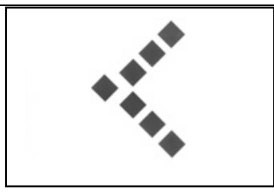
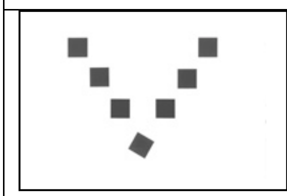
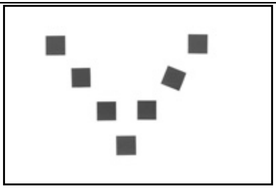
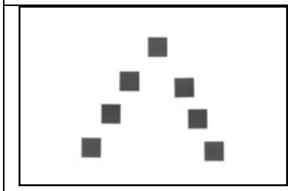
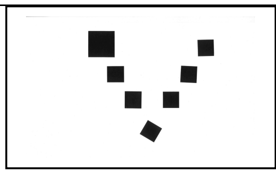
		1

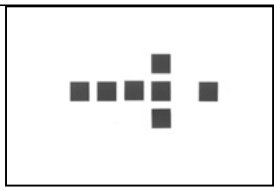
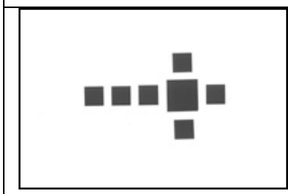
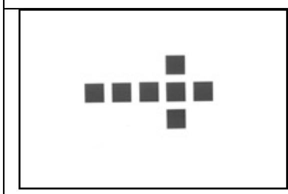
Two Rows		0
		1
		1
		1
		1
		1
		1
		0

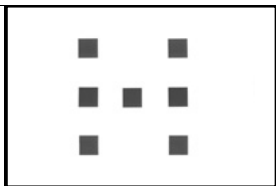
		0

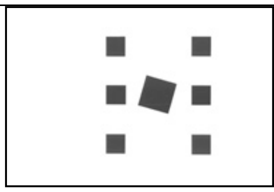
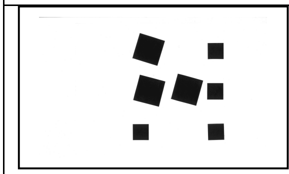
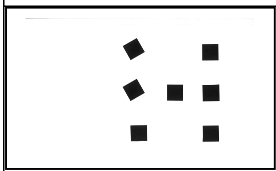
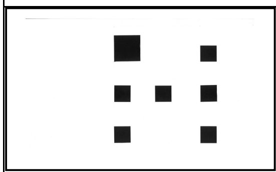
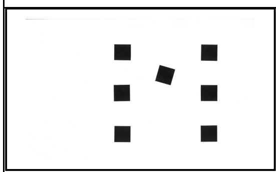
Circular		0
		0
		1
		1

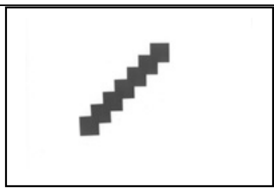
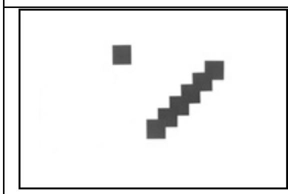
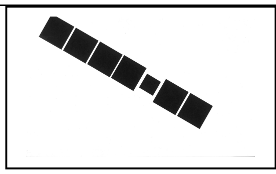
V		1
		1

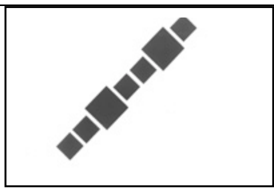
		1
		1
		0

T		1
		1
		0

H		1

		**1**
		**0**
		**0**
		**0**
		**1**

Diagonal		**0**
		**1**
		**1**

		**0**
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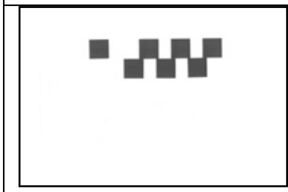
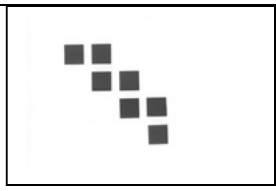
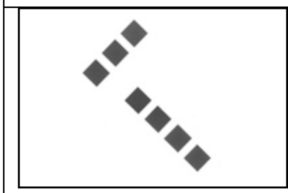
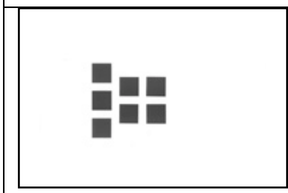
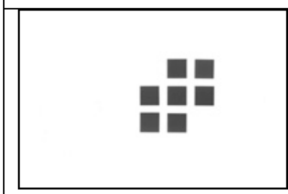
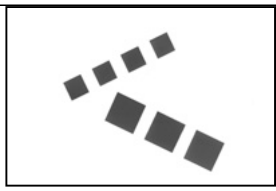
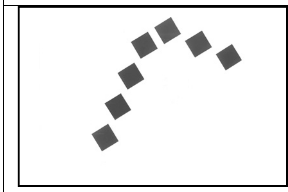
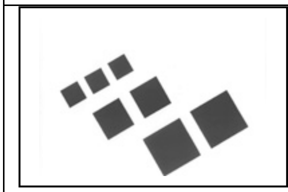
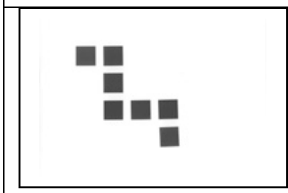
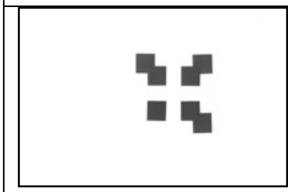
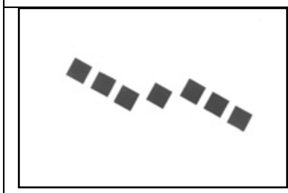
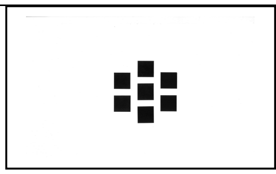
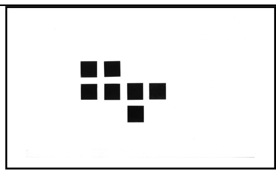
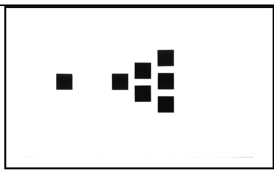
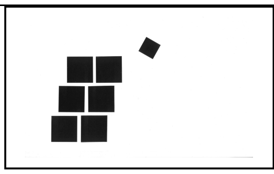
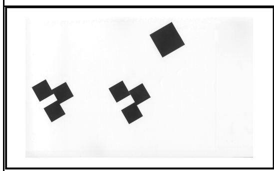
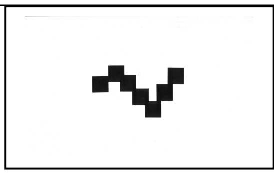
		**1**
Mixed		**0**
		**0**
		**0**
		**0**

		**0**
		**0**
		**0**
		**0**
		**1**
		**1**
		**0**
		**0**

		**1**
		**1**
		**1**
		**0**