Combining Genetic Algorithms and Neural Networks:

The Encoding Problem

A Thesis

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Degree

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Dedication

For Claudine

Acknowledgment

I would like to thank my major professor, Dr. Bruce MacLennan for his support and the freedom he gave me for this thesis. I would also like to thank the other committee members, Dr. David Straight and Dr. Michael Vose. I am grateful for the help of other researchers, especially David White, which enabled me to get a broad view on current research.

Abstract

Neural networks and genetic algorithms demonstrate powerful problem solving ability. They are based on quite simple principles, but take advantage of their mathematical nature: non-linear iteration.

Neural networks with backpropagation learning showed results by searching for various kinds of functions. However, the choice of the basic parameter (network topology, learning rate, initial weights) often already determines the success of the training process. The selection of these parameter follow in practical use rules of thumb, but their value is at most arguable.

Genetic algorithms are global search methods, that are based on principles like selection, crossover and mutation. This thesis examines how genetic algorithms can be used to optimize the network topology etc. of neural networks. It investigates, how various encoding strategies influence the GA/NN synergy. They are evaluated according to their performance on academic and practical problems of different complexity.

A research tool has been implemented, using the programming language C++. Its basic properties are described.

Preface to the Publication at the Ohio State FTP Site

This piece of work is my Master thesis at the University of Tennessee, and my study thesis at the University of Erlangen as well. I wrote it with the intention to explore the current state of research in the field of combining genetic algorithms and neural networks.

If you have questions, or if you are interested in my code, please contact me at: kohn@cs.utk.edu.

Table of Content

Introduction

"Genetic Neural Networks.
I believe that this is going to become the core of connectionism"
Frederic Gruau, 1994

Connectionist Philosophy

Genetic algorithms and neural networks have received great acclaim in the computer science research community since the 1980s. For the most part, this results from successful applications of these new computing models, but also, because the concepts share the spirit of a movement that goes beyond science.The major principle of this movement is the idea that for a broad set of complex problems self-organization, the exploitation of the interaction of independent small units, is stronger than central control.

The effect of this principle can be observed in several phenomena of human life. In politics, we just experienced the decay of totalitarian systems all over the world. There is general consent that a democratic society is more likely to find a policy that increases the standard of living of its members. This exemplifies the rejection of central control, although this idea was widespread during history - as in Plato's "The Republic", where he envisioned a government of philosophers. However, the majority opinion of a society of educated people has been demonstrated to be more sensitive to new, important issues.

In economics we experience the heyday of capitalism, of the free-market economy. The communistic idea, that is possible, desirable and more efficient to plan and control the distribution of labor and goods, has been proven unsuccessful in many different varieties. The interaction of several egoistic economic units has been shown to be far more successful.

This principle of self-organization of interdependent units can also be observed in the human organism itself in several ways: the skin is one example out of many. It consists of a network of numerous cells that interact in the task of forming an protective layer for the body.

Also, the human mind is not controlled by a central observer, a homunculus that acts through the pineal gland, as some philosophers believed. It rather can be observed that several subsystems interact independently. Modern theories of consciousness take this into account [Dennet, 1991].

The scientific reflection of this philosophy is rooted in mathematical chaos theory which deals with highly iterated non-linear systems. Its ambition is to examine and understand the processes that take place and produce the efficiency of self-organized dynamic systems.

It is important to state that not every self-organized system is successful per se. A democracy requires an educated society and free distribution of information, capitalism works best if the rate of competition is high and oligopolic corporations do not dominate the markets.

Computer science answered this movement with the emergence of connectionist computing models: genetic algorithms and networks. Although quite different in their nature, they both incorporate the principle of self-organization. This rejects completely the traditional programming paradigm.

Classical Computer Programming

The classical view on programming can be illustrated by figure 0.1. Traditionally a given problem has to be carefully examined. A solution in the form of a computer program requires that every single possible case has to be considered. Only when the problem is completely analyzed, can it be represented by an algorithm. Finally, this allows the implementation of a computer program.

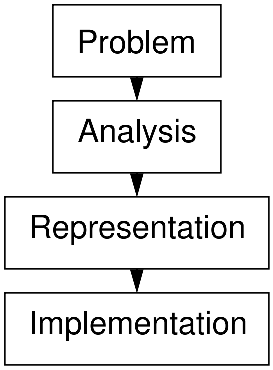


Figure 0.1: Classical Computer Programming

However, considering reasonable applications, the available resources would be exceeded by far, if every instance of the problem were to be implemented by its own set of instructions. Thus, general rules have to be constructed. Yet these rules are sometimes very difficult to obtain, especially if one leaves the safe realm of mathematics and engages in more human kinds of problems.

A good example is handwriting recognition. Figure 0.2 illustrates how different people write an single letter. For the trained human eyes it is no problem to recognize the letter “A” in each of the patterns. For the computer, however, handwriting recognition is still one of the toughest fields of research. The reason is obvious: There are just no clear rules how an “A” is supposed to look.

Figure 0.2: Different Ways to Write the Letter “A”

The New Approach

The non-declarative programming paradigm avoids the requirement of such rules. If at all, these kinds of rules emerge as a by-product. The paradigm is shown in figure 0.3.

Instead of analyzing the problem a training framework is feed with a large amount of training patterns, which are instances of the problem. During training, the system learns these patterns. Moreover, since it is generally not possible to process all possible instances, the system gains the ability to compute new unlearned patterns appropriately.

Self-organizing systems have been shown to be more fault-tolerant and more adaptable for new data. To stress the first point with a frequently used example: The loss of 10% of the nodes in a neural net or the change of 10% of the bits in a genetic encoding only slightly decreases their performance in most cases. On the other hand, the change of only a few bytes in classical computer program is often fatal.

The design of self-organized systems is principally different from the classical central control task. Research in this field is just beginning to understand the mechanisms.

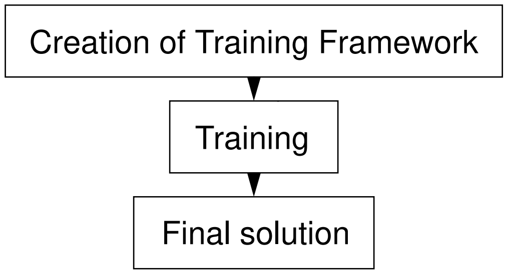


Figure 0.3: The Non-Declarative Programming Approach

Goldberg points out in [Goldberg, 1989] that designers of self-organized systems tend to fall back into traditional “Western scientific thinking”: splitting a problem into pieces and focussing and problem-specific subtasks while missing the big picture. He argues for guidance from nature and indirect changes at the local units rather than at the global system.

However, NN and GA are not the new computing model for all purposes that try to replace classical computer programming. For instance, in mathematical and most traditional data-base applications, their application value is only marginal.

Cognitive Inversion

It is an interesting observation that state of the art artificial intelligence research is very successful in tasks that are generally considered as very difficult. For instance, it seems just a matter of time, until the next chess world champion will be a computer program. However, AI falls short, when it comes down to tasks like speech recognition, which are very simple for human beings and performed without any effort (see figure 0.4).

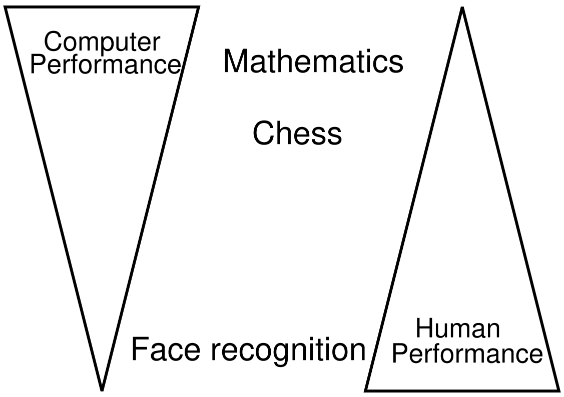


Figure 0.4: Cognitive Inversion

This effect is called cognitive inversion. Let us take a look at the different demands of the tasks mentioned. Chess playing requires a lot of logical reasoning: What happens when one chessman moves to a certain place? And so on. Speech recognition, however, is learned by years of experience, especially during early age.

Today’s chess-playing programs use the rules of the game to compute a huge amount of possible moves and the resulting game situation in order to find an optimal move. For speech recognition, we do not have these kind of rules. The task is to distinguish meaningful information from noise.

The promise of genetic algorithms and neural networks is to be able to perform such information filtering tasks, to extract information, to gain intuition about the problem. Since these are computing strategies that are situated on the human side of the cognitive scale, their place is to find solutions to problem that are more human-like.

Combining Genetic Algorithms with Neural Networks

The idea of combining GA and NN came up first in the late 80s, and it has generated a intense field of research in the 1980s. Since both are autonomous computing methods, why combine them? In short, the problem with neural networks is that a number of parameter have to be set before any training can begin. However, there are no clear rules how to set these parameters. Yet these parameters determine the success of the training.

By combining genetic algorithms with neural networks (GANN), the genetic algorithm is used to find these parameters. The inspiration for this idea comes from nature: In real life, the success of an individual is not only determined by his knowledge and skills, which he gained through experience (the neural network training), it also depends on his genetic heritage (set by the genetic algorithm). One might say, GANN applies a natural algorithm that proved to be very successful on this planet: It created human intelligence from scratch.

The topic of this thesis is the question of how exactly GA and NN can be combined, i.e. especially how the neural network should be represented to get good results from the genetic algorithm.

Overview

Chapter 1 introduces the basic concepts of this thesis: neural networks and genetic algorithms. Recent research in the GANN field is reviewed in chapter 2. Finally, chapter 3 reports experimental results.

1 Defining the Problem

1.1 Neural Networks

Both NN and GA were invented in the spirit of a biological metaphor. The biological metaphor for neural networks is the human brain. Like the brain, this computing model consists of many small units that are interconnected. These units (or nodes) have very simple abilities. Hence, the power of the model derives from the interplay of these units. It depends on the structure of their connections.

Of course, artificial neural networks are ages away from the dimensions and performance of the human brain. The brain consists of about 10 to 15 billion neurons [Schiffmann, 1991] with an average of about one thousand connections each. Today’s artificial NN have rarely more than a few hundred nodes, most of them much less. Also, the exact structure of brain neurons is more complex than the simple computer model, it is still not completely explored.

There are several different neural network models that differ widely in function and applications. In this thesis, however, I will only examine feed-forward networks with back-propagation learning. They draw the most attention among researchers, especially in the GANN field.

From a mathematical point of view, a feed-forward neural network is a function. It takes an input and produces an output. The input and output is represented by real numbers.

A simple neural network may be illustrated like in figure 1.1.

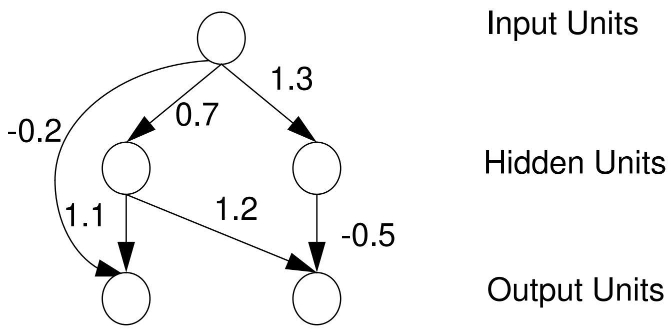


Figure 1.1: A Neural Network

This network consists of five units or neurons or nodes (the circles) and six connections (the arrows). The number next to each connection is called weight, it indicates the strength of the connection. Connections with a positive weight are called excitatory, the ones with a negative weight are called inhibitory.

The constellation of neurons and connection is called the architecture of the network, which is also called the topology.

This is a feed-forward network, because the connections are directed in only one way, from top to bottom. There are no loops or circles. It is, however, not a strictly layered network.

In a strictly layered network, the nodes are arranged several layers. Connections may only exists to the nodes of the following layer . Yet in our case, there is an connection from the input layer to the output layer . You may call it a layered network, because the nodes of each layer are not interconnected. The word “layered”, however , is most often used synonymous with “strictly layered”.

Computation

Figure 1.2 illustrates how information is processed through a single node.

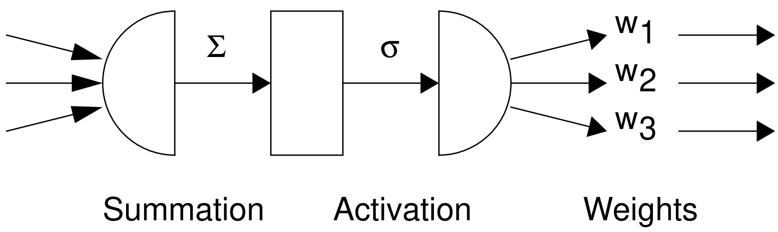


Figure 1.2: Information Processing in a Neural Network Unit

The node receives the weighted activation of other nodes through its incoming connections. First, these are added up (summation). The result is passed through a activation function , the outcome is the activation of the node. For each of the outgoing connections, this activation value is multiplied with the specific weight and transferred to the next node.

A few different threshold functions are used. It is important that a threshold function is non-linear , otherwise a multilayer network is equivalent to a one layer net. The most widely applied threshold function is the logistic sigmoid :

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

There are a few other activation function in use: scaled sigmoid, gaussian, sine, hyperbolic tangent, etc. However , the sigmoid is the most common one. It has some benefits for backpropagation learning, the classical training algorithm for feed-forward neural networks.

Back-Propagation Learning

At the beginning the weights of a network are randomly set or otherwise predefined. However , only little is known about the mathematical properties of neural networks. Especially, for a given problem, it is basically impossible to say which weights have to be assigned to the connections to solve the problem. Since NN follow the non-declarative programming paradigm, the network is trained by examples, so called patterns .

Back-propagation is one method to train the network. It has many parents, it was made popular for neural nets by Rumelhart, Hinten et Williams [Rumelhart, 1986]. It is a very reliable, however a little bit slow training strategy .

The training is performed by one pattern at a time. The training of all patterns of a training set is called an epoch . The training set has to be a representative collections of input-output examples.

Backpropagation training is a gradient descent algorithm. It tries to improve the performance of the neural net by reducing its error along its gradient. The error is expressed by the root-mean-square error (RMS), which can be calculated by:

$$E = \frac{1}{2}\sum_{p}\left\|t_p - o_p\right\|^2$$

The error (E) is the half the sum of the geometric averages of the difference between projected target (t) and the actual output (o) vector over all patterns (p). In each training step, the weights (w) are adjusted towards the direction of maximum decrease, scaled by some learning rate lambda.

$$\nabla E = \left(\frac{\delta E}{\delta w_1}, \frac{\delta E}{\delta w_2}, \ldots, \frac{\delta E}{\delta w_n}\right)$$

$$w_{new} = w_{old} - \lambda \nabla E$$

The sigmoid function has the property

$$\frac{d}{dx}\sigma(x) = \sigma(x)\,(1 - \sigma(x))$$

That means that the derivative of the sigmoid can be computed by applying simple multiplication and subtraction operators on the results of the sigmoid function itself. This simplifies the computational effort for the back-propagation algorithm. In fact, the equations for weight changes are reduced to:

$$\Delta w_{from,\, to} = -\lambda o_{from} \delta_{to}$$

$$\delta_{output} = -(t_{output} - o_{output})$$

$$\delta_{hidden} = \sigma'(s_{hidden}) \sum_{i} \delta_i w_{hidden,\, i}$$

There are different functions for connections to hidden and output nodes. The unprocessed sum (s) for each neuron has to be stored, before the activation function is applied to it. Then, basic algebra operations like multiplication and subtraction are sufficient to perform the weight changes.

These equations describe the basic back-propagation algorithm. There are numerous attempts of its improvement and speed-up. Surveys of these can be found in [White, 1993] or [Schiffmann, 1992b].

1.2 Genetic Algorithms

The biological metaphor for genetic algorithms is the evolution of the species by survival of the fittest, as described by Charles Darwin. In a population of animals or plants, a new individual is generated by the crossover of the genetic information of two parents.

The genetic information for the construction of the individual is stored in the DNA. The human DNA genome consists of 46 chromosomes, which are strings of four different bases, abbreviated A, T, G and C. A triple of bases is translated into one of 20 amino acids or a "start protein building" or "stop protein building" signal [Boers, 1992]. In total, there are about three billion nucleotides. These can be structured in genes, which carry one or more pieces information about the construction of the individual. However, it is estimated that only 3% of the genes carry meaningful information, the vast majority of genes - the "junk" genes - is not used.

The genetic information itself, the genome, is called the genotype of the individual. The result, the individual, is called phenotype. The same genotype may result in different phenotypes: Twins illustrate this quite well.

A genetic algorithm tries to simulate the natural evolution process. Its purpose is to optimize a set of parameters. In the original idea, proposed by John Holland [Holland, 1975], the genetic information is encoded in a bit string of fixed length, called the parameter string or individual. A possible value of a bit is called an allele [White, 1993]. In this thesis, a series of different encoding techniques are used, but the basic principles apply as well.

Each parameter string represents a possible solution to the examined problem. For the GANN problem, it contains information about the construction of a neural network. The quality of the solution is stored in the fitness value.

The basic GA operators are crossover, selection and mutation. Figure 1.3 illustrates the principle structure of a genetic algorithm. It starts with the random generation of an initial set of individuals, the initial population.

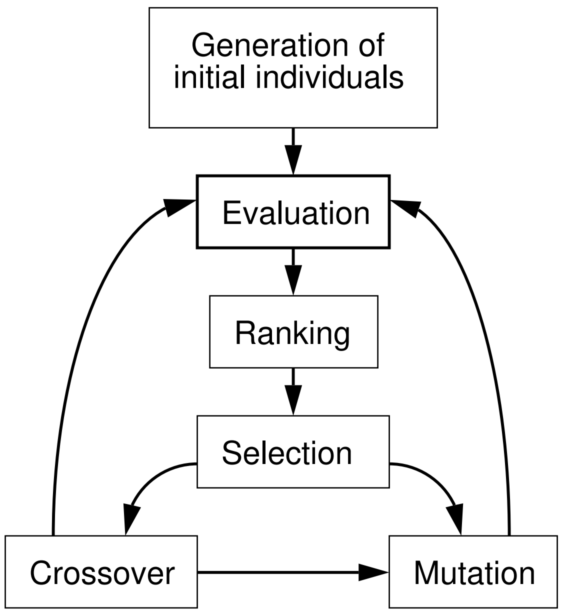


Figure 1.3: The Principle Structure of a Genetic Algorithm

The individuals are evaluated and ranked. Since the number of individuals in each population is kept constant, for each new individual an old one has to be discarded, in general the one with the worst fitness value.

There are two basic operators to generate new individual: mutation and crossover. The more simple one is mutation. During mutation, a couple of bits of the parameter string are flipped at random. Mutation may be applied to offspring produced by crossover or , as an independent operator , at random to any individual in the population.

Crossover

Crossover simulates the sexual generation of a child, or offspring from two parents. This is performed by taking parts of the bit-string of one of the parents and the other parts from the other parent and combining both in the child. There a three basic kinds of crossover: one-point, two-point and uniform.

One-point crossover is illustrated in Figure 1.4. Both parent bit-strings are cut at the same point. So, the child can be generated by taken one part from each parent. Notice that the parts are not moved. Also, the randomly selected cutting point is independent from the actual meaning of the bits. One parameter of the bit string may be encoded in more than one bit, and its encoding cut in two pieces during crossover , thus resulting in a new value - different from either parent.

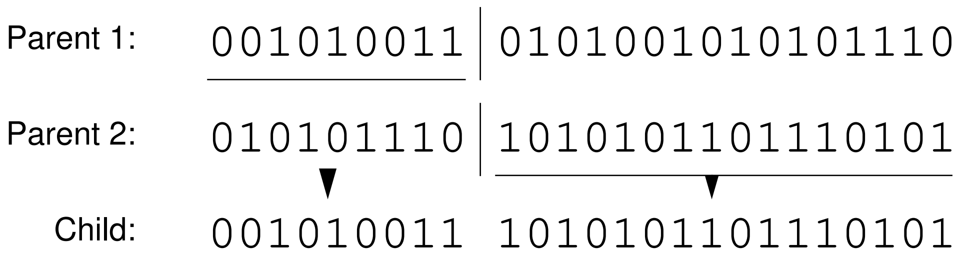


Figure 1.4: One-Point Crossover

Two-point crossover (figure 1.5) differs from the previous version merely in the point that two random cuts are made, so three pieces have to be put together in order to produce an offspring.

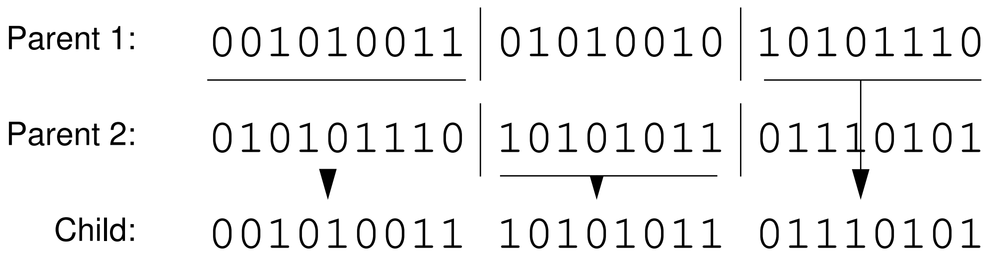


Figure 1.5: Two-Point Crossover

These two are the two original crossover operations. The third one, uniform crossover is suggested in [Syswerda, 1989]. It is illustrated in figure 1.6. Here, for each bit, it is randomly decided, if it is copied from parent one or two.

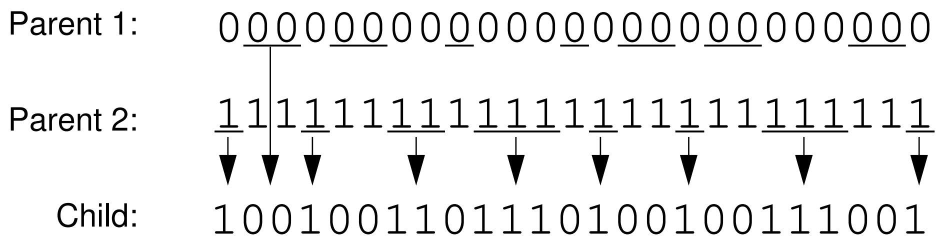


Figure 1.6: Uniform Crossover

(only one arrow from parent 1 shown)

During a generation a fixed number of crossovers and mutations are performed.

Selection

The selection of individuals for cross-over and mutation is biased towards good individuals. In the classical fitness-based roulette-wheel, the chance of an individual to be selected is based on its relative fitness in the population (see figure 1.7).

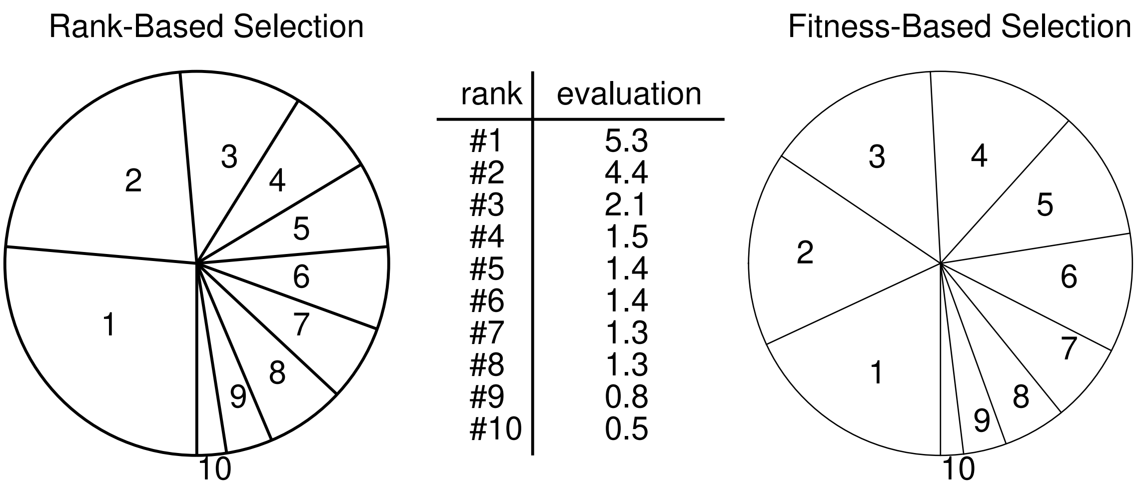


Figure 1.7: Rank-Based vs. Fitness-Based Selection

This works fine at the beginning, but towards the end, the fitness values of the individuals vary only slightly . An alternative is proposed in [Whitley , 1989] and [White, 1993]: The selection chance is now no longer based on the relative fitness, but the rank in the population. For instance, in a population of ten individuals, the chance of the first-ranked individual is 10 to 55, the chance of the 10th individual is 1 to 55, since

$$\sum_{n=1}^{10} n = 55$$

This mechanism also releases the designer of a GANN problem from considerations about the exact values of the fitness function. It is merely important, that better individuals get better fitness values.

Simple Encoding Considerations

Similar information should be encoded in similar ways, in order to have a continuous search space, which is a basic requirement for hill-climbing algorithms such as GA and NN [Williams, 1994].

Some common sense is required for the designing of a bit encoding, if more than one bit is used. For instance, consider we want to represent the network by encoding the possibilities "disconnected", "inhibitory" and "excitatory". As pointed out in [Marti, 1992a], representation A is better than the B:

```
A: 00, 01 Disconnected;   10 Inhibitory;   11 Excitatory
B: 01, 10 Disconnected;   00 Inhibitory;   11 Excitatory
```

The logical distance between a excitatory and a inhibitory connection ought to be reflected in the bit-distance of the encoding. In B, two bits have to be changed to make the transition.

Variations of the Crossover Operator

One open field of research is the crossover operator. In [Eshelman, 1989] the bias of different crossover types is examined and a theoretical and empirical argument for a novel shuffle crossover is made: Before one-point crossover is applied to the bit strings, the position of the bits is changed according to a randomly generated shuffle scheme.

Also, Bersini and Seront [Bersini, 1992] came up with a new genetic operator called GA simplex. The following algorithm illustrates it in short:

```
Input: 2 parents x1, x2
Output: 1 child c
1st: Rang parents by fitness value ff(x1)>ff(x2)
2nd: For each i'th bit of the strings:
       if x1(i) = x2(i) then c(i) = x1(i)
                         else c(i) = random
```

Maniezzo states in [Maniezzo, 1993] that he improved the mechanism by changing the else-condition to the assignment `c(i)=negate(x3(i))` for an additional parent `x3`. This version is implemented in the ANNA ELEONORA system. Maniezzo argues that GA simplex is a more local operator, opposed to the more global mutation and crossover.

Parallel Genetic Algorithms

Genetic algorithms are a good object for parallelization. The crossover, mutation and evaluation of different individuals during one generation are independent from each other. So its execution in parallel is a simple task.

Moreover, there are several approaches to even increasing the GA's ability for parallelization. Tanese proposes in [Tanese, 1989] the distributed GA, which, for instance, is implemented in White's GANNet [White, 1993]. This idea is also known as the "island model" [Maniezzo, 1994]. The population of individuals is split into a couple of isolated subpopulations. For each of these, the GA works autonomously. Within a certain number of generations, each subpopulation sends its best member to another subpopulation. The target group alternates throughout the set of subpopulations.

Another approach towards higher parallelism expresses itself in the fine-grained parallel GA [Maderick, 1989]. In this algorithm, crossover is restricted to individuals that are neighboring in a planar (or toroidal) grid. It is implemented in the ANNA ELEONORA project [Maniezzo, 1994].

Parallel GAs allow huge population sizes without time increase. Since the GA operations are very simple, implementation in VLSI chips is possible.

Genetic Algorithms vs. Evolutionary Programming

Besides genetic algorithms, there are a couple of related evolutionary optimization systems, such as evolutionary programming [Fogel, 1993][McDonnel, 1993], or genetic programming [Koza, 1991]. Some of the approaches reviewed in chapter 3 use these systems. In fact, only few stick to the original GA paradigm, which demands a fixed-length bit string.

The main distinctions of GA are according to [Fogel, 1993]: First, GA operate on the coding of parameters instead of the parameters itself. Second, the number of offspring of each parents is relative to its fitness and finally , GA operators use semantically meaningless operators such as crossover , instead of various mutation operators that follow naturally from a given problem.

The GA is basically a general problem solver that does require the adaptation of its functionality to the problem that it is applied to.

1.3 Encoding the Network

The general idea of combining GA and NN is illustrated in figure 1.8.

Information about the neural network is encoded in the genome of the genetic algorithm. At the beginning, a number of random individuals are generated. The parameter strings have to be evaluated, which means a neural network has to be designed according to the genome information. Its performance can be determined after training with back-propagation. Some GANN strategies rely only on the GA to find an optimal network; in these, no training takes place.

Then, they are evaluated and ranked. The fitness evaluation may take more into consideration than only the performance of the individual. Some approaches take the network size into account in order to generate small networks. Finally , crossover and mutation create new individuals that replace the worst - or all - members of the population

This general procedure is quite straight-forward. The problem of combining GA and NN, however , lies in the encoding of the network.

The new ideas and concepts of GA and NN bring new life into Artificial Intelligence research. But still, we encounter again an old problem: the problem of representation.

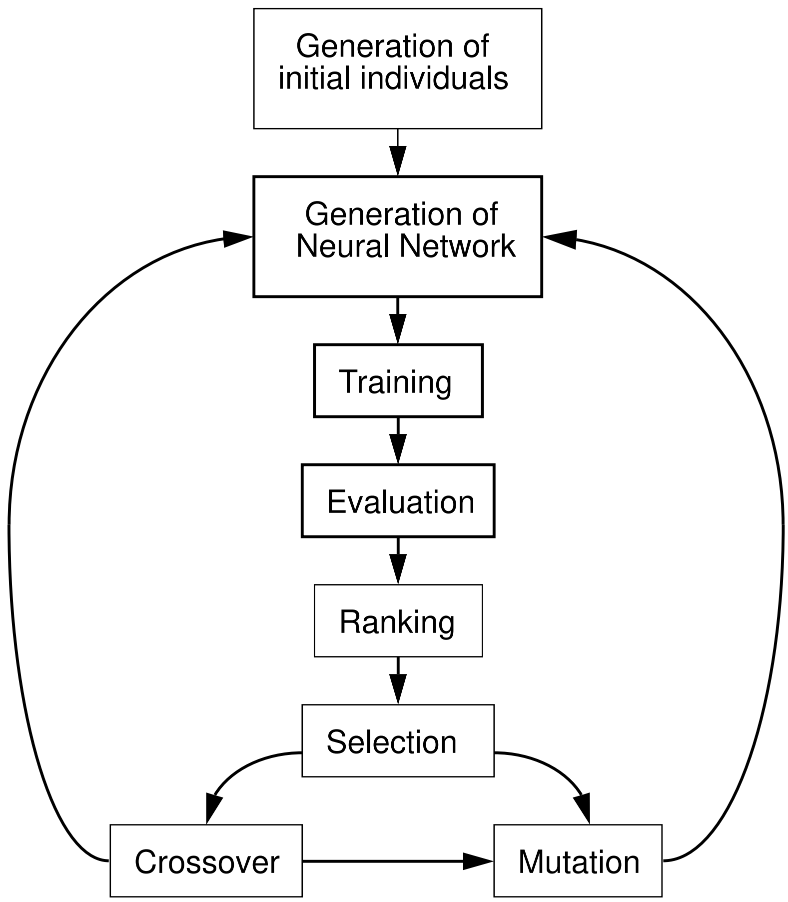


Figure 1.8: The Principle Structure of a GANN System

2 Various Approaches

Since first attempts to combine GA and NN started in the late 1980s, other researchers have joined the movement and created a flood of journal articles, technical reports etc.

A broad variety of problems have been investigated by different GANN approaches, such as face recognition [Hancock, 1991], animats [Maniezzo, 1994], classification of the normality of the thyroid gland [Schiffmann, 1993], color recipe prediction [Bishop, 1993] and many more.

Also, a variety of different encoding strategies have been implemented. This chapter tries to structure this information with focus on feed-forward networks with back-propagation. It does not emphasize on the complete review of single approaches, it rather attempted to gather more general information and find general patterns.

2.1 Basic Research

The Search for Small Networks

Most of the encoding strategies incorporate the network size in the evaluation function in order to find optimal networks that use few neurons and connections. Often, this results in two phases of the search. First, a good network is searched for . Then, the network size of the best individuals decreases (refer to, for instance, [White, 1993]).

The Problem of Overfitting

One classical problem of neural networks is called overfitting, which occurs especially with noisy data. Is has been observed that excessive training results in decreased generalization. Instead of finding general properties of the different input patterns that match to a certain output, the training brings the network closer to each of the given input patterns. This results in less tolerance in dealing with new patterns.

For the GANN approach a solution is proposed in [Wong, ?].It is suggested to use for the evaluation of the network performance a different set of patterns than for the training. Hence, only networks that generate the ability to generalize are evaluated high. This method was implemented in an approach called GENETICA.

Global vs. Local Search

Although GA and NN have in common that they are general search strategies, empirical studies show [Kitano, 1990b] that they vary in their range. GA perform a more global search than NN with back-propagation. This point is also stressed by White [White, 1993].

Figure 2.1 illustrates the convergence of the strategies. Back-propagation takes more time to reach the neighborhood of an optimal solution, but then reaches it more precisely . On the other hand, genetic algorithms investigate the entire search space. Hence, they reach faster the region of optimal solutions, but have difficulties to localize the exact point. This happens, because for the final “fine-tuning” of the solution relies almost entirely on mutation.

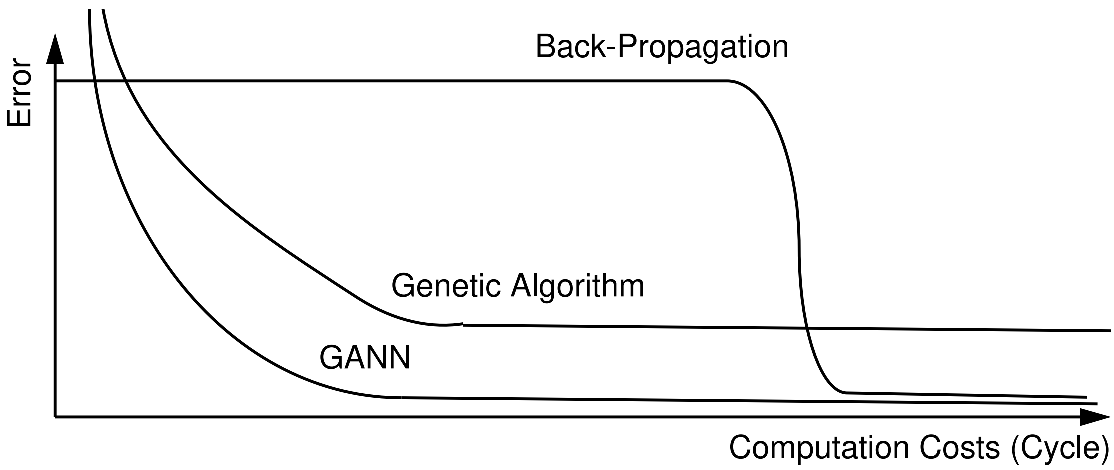


Figure 2.1: Search Speed according to [Kitano, 1990b]

Combining both search strategies seems to be the best thing to do. And as a matter of fact, experiments show that the GANN approach outperforms GA as well as NN in finding as satisfying solution. In the very long run, however, the NN alone is more precise [Kitano, 1990b].

Long Genomes Create Problems

It is a largely observed fact that GANN systems have difficulties with large networks, see for instance [Kitano, 1990b], [Whitley, 1991] and [White, 1993]. While functions like XOR have been successfully applied to nearly all approaches, reports of complex tasks with many input and output nodes are rather rare.

Structural-Functional Mapping Problem

One problem of encoding neural network information into a genome is what Whitley calls the structural-functional mapping problem [Whitley, 1990, 1992], which is also refered to as <u>permutation problem</u> [Hancock, 1992] or <u>competing conventions problem</u> [Hancock, 1992], [Whitley, 1992]. In most encoding strategies, it is possible that the same, or nearly the same, phenotype may have quite different genotypes. The reason for this effect is rooted in the effect that the function of certain neurons is not determined by their position in the network, but their connectivity in respect to other neurons.

To illustrate this, consider the following situation:

```
Parent 1: A B | C D
Parent 2: C D | A B
Child:    A B A B  or  C D C D
```

The letters `A`, `B`, `C`, and `D` represent (hidden) neurons with a certain functionality. Although they are arranged differently in the two parents, they fulfill combined the same performance. Both possible children, however, will be completely different, since they inherit equal nodes from both parents.

A GANN encoding strategy has to pay attention to this effect, since similar parent networks should produce similar children during crossover. However, there are only few attempts to take this into account, such as a strategy to reduce the search space by including only one of a set of equivalent architectures [Srinivas, 1991]. Other research suggests to avoid crossover [Karunanithi, 1992].

However , other research suggest that the structural-functional mapping problem does not have a significant impact on the GA performance. Thus, sophisticated attempts to bypass it, rather harm the efficiency of the GANN system [Hancock, 1992].

Baldwin Effect

GANN systems optimize neural networks in two ways: evolution by the genetic algorithm and learning by back-propagation. There are a couple of possibilities to combine both elements. In [Gruau, 1993] the two main varieties are defined as Lamarckian learning and Baldwin learning. Yet, there are also more sophisticated approaches to combine GA and back-propagation, such as the ones proposed in [McInerrney , 1993].

In the first case, the weights that are improved by the evaluation process are coded back into the chromosome. This undermines the ability of the genetic algorithm to perform hyperplane sampling, since the codes are altered during evaluation. Still, in the case of cellular encoding (see section 2.3), it improves the GANN system the most [Gruau, 1993].

The second case is more close to natural Darwian evolution and profits from the Baldwin effect, which was first described in the 19th century . It impact on genetic algorithm was first suggested in [Hinton, 1987], though this report was criticized by Belew [Belew , 1989].

In Baldwin learning, although the improved weights are discarded after evaluation, the learning guides the evolutionary search. If an encoded network is close to an optimum, back-propagation will reach this optimum, thus resulting in a good fitness value. Since the bit-strings that encode networks that are close to one optimum share a lot of bit patterns, the genetic algorithm is able to exploit these by hyperplane sampling.

Gruau shows that the Baldwin effect is able to improve the evolution of networks [Gruau,1993].

2.2 Direct Encoding

In this thesis, the term “direct encoding” (see also [Whitley , 1992]) refers to encoding strategies that directly encode parameters of the neural net such as weight values, connection information, etc. into the genome. This is opposed to “indirect encoding”, where rules or alike are encoded which carry information how the network has to be constructed.

2.2.1 Connection-based Encoding

Most of the encoding strategies that can be encountered in literature are connection-based. This means, that they encode and optimize the connectivity of a network architecture that is predefined.

Innervator

In [Miller , 1989], a GANN system called Innervator is described that searches for effective architectures for simple functions such as XOR. Based on a five-node feed-forward network model, each connection is encoded by a bit. For fitness evaluation, each generated individual is trained over a certain number of epochs. A fast convergence towards architectures that are able to solve the task are reported.

GENITOR

Maybe the most influential approach is Whitley’s GENITOR [Whitley, 1990]. A lot of researchers copied or reinvented his encoding strategy in order to, for instance, evaluate the quality of the GANN idea (such as [Kitano, 1990b]).

There are several version of the GENITOR algorithm, the basic one encodes the weights of a given (layered) topology in bit-strings [Whitley, 1990]. Figure 2.2 illustrates this. The index-bit indicates if the connection exists at all, and the weight-encoding bits are a binary representation of the weight value. Whitley reports a 8-bit encoding, “ranging between -127 to +127 with 0 occurring twice” [ibid., p. 351].

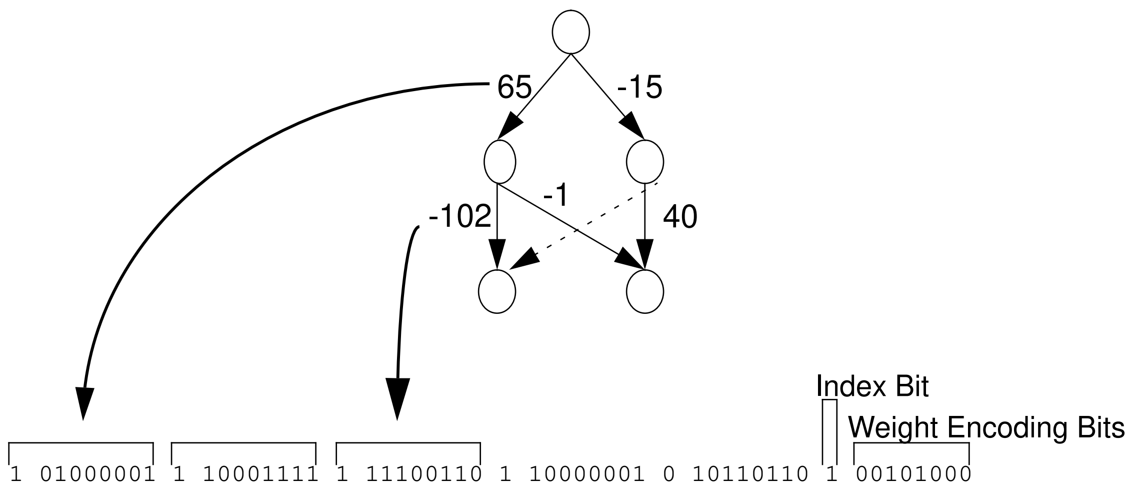


Figure 2.2: Binary Weight Encoding according to GENITOR

The illustration merges two variation of the GENITOR algorithm: The weight-optimization version and the network pruning algorithm. The first uses just the weight-encoding bits, the second merely the index-bit. For the later, the weight values of an already generated optimal network are used, the goal is to find a minimal network with good performance. Of course, the number of weights pruned has to be considered in the fitness function.

GENITOR requires that a basic (maximal) architecture has to be designed for each problem. Whitley uses layered networks. The resulting encoding format is a bit-string of fixed length. The standard GA has no difficulties to deal with this genome. Since crossover can take place at any place of the bitstring, a child may have a different weight value than either one of the parents. So, topology and weight values are optimized at the same time.

Whitley reports that GENITOR tends to converge to a single solution, the diversity is reduced fast. It seems to be a good “genetic hill-climber”. The approach was applied to simple boolean functions.

Real-Valued Encoding

An encoding strategy similar to GENITOR was proposed in [Montana, 1989, 1991]. It encodes the weights as real number, thus the genome is a list of real numbers. A couple of adapted mutation operators are used that apply to the changed format. Results in of the successful application of this encoding strategy to classification tasks are reported.

Variable Length of Weight Encoding

An interesting improvement of Whitley's GENITOR is proposed by Maniezzo [Maniezzo, 1993, 1994]. He is adding the evolution of granularity to the original approach. He argues that the binary encoded weights result in a bit-string that is too long for efficient evolution of the genetic algorithm. Thus, he encodes the number of bits per weight in the parameter string. This enables the algorithm to first efficiently find a proper topology with a small number of bits. At a later stage, the fine tuning of the individuals occurs with an increasing number of bits per weight.

Maniezzo reports good results of his approach with quite simple boolean functions such as two bit addition, four bit parity, or XOR.

Shuffle of Encoding Positions of Connections

In [Marti, 1992b], an "outer" genetic algorithm is proposed. Its purpose is to optimize the placement of the connection encodings on the genome. Experimental results show that the performance of the standard weight-based encoding scheme can be improved by a advanced placement. Marti encoded each weight with 2 bits, which represent either "disconnected" (01,10), "inhibitory" (00), or excitatory (11).

2.2.2 Node-based Encoding

The class of connection-based encoding strategies have the disadvantage that a basic (maximal) network architecture has to be designed. As mentioned before, however, the choice of the number of neurons is difficult to make. It would be an advantage, if the user of a GANN system would be released from this decision. A solution is promised by node-based encoding strategies. As indicated by the name, the parameter string does no longer consists of weight values, but entire node information.

Schiffmann

A quite simple example of node-based encoding was developed by Schiffmann, Joost and Werner [Schiffmann, 1991, 1992, 1993]. The parameter string is a list of nodes including connectivity information. In an early version called "BP-Generator" [Schiffmann, 1991], this connectivity information included weight values. The later version is reduced to mere existence information of a connection.

Schiffmann argues in [Schiffmann, 1992]: "So we obtain topologies which can be trained very fast during the given number of learning passes."

The following mutation operators are proposed in [Schiffmann, 1991]: Removal of weak connections, addition of new units with weak connections and addition of weak connections between existing units. Similar mutation operators are proposed in [Bornholdt, 1992]. The crossover operator [Schiffmann, 1992, 1993] is illustrated in figure 2.3.

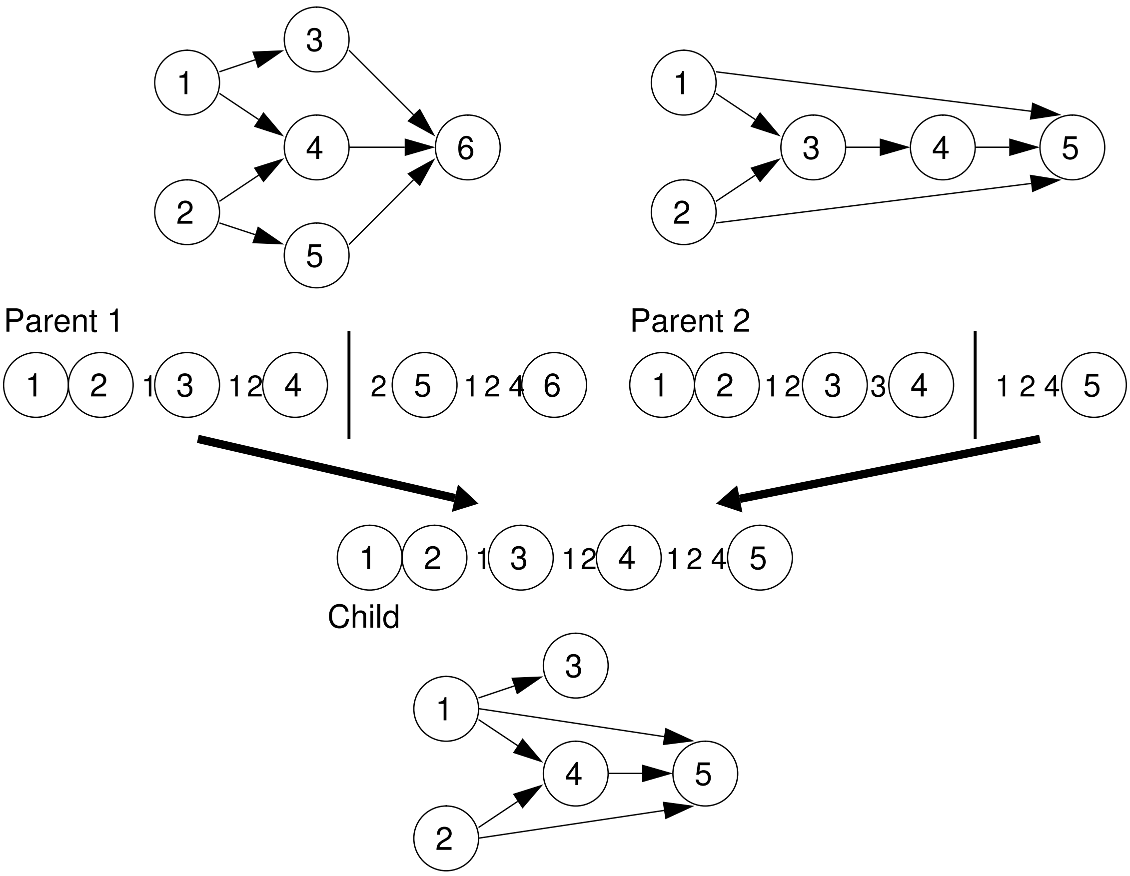


Figure 2.3: Crossover according to [Schiffmann, 1993, p.678]

The crossover points can be only set between nodes, crossover does not split connectivity lists. The crossover point in the second parent has to be chosen adequately . Hidden units that have no input or output connections are removed from the parameter string.

Successful application of this system is reported not only for basic mathematical functions, but also a medical problem: the classification of thyroid gland data, which resulted in networks with 48 to 50 neurons and 276 to 286 connections.

GANNet

A node-based encoding for layered networks called GANNet is proposed by [White, 1993]. Its basic structure is quite similar to the previous one. The parameter string is a list of neurons with connectivity and placement information.

However , the architecture of the neural net is restricted in a couple of ways. The number of input connections per node is limited to four . Also, only layered networks with connections between adjacent layers. Each hidden and the input layer include a bias unit.

In further difference to Schiffmann’ s encoding, the weight values of the connections are encoded, too. A pointer in the node information block defines the node in the previous layer from which each input connection is coming.

Both sigmoid and gaussian activation functions are used, with preference for sigmoid: 80% of the initialized nodes are sigmoid. This information is also stored for each node. The start of a new layer in the neuron list is indicated by a set flag for the first node of a new layer .

The crossover points are placed between two nodes. Different crossover points in the two parent strings result in networks with any number of nodes. Mutation is applied to the offspring. By chance, weights are changed. Always, the weight values are optimized by a certain number of back-propagation cycles and these changes are incorporated in the genome.

Results are reported with synthetic mathematical problems, XOR and classification of FLIR data.

Koza

Koza applies his genetic programming paradigma to neural networks by choosing a node-based encoding strategy [Koza, 1991b]. The nodes are not encoded in a parameter string, but rather in a parameter tree.

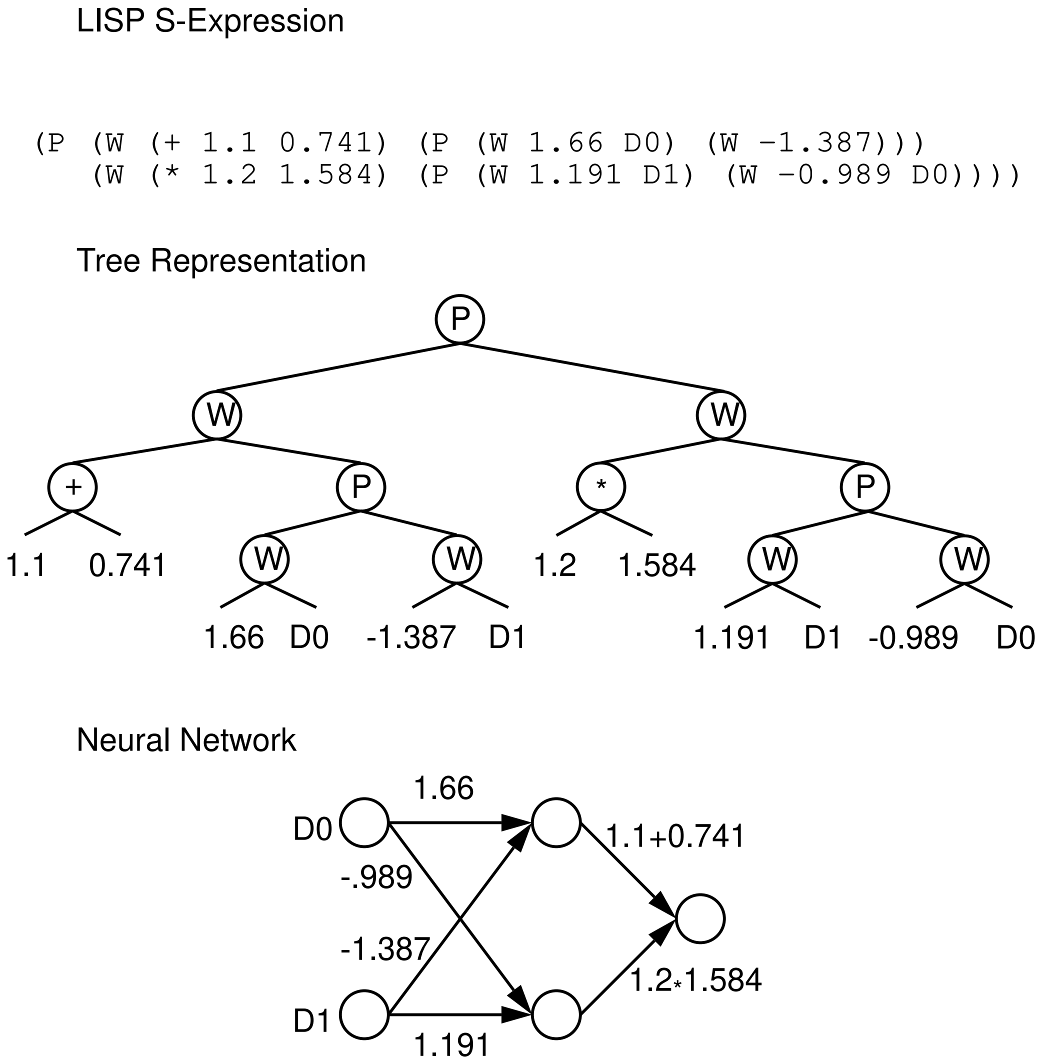


Figure 2.4: Tree Encoding according to [Koza, 1991b]

Figure 2.4 illustrates this at hand of an example. `P` represents a node ("processing element"), `W` is in place of a weight. The representation has to be read from the output. Each output requires an own tree, so basically the output nodes are independent. A neuron can have any number of sub-trees that start with an weight. A weight has two sub-trees: one that contains the weight value, the other the source of the connection, which has to be a processing unit or an input. The two input nodes are represented by `D0` and `D1`. The weight value can be encoded either by a real number or an expression.

Crossover takes place by exchange of sub-trees. Restrictions apply, so the resulting tree is organized as mentioned above.

Results with basic mathematical functions are reported in [Koza, 1991b].

Related Strategies

Related to these kinds of node-based encoding are contributions such as “GA-delta” [Munro, 1993], where only one layer of neurons are optimized via a genetic algorithm. A very simple encoding is proposed by Bishop and Bushnell, who merely encode the number of neurons per layer for a color recipe prediction task [Bishop, 1993].

2.2.3 Layer-based Encoding

GENESYS

The first layer-based encoding scheme was proposed in [Harp, 1989, 1991]. The genome consists of a certain number of areas, each of which encodes one layer of the network.

The nodes of each layer are arranged in three dimensions. Each area contains a layer ID, information about the number and arrangement of nodes, and a varying number of projector fields that contain connectivity information.

The projector fields address a segment of areas in the three-dimensional node arrangement a target area. This target area is either specified by the area ID (absolute mode) or in relation to the area, in which the projector is encoded. A density parameter indicates, how many nodes in the segment are connected. Also, the learning rate and its exponential decay (“eta-slope”) are encoded individually for each projector field.

The successful implementation of this encoding scheme was applied to tasks ranging from XOR to a 4x8 number recognition task.

Mandischer

A variation of this encoding scheme is presented in [Mandischer, 1993], which is based on layers. The basic structure is a list of network parameters and layer blocks (refer to figure 2.5). Weight values are not encoded. The encoded network parameters define learning rate and momentum term for back-propagation training.

For each layer, the layer size and informations about output connections and input connections are stored. The output connection information ensures that each node is connected to the next adjacent layer. The input connections may come from any previous layers, specified by the “destination” value. The “radius” specifies the spread of the connections to nodes in the connected layer, the “destination” the number of nodes in this area. Destination, radius, and density are given relative to the number of layers respectively nodes.

Mutation is applied to either learning rate, momentum term, size of one randomly selected layer, radius, or density of a randomly selected connection area. Crossover points are selected between layers. Again, this point is chosen relative to the number of layers.

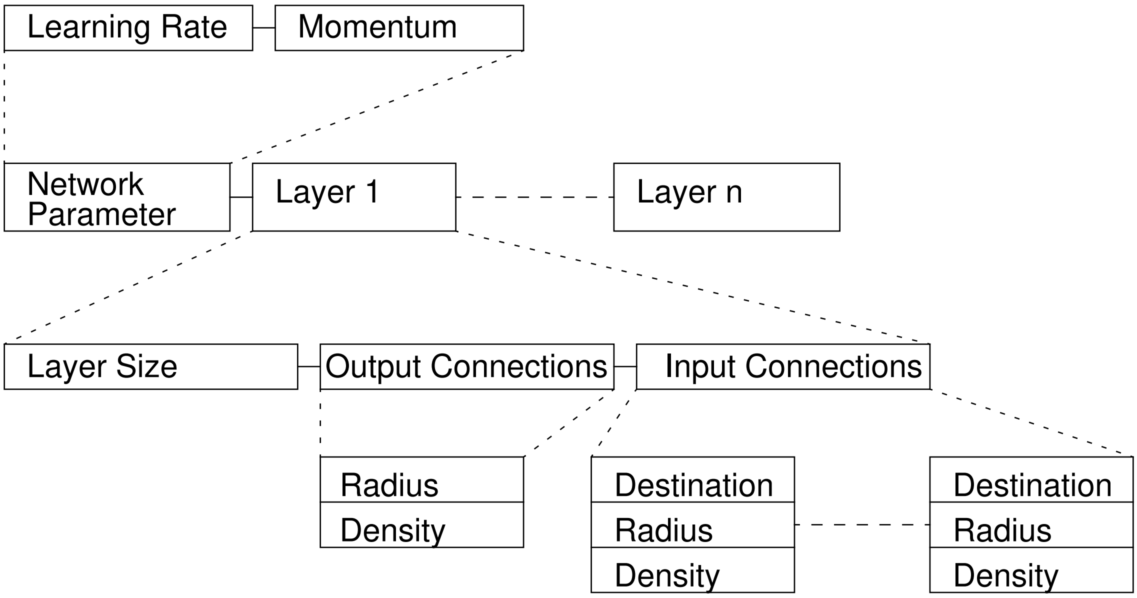


Figure 2.5: Encoding Scheme according to [Mandischer, 1993]

The system was applied to rather complicated task such as 9x9 pixel edge/corner detection, 8x1 1 pixel letter recognition, a task that included 279 vectors containing control knowledge with 1 12 real valued components, and the approximation of a Mexican hat function.

2.2.4 Pathway-based Encoding

A different approach is taken in [Jacob, 1993]. Here, not connections, nodes or layers are encoded, but pathways through the network. A path is defined as a list of neurons beginning with a input neuron and ending with an output neuron. There is no further restriction to the order of nodes in the paths. Hence, the strategy does not necessarily define feed-forward networks. Figure 2.6 illustrates the encoding at hand of an example.

Paths

$p_1 = i_1 - 1 - 2 - 2 - 3 - o_1$
$p_2 = i_1 - 3 - o_1 - 1 - o_1$
$p_3 = i_2 - 2 - 1 - o_2$

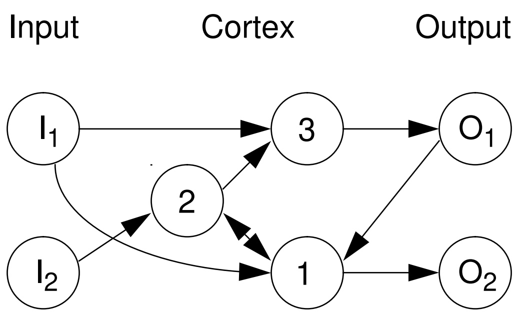


Figure 2.6: Pathway Encoding according to [Jacob, 1993]

Crossover points are selected between paths. The algorithm uses two-point crossover , with different crossover points for the two parents. So, parameter strings with any number of pathways can be generated. However, the number of nodes is limited from the beginning.

Four different mutation operators are used: creation of a new path, removal of a path, insertion of a neuron to a path, and finally removal of a neuron.

First, the just described genetic algorithm searches for a good topology, but no weights are set. Since this topology is in general not a feed-forward network, back-propagation cannot be used for the generation of weights. Therefore, a second genetic algorithm looks for optimal weights for the evolved topology.

The algorithm has been applied to control tasks such as ball balancing.

2.3 Indirect Encoding

The encoding strategies mentioned in section 2.2 share a common property: They directly encoded parameter such as connectivity or weight values in the genome. Opposed to that, this section presents some indirect encoding strategies, which is also called "recipe" encoding in [Schiffmann, 1993].

Here, not the parameter themselves, but production rules, that define how to generate these parameters are encoded. This is biologically motivated by the fact, that in case of the human brain, there are much more neurons than nucleotides in the genome - see for instance [Happel, 1994]. So, there has to be a more efficient way of description.

As pointed out in [Boers, 1992], the organization of a biological organism shows a great deal of modularity. Its division into cells and the division of the brain into neurons exemplifies this. The skin is composed of the same kind of skin cells all over the body. Encoding strategies that use rules to copy units with the same function can be more efficient in producing large networks.

Kitano

Probably the first indirect encoding scheme was proposed in [Kitano, 1990a], also called grammar encoding method. The encoded rules rewrite an initial 2x2 weight matrix, whose structure is similar to the one used in Innervator (see section 2.2.1). However, the entries are non-terminal symbols of the grammar. During a fixed number of rewriting steps, each symbol in the grammar is replaced by a 2x2 matrix of symbols, hence increasing the number of nodes by factor 2 and the number of connections by factor 4.

Kitano argues for the superior scalability of this encoding method, although only a simple encoder/decoder task was examined.

Gruau

Maybe the most sophisticated encoding method is developed by Frederic Gruau [Gruau, 1992, 1992b, 1994], which is called cellular encoding. The genome encodes an set of instructions that are applied to an initial network, consisting of one hidden node. During the execution of the instructions, a larger network evolves.

These instructions cover operations such as duplication of a node, deletion of a connection, sequential division and a couple of more complex operations that include the use of registers. Recursive calls allow the modular constructions of large networks with a relative small instruction set.

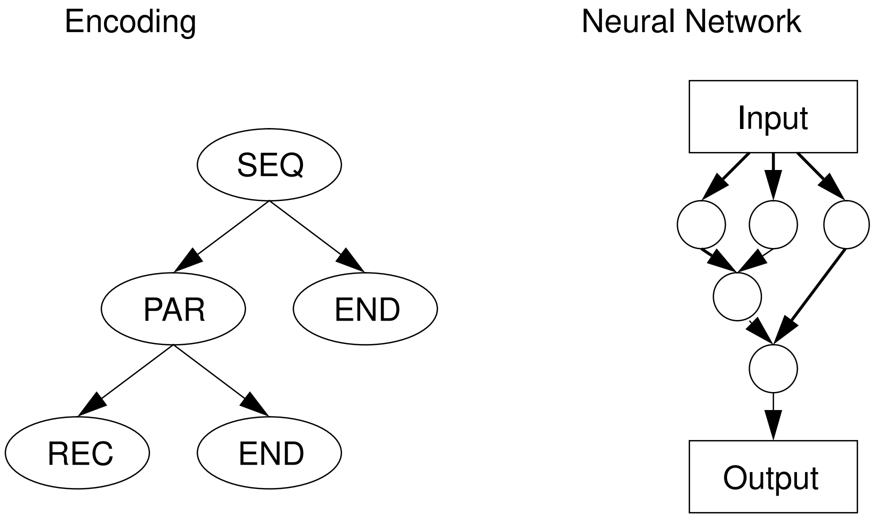


Figure 2.7: Cellular Encoding according to [Gruau, 1994]

The instructions are structured in a tree. Figure 2.7 gives an example. `SEQ` performs a sequential division of a node, `PAR` duplicates a node, `REC` is a recursive call to the previous subtree and `END` ends the encoding process for a node. The life parameter of the initial cell is set to 2, which restricts the number of recursive calls.

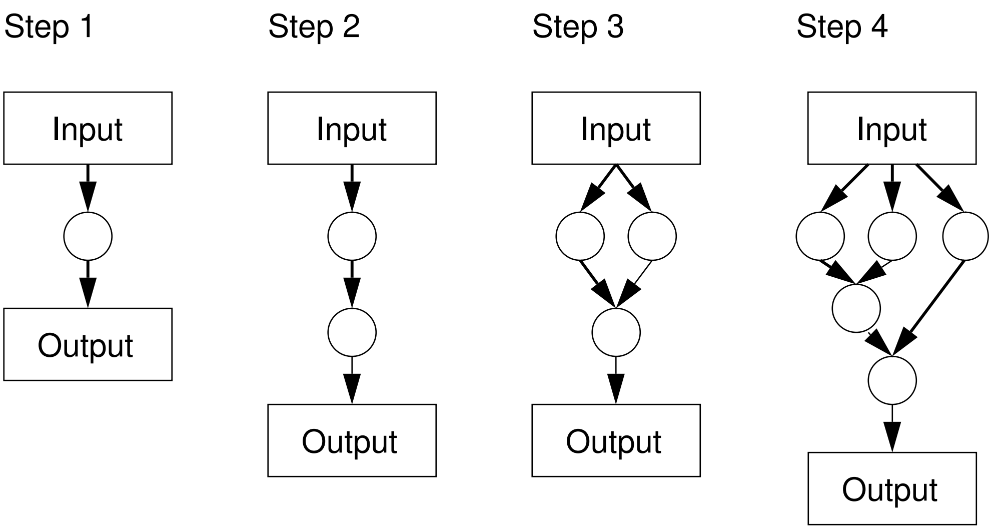


Figure 2.8: The Cellular Development of a Network

The cellular development (figure 2.8) of the network starts with the `SEQ` instruction and a single node (step 1). It divides the initial node into two sequential nodes, producing a network with two nodes, the first takes the input connections, the second the output connections. Both nodes are connected (step 2). The `SEQ` instruction is accompanied by two branches, each of them refers to one of the new nodes. The subtree of the second node consists merely of an `END` statement, which converts the node into a terminal node. The subtree of the first node starts off with an `PAR` statement, which duplicates the node (step 3). The `PAR` statement has also two branches for the resulting nodes. Here, the first is `REC`, a recursive call to the `SEQ` statement. The second is an END statement. The recursive call repeats the just mentioned process. A sequential division (SEQ) and a node duplication (PAR) takes place.

The crossover and mutation operations are oriented on the genetic programming paradigm [Koza,1991]. Crossover takes place in the form of exchange of subtrees between two parents.

Lindenmayer -Systems

Lindenmayer -Systems are based on a biological model proposed by Aristid Lindemayer [Lindenmayer , 1968]. It tries to simulate the cellular development of organisms, where cells only exchange informations with their neighbors without central control.

Boers and Kuiper [Boers, 1992] describe how this model can be used to encode neural networks. A string that represents the networks is generated by a set of production rules, which derive the string from a start symbol. The production rules have the basic format:

```
L < P > R = S
```

A symbol P is transformed into a string of symbols S, if its left neighbor is L and its right neighbor is R in the so far derived string. In opposition to context-sensitive languages, all productions that are applicable at one time are applied.

In figure 2.9, the production starts with the symbol A and derives the string [C,C1][C,C]C. The brackets [] indicate a module, and the number 1 refers to the next unit that is not a neighbor . Units that are neighbored are connected, a comma separates units that are not connected.

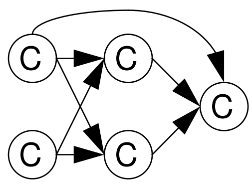
Production Rules	Resulting String	Neural Network
A = BBB B > B = [C,D] B = C C < D = C D > D = C1	[C,C1][C,C]C	

Figure 2.9: Construction of a Network according to [Boers, 1992]

The rules are encoded as strings of the symbols 2, 3, 4, 5, [,], A, B, C, D, E, F, G, H, * and ",", where * stands for either =, < or >, depending on the context. Each of these symbols is encoded with 4 bits. So, the original GA operators mutation and crossover can be used.

This way of encoding results in a lot of illegal strings that can not interpreted as production rules. Therefore, a couple of error -recovery methods are used.

Results with XOR and simplified letter recognition tasks are reported.

3 Experiments

All experiments reported in this chapter were conducted using a tool written in C++. The tool allows a variety of GANN experimental designs that follow the following pattern:

An initial population of individuals is created. The creation of the individuals depends on the encoding strategy and does not neccessarily represent a functional neural network.

The initial population is evaluated, which includes a certain number of back-propagation training cycles. This number is restricted by a pre-defined maximum, but there may be less training, if a target error is reached before completion. The fitness of an individual is defined by

$$fitness = \frac{actual \cdot training \cdot epochs}{maximum \cdot training \cdot epochs} \times network \cdot error$$

The lower this value, the better the individual. This is contrary to most traditional definitions of fitness. Therefore, we will not use the ambiguous term "higher" fitness, but better fitness, if we talk about the fitness of better individuals with lower fitness value. The term worse fitness shall be used for worse individuals, thus higher fitness value.

The maximum number of training cycles may be set relative to the size of the network. This results in the preference of small networks. The measurement for the size of a network is its number of connections, which goes fairly linear with the computational cost of training.

The entire training process may be repeated a number of times and the average fitness of the evaluations computed. This allows more adequate measurement of mere architecture optimization tasks, where the weights are set to random values each time before the training process.

During each generation, a defined number of crossover and mutation operators are applied, the exact effect of which depends on the encoding strategy. A crossover-mutation rate defines the chance that mutation is also applied offsprings generated by crossover. The selection of individuals for these operators is done by ranked-based roulette-wheel selection, as described in section 1.2.

An offspring produced by crossover is put into the population in exchange to the worst individual, if it has a better fitness value. Similarly, the result of a mutation operator only replaces its original, if it is an improvement in terms of fitness.

The number of generations is restricted by a maximum number and a threshold for target fitness.

3.1 Problems

We will investigate a set of problems that rang from simple boolean functions up to more complicated real-valued functions.

Simple Boolean Functions

Rumelhart [Rumelhart, 1986] proposed a couple of simple boolean functions to demonstrate the performance of back-propagation. Most of the researchers in the field of GANN applied a subset of the same problems to their systems. In this thesis, XOR and low-bit adding is investigated.

XOR is the simplest boolean function that is not linearly separable. Therefore, this problem can not be solved by a neural net without hidden neurons. This fact made this function quite popular in the NN research community and nearly no developer of a GANN system ignored it either .

The adding problem is a good test for the scalability of the GANN design. The number of input and output neurons can be set arbitrarily to $2n$ and $n + 1$ respectively .

Sine

Opposed to the boolean functions, sine takes real valued inputs and produces real valued outputs. To keep both input and output ranges in the limits between 0 and 1, we used training patterns for the slightly adapted function:

$$\frac{1}{2}(\sin(2\pi x) + 1)$$

A graph is displayed in figure 3.0. An arbitrary number of training patterns can be used. More patterns increase the accuracy of the problem.

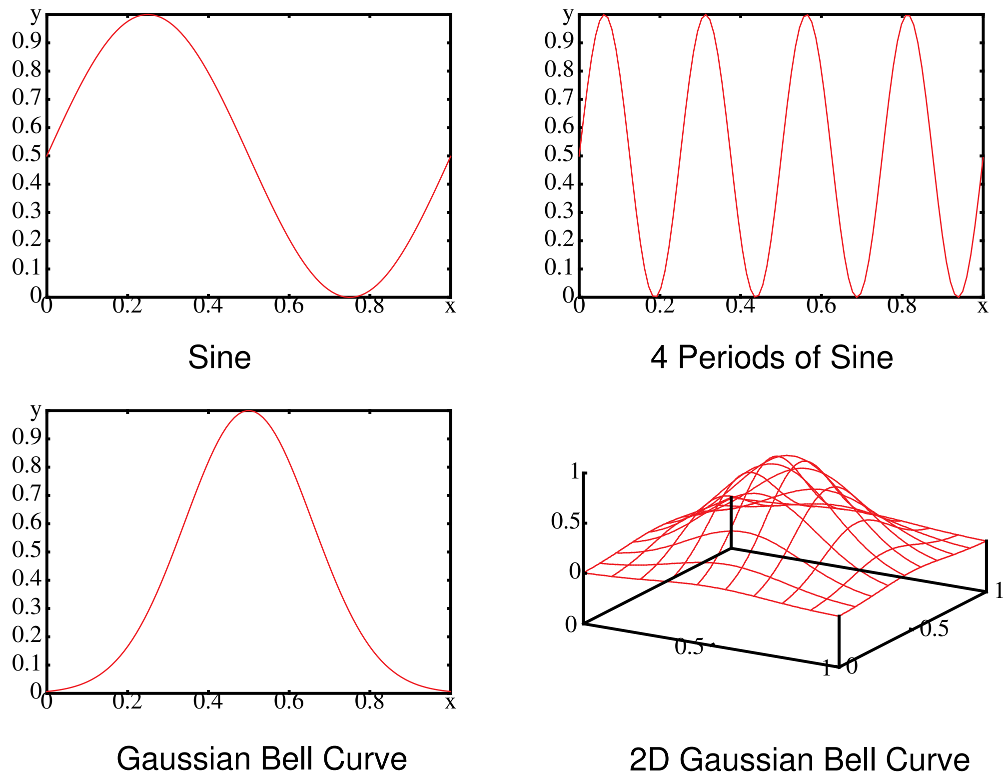


Figure 3.0: Four Real-Valued Functions

4 Periods of Sine

In this variation of the function above, four periods of sine are used. This results in a more difficult problem. Also, the function has to be slightly transformed in order to fit into the [0,1]x[0,1] input-output space:

$$\frac{1}{2}(\sin(8\pi x) + 1)$$

Gaussian Bell Curve

Also, the Gaussian Bell Curve, which is widely applied in the field of statistic is used as a problem for the evaluation of GANN systems. The formula for this function is:

$$\exp(-20(x-0.5)^2)$$

2-Dimensional Gaussian Bell Curve

Finally, a real valued function with two input parameters is also considered. The function is the two-dimensional version of the above described Gaussian Bell Curve. It is defined as:

$$\exp(-10((x-0.5)^2 + (y-0.5)^2))$$

Figure 3.0 displays the graphs of the three real-valued functions.

3.2 Encoding Strategies

We implemented a weight-based encoding strategy that is based on Whitley's GENITOR (refer to section 2.2.1). The system supports all kinds of architectures, but we focused especially on fully connected topologies, i.e. all feed-forward connections are possible.

Each weight of a given architecture is represented by n bits. The index bit indicating the existence of a connection is optional. If it is used, merely $m = n - 1$ bits encode the weight value. If a network is created, the weights are initially set to integer values between $-2^{m-1} - 1$ and $2^{m-1} + 1$, excluding 0.

It is also possible to encode just the connectivity of the network. In this case, the weights are set to random values in the interval $[-1, 1]$. The range of the weight values may be changed by a scaling factor.

The encoding strategy supports one-point, two-point and uniform crossover.

3.3 Experiments on Weight Optimization

The first section of experiments focuses on weight-optimization. A fixed architecture is used, and merely the weight values are encoded in the parameter string. The experimental setting is based on [Whitley, 1990].

The first experiment tackles XOR. A fully-connected five node architecture is used and the target is a fitness of 0.001 (root mean square error of 0.01 within 10 epochs).

> **Experiment 1:** 900 generations, target fitness 0.001, 1 population with 30 individuals, variable number of crossovers, mutations and crossover-mutation rate. 100 epochs, target error 0.01, learning rate 0.8. XOR. Weight-based encoding: 5 total nodes, 7 total bits/weight (no index), mutation rate 20. Two-point-crossover.

The results of 50 runs of the experiment are presented in table 1, ordered with the best ones first. The median is printed in bold type. The numbers in the table indicate the number of individuals generated during the run of the experiment, until the target fitness is reached. This is 30 random individuals for the initial population and 10 generated by crossover and mutation for each generation.

The table suggests that an average of about 300 to 700 individuals have to generated in order to find a network that suffices the target fitness.

GANN vs. Backpropagation Training

How can we judge these results? Figure 3.1 displays, how plain back-propagation deals with the situation, if the initial weights are set to random values in the interval $[-1, 1]$.

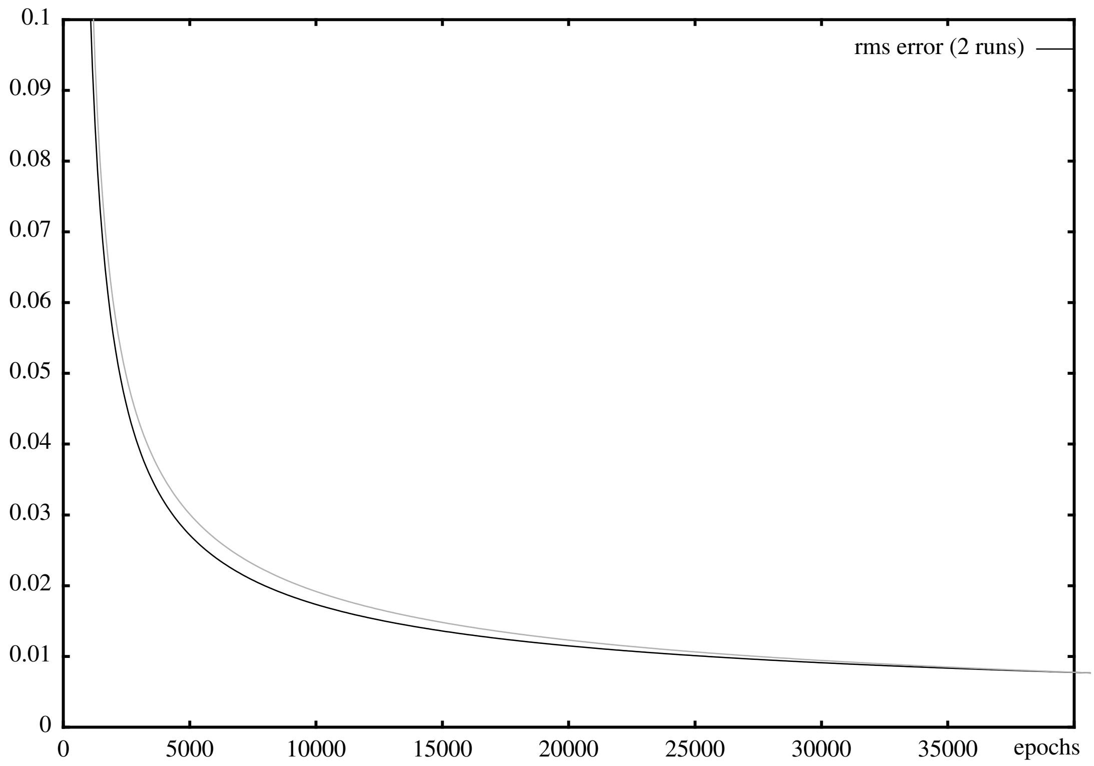


Figure 3.1: Backpropagation Training of the XOR Function

The figure suggests that backpropagation training takes about 35000 training epochs to train XOR to a five node fully-connected network. How does that relate to the generation of 350 individuals by the GANN system (average case for 5 crossover, 5 mutation, cro-mut-rate 20). During the experimental run of both algorithms on a SPARC workstation, about 20 seconds of computation time was spent in both cases.

Table 1: Number of Individuals Evaluated for XOR (50 experimental runs)

10 mutations	5 mut., 5 cro. (cro-mut-rate 2)	5 mut., 5 cro. (cro-mut-rate 20)	10 crossovers (cro-mut-rate 20)
30	30	90	50
100	100	110	50
180	100	120	60
190	110	140	80
210	120	150	90
210	130	160	100
220	140	180	100
220	170	190	110
240	180	200	110
270	190	200	120
310	220	210	140
310	230	220	160
320	240	230	160
320	240	230	240
330	260	250	250
350	270	250	290
350	270	260	340
380	280	260	400
380	280	270	460
390	300	270	490
390	300	280	500
400	320	280	510
430	330	300	520
440	340	300	620
490	350	310	650
540	**360**	**320**	**670**
540	360	360	800
620	390	370	810
640	400	390	830
690	410	390	990
710	440	390	1100
720	440	410	1480
730	450	410	1510
750	450	410	1640
850	470	420	1790
880	480	420	2980
900	530	440	3080
1040	530	490	4490
1050	530	670	4580
1080	560	710	5280
1100	590	850	5430
1140	590	900	5640
1170	650	940	6010
1230	750	1790	7180
1240	780	2070	7700
1260	1000	5080	8780
1290	1000	8670	>9030
1360	1010	>9030	>9030
1750	1890	>9030	>9030
2170	2670	>9030	>9030

The GANN system spends the vast majority of its computational time in the back-propagation training of its individuals for their evaluation. Each individual is trained over 100 epochs, which totals in 35000 epochs. So, both approaches lead to astonishingly similar results.

However , this comparison has to be questioned in a couple of ways. It applies only to this special situation. Both, the performance of the GANN system and neural network training alone depend on a variety of parameter that do not equally apply to both approaches. A generation of a genetic algorithm is something principally different than an epoch of a neural network.

GANN vs. Random Search

A different criterion to evaluate the quality of GANN system is its performance in comparison to random search. Random search in this case means the random generation of individuals by the encoding strategy . We use the same parameters as in experiment 1.

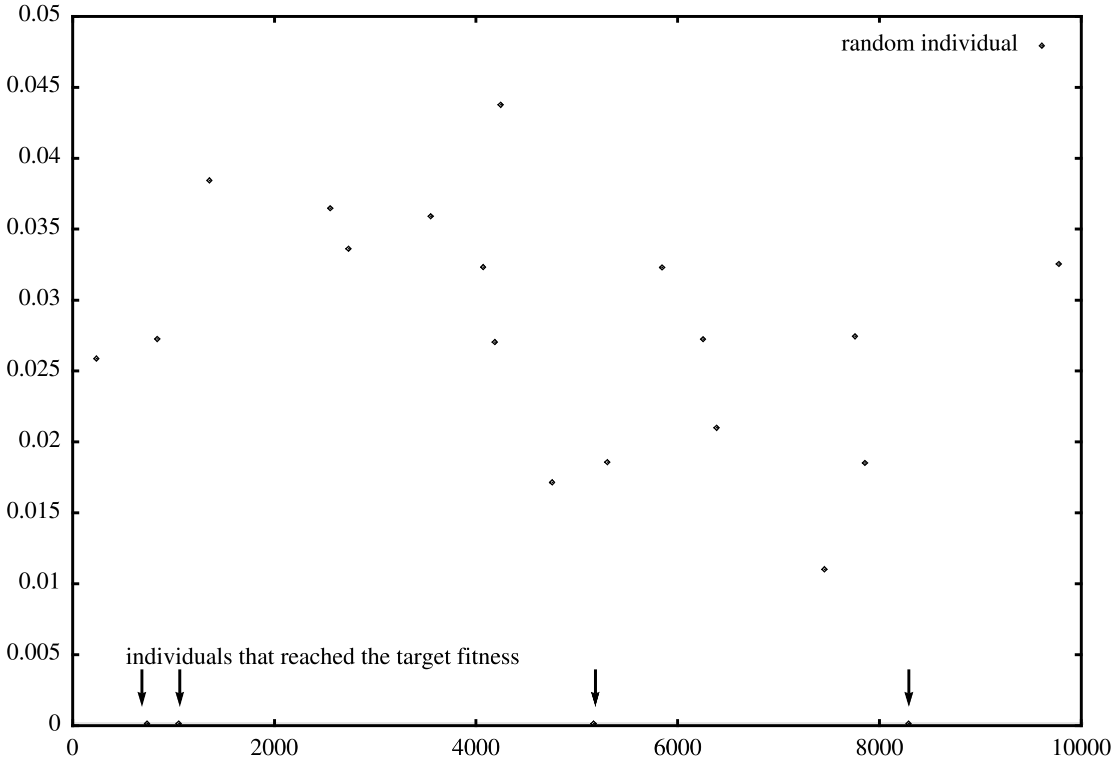


Figure 3.2: Best Fitness Values of Random Individuals

While the vast majority of random individuals have fitness values of circa 0.5, 0.707 and 0.866, an empirical study of 10000 random individuals also produced 4 individuals that reach the target fitness of 0.001. Figure 3.2 provides more detail of this study .

Considering this data, a random search has to examine 2500 individuals in order to find one with the desired target fitness. If we compare this with the 350 individuals in one of the GANN experiments, we can state that GANN outperforms random search by the factor 2500/350, which is about 7.

Gray Coding

Studies [Caruana, 1988] have shown that the performance of genetic algorithms may be increased by using an alternate form of encoding integer numbers called gray coding. Figure 3.3 displays the gray codes for the numbers 0-7 opposing to their binary codes.

Number	Gray Codes	Binary Codes
0	000	000
1	001	001
2	011	010
3	010	011
4	110	100
5	111	101
6	101	110
7	100	111

Figure 3.3: Examples of Gray Codes

For gray coding, the hamming distance between two neighboring numbers $(n, n+1)$ is constant 1 for any n. The hamming distance is the number of different bits between two codes. For binary coding it varies. In the example given, it is up to 3 for (3,4). These “hamming cliffs” make the fine-tuning transition task for the GA difficult.

Empirical studies on genetic algorithms in general suggest that gray coding improves the GA for some functions, or at least have the same effect as binary coding.

We examine how gray coding changes the performance of the GANN system in experiment 2. This experiment uses the same parameter as experiment 1, except for the fact that gray coding is applied to the single weight values. The detailed results of 50 runs is shown in Table 3.

Experiment 2: 900 generations, target fitness 0.001, 1 population with 30 individuals, variable number of crossovers, mutations and crossover-mutation rate. 100 epochs, target error 0.01, learning rate 0.8. XOR. Weight-based encoding: 5 total nodes, 7 total bits/weight (no index), mutation rate 20. Gray coding.

Table 2 presents how binary and gray coding compare, if we use the median as a measurement. The median in this case is the result of the 25th best run out of 50 for each experiment. Since the mean average is harmed by a few bad runs, the median is a better choice to evaluate the performance of weight training.

Table 2: Comparison of Gray and Binary Coding

	10 mutations	5 mutations 5 crossovers cro-mut-rate 2	5 mutations 5 crossovers cro-mut-r. 20	10 crossovers cro-mut-r. 20
Binary Coding	540	360	320	670
Gray Coding	660	360	280	1640

Table 3: Experimental Results of Evolving XOR using Gray Coding

10 mutations	5 mut., 5 cro. cro-mut-rate 2	5 mut., 5 cro. cro-mut-rate 20	10 crossovers
30	30	40	30
30	30	60	50
40	110	60	60
130	130	80	90
160	130	80	110
180	130	90	120
190	140	120	120
210	140	120	120
250	140	130	130
260	150	130	220
280	150	130	240
310	150	140	250
380	170	140	340
450	200	170	360
520	210	170	360
540	230	180	410
540	240	180	440
560	250	180	460
570	260	200	500
580	290	210	570
590	300	210	660
640	330	220	800
650	340	240	960
660	350	250	990
660	**360**	**250**	**1640**
680	420	260	1680
730	520	260	1870
740	530	290	1920
780	550	300	2080
780	580	310	2140
800	590	310	3030
860	600	320	3130
880	600	370	3480
880	700	380	3640
880	700	390	4230
900	720	410	4970
910	740	430	5180
950	740	450	5880
990	790	500	6540
1000	790	500	6740
1060	800	530	6900
1060	850	530	7270
1080	910	540	>9030
1090	950	560	>9030
1120	1050	560	>9030
1120	1200	590	>9030
1250	2340	630	>9030
1440	2430	630	>9030
1620	3200	740	>9030
1810	5600	1000	>9030

The results show that for both gray and binary coding a mixture of crossover and mutation operators converges faster than either crossover or mutation alone. Also, mutation seems to be slightly more effective in the task of reaching a solution fast than crossover.

Also, a crossover mutation rate of 20 is superior to a rate of 2 in both cases. This rate defines how often mutation is applied to the offspring of crossover. So, with a rate of 20, the offspring is mutated only in 1 out of 20 cases.

However, the introduction of gray coding is not preferable. On the contrary, it slows down the evolutionary process in most cases.

Selection of Operators and Encoding Type for Sine

To verify these findings, we examine the evolution of a five-node fully-connected neural network for the sine function. Sine is a more difficult task, as a random search for an solution suggests: Within 80,000 randomly generated networks, only very few have fitness values below 0.1.

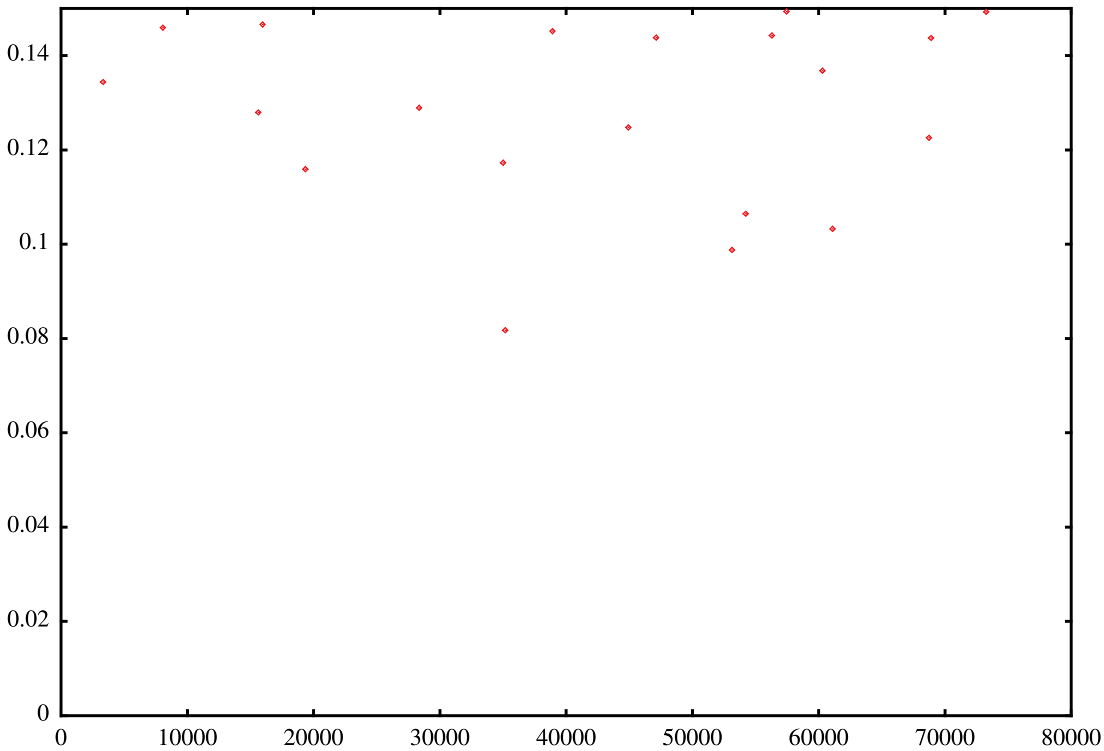


Figure 3.4: Best Fitness Values of Random Sine Networks

Experiment 3: 900 generations, target fitness 0.001, 1 population with 30 individuals, variable number of crossovers, mutations and crossover-mutation rate. 100 epochs, target error 0.01, learning rate 0.8. Sine with 17 training patterns. Weight-based encoding: 5 total nodes, 7 total bits/weight (no index), mutation rate 20. Two-point-crossover.

Using the same parameters as in experiment 1, the GANN system never reaches the target fitness of 0.001 in the 21 runs of each version of the experiment. Table 4 displays the final fitness values after 900 generations. The median - the 11th best run out of 21 - is printed again in bold type.

Table 4: Fitness after 900 Generations for Sine

10 mutations	5 mutations, 5 crossovers (cro-mut-rate 2)	5 mutations 5 crossovers (cro-mut-rate 20)	10 crossovers (cro-mut-rate 20)
0.0262927	0.0262347	0.0241474	0.0309672
0.0343965	0.0335057	0.0273759	0.0342695
0.0362376	0.0338501	0.0285026	0.0405706
0.0369155	0.0345520	0.0314216	0.0433516
0.0374821	0.0346752	0.0327999	0.0461073
0.0386209	0.0375245	0.0366941	0.0473017
0.0396562	0.0379173	0.0371354	0.0477327
0.0413063	0.0396147	0.0386946	0.0495430
0.0412722	0.0409227	0.0401896	0.0645487
0.0417484	0.0423005	0.0405493	0.0757391
0.0434693	**0.0443224**	**0.0420645**	**0.0801280**
0.0438430	0.0444928	0.0437945	0.0894230
0.0448293	0.0446978	0.0457060	0.0885142
0.0478439	0.0449794	0.0491868	0.0930273
0.0484388	0.0450663	0.0542150	0.1128250
0.0486863	0.0492701	0.0558863	0.1309260
0.0505658	0.0642964	0.0562682	0.1310140
0.0518176	0.0916236	0.0647300	0.1399360
0.0607796	0.1311020	0.1005830	0.1520440
0.0639127	0.1352570	0.1359760	0.1553080
0.0740992	0.1473870	0.1477130	0.1712730

The general picture is the same as for XOR: Both crossover and mutation are required for a optimal set of GA operators. Crossover alone is a weak operator . Also, a crossover -mutation rate of 20 seems to be better than 2.

The Optimal Number of Crossover and Mutation Operators

So far , we have found that mutation alone works better than crossover alone, but the best option is a mixed set. In a extended version of the first two experiments, we are looking for the optimal composition of this set. T able 5 and 6 present the result of these experiments in detail, the median is printed in bold type.

The results suggest that the relation between the number of mutation and crossover operators does not really matter , except that both, especially mutation, are required for an optimal use of the GANN system. Also, the choice between gray or binary coding seems to be somewhat irrelevant.

Table 5: XOR with Binary Coding

10 mut	9 m 1 cro	8 m 2 cro	7 m 3 cro	6 m 4 cro	5 m 5 cro	4 m 6 cro	3 m 7 cro	2 m 8 cro	1 m 9 cro	10 cro
30	30	30	40	30	90	30	30	70	30	50
100	40	50	60	70	110	30	40	70	30	50
180	40	60	80	90	120	70	60	70	40	60
190	50	90	80	90	140	70	80	90	40	80
210	120	110	100	100	150	70	110	100	80	90
210	130	130	110	120	160	80	110	110	90	100
220	130	180	120	160	180	100	110	110	120	100
220	170	190	120	170	190	130	120	120	140	110
240	190	190	160	170	200	150	130	130	140	110
270	210	190	170	170	200	160	130	130	160	120
310	220	220	190	190	210	160	130	140	190	140
320	230	230	190	210	220	180	140	190	210	160
320	230	240	200	210	230	190	160	200	220	160
330	250	240	200	220	230	200	160	210	230	240
350	250	240	210	230	250	200	180	220	230	290
350	290	250	220	240	250	210	190	260	250	340
380	290	250	230	250	260	220	190	270	270	400
380	300	260	280	250	260	220	200	270	320	460
390	310	270	280	260	270	220	200	330	320	490
390	320	280	290	270	270	230	240	330	320	500
400	320	290	300	280	280	250	260	350	430	510
430	390	300	310	280	280	310	260	360	450	520
440	440	320	320	290	300	310	260	360	510	620
490	440	330	330	290	300	320	280	360	540	650
540	**490**	**350**	**340**	**310**	**310**	**330**	**300**	**420**	**640**	**670**
540	530	360	380	310	320	340	310	510	680	800
620	570	390	390	330	360	350	310	510	710	810
640	570	420	420	340	370	350	330	530	750	830
690	580	440	420	350	390	400	350	540	830	990
710	630	470	460	350	390	410	370	540	950	1100
720	640	480	460	370	390	480	400	620	1020	1200
730	650	480	480	380	410	500	410	620	1110	1480
750	660	490	500	430	410	520	450	790	1130	1510
850	670	490	520	530	410	570	460	790	1140	1640
880	690	510	560	610	420	590	520	910	1180	1790
900	740	540	560	620	420	630	520	910	1230	2980
1040	810	580	610	660	440	750	530	1250	1360	3080
1050	820	580	650	680	490	760	570	1430	1420	4490
1080	820	580	670	730	670	770	620	1430	1460	4580
1100	900	610	720	730	710	790	730	1560	1630	5280
1140	900	660	800	750	850	1090	940	2080	1890	5460
1170	950	680	840	770	900	1500	1000	2080	1940	5640
1230	1000	700	850	780	940	1810	1190	2230	3230	6010
1240	1080	700	880	860	1790	2010	1350	3970	3440	7180
1260	1180	800	940	940	2070	2070	1660	3970	5870	7700
1290	1440	940	970	990	5080	2120	1710	4400	8770	8780
1360	1440	1040	1010	1100	8670	2480	2660	6780	9030	9030
1750	1500	1170	1020	2330	9030	4190	3610	9030	9030	9030
2170	1860	4950	1020	2400	9030	4750	9030	9030	9030	9030
2800	6100	6460	1130	5180	9030	4810	9030	9030	9030	9030

Table 6: XOR with Gray Coding

10 mut	9 m 1 cro	8 m 2 cro	7 m 3 cro	6 m 4 cro	5 m 5 cro	4 m 6 cro	3 m 7 cro	2 m 8 cro	1 m 9 cro	10 cro
30	50	30	30	30	30	30	30	30	30	30
30	70	30	30	90	30	50	50	50	50	50
130	70	30	70	140	30	50	70	80	50	60
160	90	30	80	140	30	90	70	90	60	90
180	90	80	110	150	50	110	70	90	60	110
190	90	90	150	150	50	120	80	120	70	120
210	110	130	160	160	60	120	90	120	90	120
260	120	140	170	170	80	140	130	120	100	120
280	130	140	190	190	90	140	140	130	100	130
380	130	140	210	190	100	160	150	140	130	220
520	150	160	210	200	110	160	150	170	140	240
540	150	180	210	200	110	170	160	190	140	340
560	160	190	210	200	130	180	160	190	150	360
590	180	230	230	210	160	200	200	240	170	360
640	190	250	240	230	190	210	200	250	170	410
780	200	260	260	240	200	220	220	250	200	440
780	220	270	260	270	200	250	220	260	200	460
800	240	300	280	290	210	250	240	260	240	500
860	250	310	290	300	210	260	240	280	250	570
880	260	340	300	310	220	290	250	290	260	660
900	310	350	310	340	230	320	260	310	260	800
910	320	360	310	360	250	330	260	360	270	960
950	320	370	310	380	250	350	260	370	270	990
990	340	380	310	390	270	360	310	380	280	1640
1000	**360**	**400**	**320**	**390**	**280**	**360**	**310**	**490**	**290**	**1680**
1060	400	410	330	390	290	380	320	520	330	1870
1060	430	420	350	390	290	380	330	540	340	1920
1080	440	440	380	400	300	390	330	550	350	2080
1090	480	440	400	400	310	410	340	590	360	2140
1120	500	440	410	440	310	420	340	630	370	3030
8240	580	450	420	450	320	450	380	670	380	3130
9030	590	470	430	450	320	470	390	670	390	3480
9030	620	470	440	460	330	550	420	690	410	3640
9030	640	480	460	500	330	560	450	710	410	4180
9030	650	480	460	500	360	590	480	780	470	4230
9030	650	510	470	510	370	820	550	850	470	4970
9030	670	520	540	540	370	960	580	970	560	5180
9030	700	530	560	580	380	1450	600	1070	560	5880
9030	720	540	600	630	420	1480	620	1080	560	6540
9030	730	580	600	630	430	1710	640	1090	610	6740
9030	760	590	620	640	440	1830	680	1190	700	6900
9030	770	630	620	780	440	2040	930	1210	730	7270
9030	800	670	660	860	540	2130	960	1220	1160	9030
9030	880	680	880	960	560	2240	1320	1240	1340	9030
9030	900	700	1000	990	630	2540	1340	2090	1370	9030
9030	930	750	1100	1250	670	7070	2210	2180	1670	9030
9030	930	830	1430	1600	730	9030	3030	2970	1770	9030
9030	980	900	1550	2440	770	9030	3700	3060	6580	9030
9030	1680	920	3470	5710	2570	9030	4860	6600	9030	9030
9030	2050	5440	4120	9030	5520	9030	9030	9030	9030	9030

Baldwin Effect

In all of our experiments to this point, the networks generated by the genetic algorithm were trained for 100 epochs prior to fitness evaluation. This is only a reasonable strategy , if the Baldwin effect (see section 2.1) improves the genetic search considerably . Training for 100 epochs takes about 95% of the computation time of the GANN system, which has to be justified.

Experiment 4 and 5 investigate the Baldwin effect for the XOR function and the 1-Bit Adder . The number of training epochs was varied from 1 to 500 in both cases.

Experiment 4: 900 generations, target fitness 0.01, 1 population with 30 individuals, 5 mutations and 5 crossovers with crossover -mutation rate 20. V arying number of epochs, target error 0.01, learning rate 0.8. XOR. W eight-based encoding: 5 total nodes, 7 total bits/weight (no index), mutation rate 20. T wo-point-crossover . Binary coding.

Experiment 5: 2000 generations, target fitness 0.01, 1 population with 30 individuals, 5 mutations and 5 crossovers with crossover -mutation rate 20. V arying number of epochs, target error 0.01, learning rate 0.8. 1-Bit Adder . Weight-based encoding: 7 total nodes, 7 total bits/weight (no index), mutation rate 20. T wo-point-crossover . Binary coding.

For XOR, no significant difference can be observed for using different number of epochs. The median is in all cases between 280 and 390. The same observation can be made for the 1-Bit Adder: The data does not suggest any significant impact of the Baldwin effect for this task, although the median number of generations is unusually high for the experimental setting with 500 epochs.

So, we have to conclude that neural network training during the run of the genetic algorithm does not pay off. In contrary , it slows down the evolution process dramatically: In the case of the research tool used, including training over 100 training cycles increased the computation time by 3000 percent.

Thus, in the following experiments, back-propagation training is not used anymore.

Table 7: The Effect of Different Numbers of NN Epochs (XOR)

1	10	20	50	100	200	500
50	30	80	50	90	40	50
60	40	90	60	110	50	90
80	70	100	60	120	60	110
90	70	120	80	140	70	110
90	90	120	150	150	90	120
110	90	130	160	160	100	140
130	100	130	160	180	120	160
150	110	130	170	190	120	160
150	120	140	180	200	120	180
180	120	150	180	200	140	190
200	150	160	180	210	180	200
200	150	180	200	220	190	210
230	150	200	200	230	210	220
230	180	220	230	230	230	230
240	180	250	230	250	230	250
240	180	250	250	250	250	260
250	220	260	270	260	250	290
250	220	270	270	260	260	320
260	230	270	290	270	270	330
270	240	290	290	270	300	340
290	240	290	300	280	310	340
290	260	290	300	280	310	350
300	270	310	320	300	320	370
320	270	320	340	300	340	380
380	**280**	**320**	**340**	**310**	**340**	**390**
380	290	380	350	320	350	390
390	380	390	360	360	360	410
390	390	400	360	370	370	410
520	390	450	380	390	400	440
520	400	470	380	390	420	470
520	420	520	420	390	440	470
560	420	550	420	410	450	480
630	430	680	430	410	450	480
640	480	690	440	410	450	500
660	500	740	450	420	480	570
720	510	790	530	420	490	630
750	510	1070	560	440	510	670
810	520	1070	580	490	510	760
1030	560	1080	850	670	570	850
1050	570	1310	900	710	810	980
1420	810	1660	980	850	830	1100
1840	920	1800	1030	900	850	1260
2370	1010	2110	1660	940	880	1330
2590	1200	2170	1870	1790	1390	1390
3250	1340	2180	2060	2070	1940	1440
6610	1520	3250	2100	5080	2850	1440
8090	1610	3270	2150	8670	2930	1650
9030	2150	3640	2290	9030	3200	1980
9030	9030	4970	2810	9030	4580	2280
9030	9030	9030	2920	9030	9030	2460

Table 8: The Effect of Different Number of NN Epochs (1-Bit Adder)

1	10	20	50	100	200	500
120	190	100	220	170	250	100
140	250	160	250	200	260	120
210	260	210	300	210	280	170
250	270	210	340	250	310	180
290	270	220	370	270	340	200
300	280	230	380	300	360	200
310	280	270	430	300	380	230
340	310	280	440	330	410	240
360	320	360	440	330	410	250
360	320	370	460	400	440	270
400	370	380	470	410	440	270
410	370	430	470	410	470	280
410	380	450	480	460	480	280
440	390	450	490	470	490	320
460	420	450	540	490	570	330
470	440	460	560	490	590	330
470	450	470	570	580	600	340
470	450	490	570	590	620	350
530	510	490	570	670	680	350
580	520	530	580	670	690	390
600	530	570	580	710	690	390
610	540	610	610	730	690	400
620	600	660	620	740	700	400
630	600	670	630	760	720	470
630	**710**	**690**	**640**	**840**	**780**	**470**
650	710	690	690	850	790	480
670	800	690	710	960	800	490
870	830	720	750	1020	810	510
1000	870	730	790	1180	870	520
1000	970	790	850	1180	910	580
1030	970	900	860	1250	930	600
1030	1090	960	1050	1290	950	650
1030	1120	980	1090	1390	1150	660
1100	1230	990	1110	1570	1210	740
1150	1330	1000	1200	1580	1250	840
1180	1630	1070	1230	1630	1520	880
1340	1740	1470	1760	1830	1840	920
1840	1970	1850	2260	2320	1900	1000
2630	2150	2450	2320	2720	2250	1150
3450	2160	2510	2940	3530	2470	1180
5890	2280	2560	4630	5130	2600	1180
6260	2320	2650	5790	5160	2720	1230
8010	3190	2700	5980	5400	2730	1460
11080	3660	2930	6390	5560	3580	1490
15260	6170	4720	9930	5760	5310	1650
16910	8570	7560	12140	13750	10750	1750
20030	11370	10030	18050	15940	20030	2400
20030	20030	20030	19170	20030	20030	6400
20030	20030	20030	20030	20030	20030	10820
99630	20030	20030	20030	20030	20030	20030

Scalability

In the previous experiments we have examined very small problems with up to 2 input and 2 output nodes (1-bit adder), and up to 17 training patterns (sine). The results were quite promising: the genetic algorithm was able improve the weight values for the neural network much faster than back-propagation.

In order to investigate the scalability of the GANN system, we examine different complexities of the adder problem. For an n bit adder, a fully connected network with $6n + 1$ nodes, i.e. $3n$ hidden nodes was used. Figure 3.5 illustrates, how back-propagation deals with the first four instances of the problem.

The graphs display the error against the number of epochs and computation time, which is measured in terms of the number of epochs times number of connections to be trained. The multiple runs of back-propagation suggest that with increasing problem size, the chance of getting stuck in a local minimum increases, which is in these cases an error of about 0.1 to 0.15. But on the other hand, the convergence speed of successful runs remains about the same: After about 30,000 time units, a fairly good weight setting is reached.

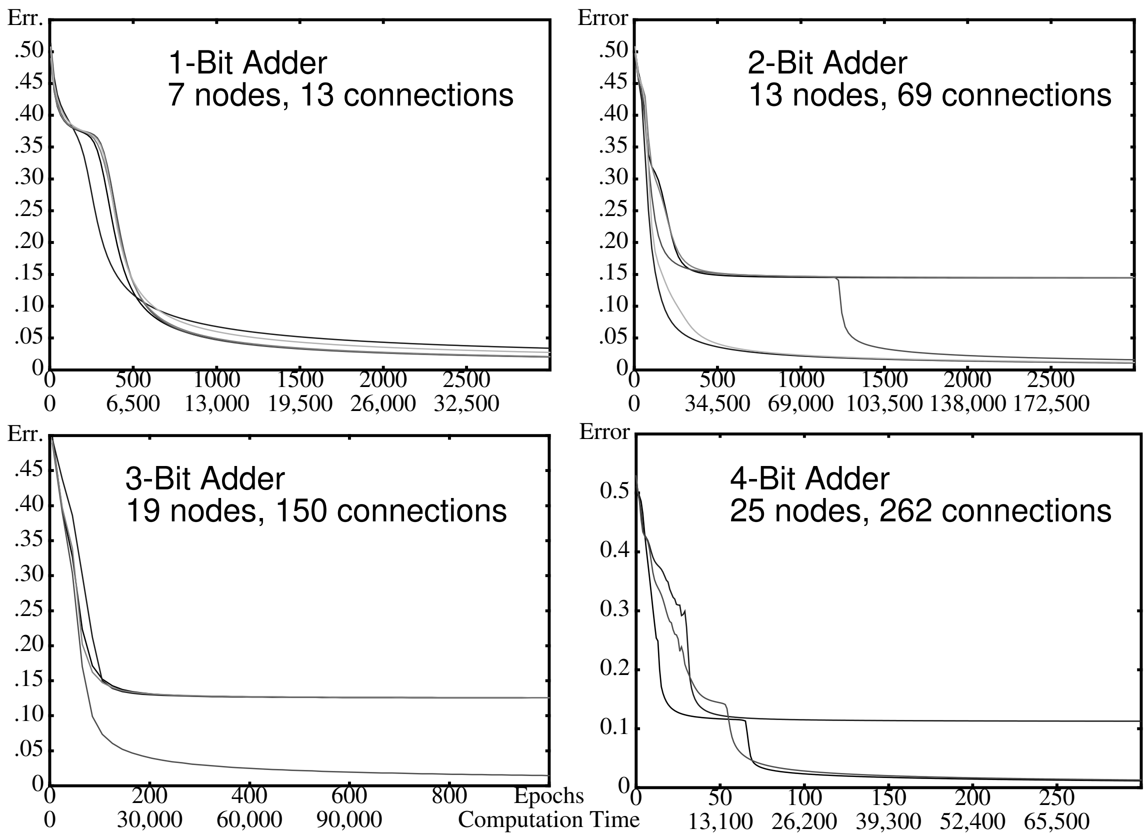


Figure 3.5: Backpropagation and the n-Bit-Adder

However, the GANN system has many more problems with relatively complex versions of the n bit adder. Figure 3.6 displays the evolution of the fitness value of the best individuals in three runs of experiment 6.

Experiment 6: 20000 generations, target fitness 0.01, 1 population with 30 individuals, 5 mutations and 5 crossovers with crossover -mutation rate 20. 1 epoch, target error 0.01, learning rate 0.8. 2-Bit Adder . Weight-based encoding: 13 total nodes, 7 total bits/weight (no index), mutation rate 20. T wo-point-crossover . Binary coding.

It illustrates that already the 2-bit adder is a task beyond the capabilities of our system. Even with a large number of generations, the systems can not come close to a weight setting that would result in an acceptable error below 0.05. Other parameter settings can not significantly improve the genetic algorithms, as additional unreported experiments suggest.

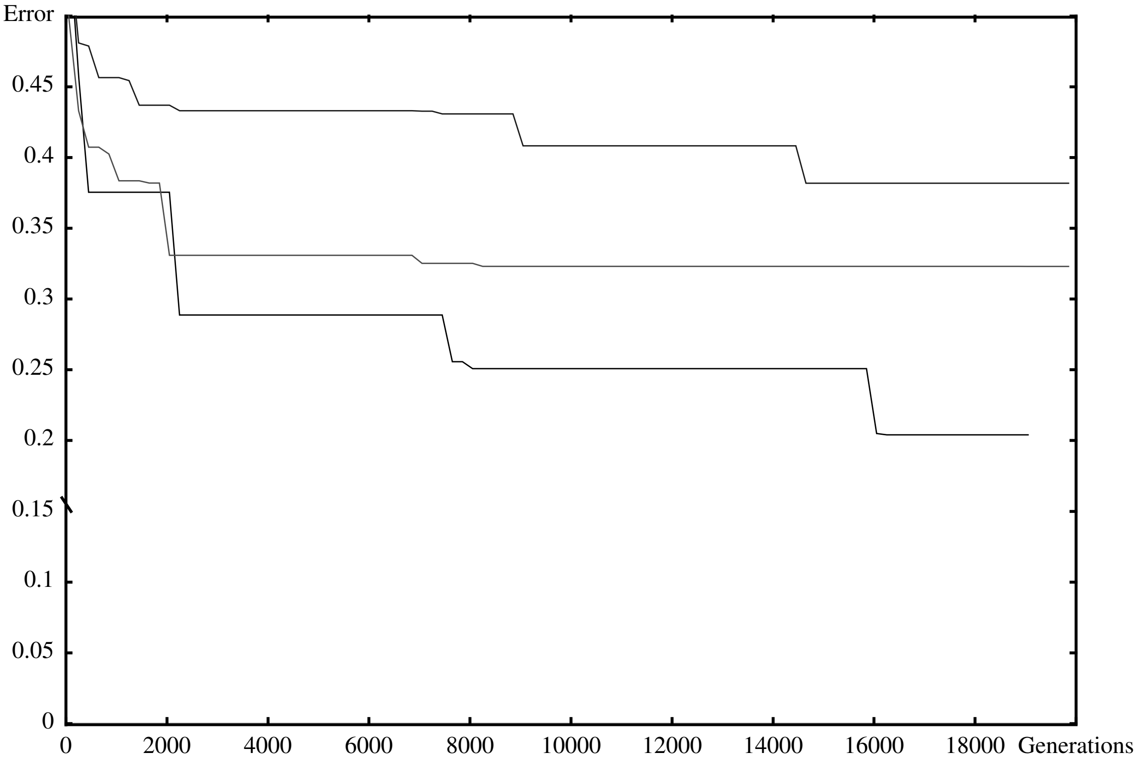


Figure 3.6: GANN and the 2-Bit Adder

This finding is consistent with reports of other research [Lindgren, 1992]. The training of NN connection weights with GA is generally feasible only for small networks. D. Whitley suggests in [Whitley , 1993] to apply GANN systems to control problems that rely on reinforcement learning. Since no target output is given, back-propagation cannot be used as a training method.

In general, control problems demand the training of a real-valued function. In case of the pole-balancing problem [W ieland, 1991], the input values represent state information such as angle and velocity of the pole. The output values represent action information such as the force that has to be applied to the pole to keep it in balance.

So, basically we can model each reinforcement control task with the training of a real valued function. The feedback we receive from the problem is merely the quality of the solution, not the optimal action as requested by back-propagation. But the GANN system can easily deal with just such reduced feedback, since it merely operated on this kind of fitness information.

Hence, for the rest of this section, we will investigate, how the evolution of weight settings for real-valued functions can be improved. The sine function serves as the chosen prototypical example. W e will investigate the influence of the GA parameters on the performance of the GANN in the task of evolving weight settings for the this function.

Number of Encoding Bits and Range of Weights

So far, we always used 7 bits for the encoding of each weight, which resulted in relatively high weight values between -64 and +64, without 0. This proved to be most efficient for boolean functions such as XOR and the n-bit adder. Real valued functions, however, require fine-tuned output values, hence fine-tuned weights. In case of boolean functions, the desired output values are extremes of the sigmoid threshold function, which has the properties

$$\lim_{x \to \infty} \sigma(x) = 1$$

$$\lim_{x \to -\infty} \sigma(x) = 0$$

So, high weight values support boolean output.

In experiment 7 we search for the optimal number of encoding bits and the optimal weight range for the real valued function sine by varying these parameters. The results of 20 runs for each constellation are reported in table 9: the fitness values after 10,000 generations are shown, the median (10th best) is printed in bold type.

Experiment 7: 10000 generations, 1 population with 30 individuals, 5 mutations and 5 crossovers with crossover-mutation rate 20. 1 epoch, learning rate 0.8. Sine with 17 training patterns. Weight-based encoding: 5 total nodes, varying number total bits/weight (no index), mutation rate 20. Two-point-crossover. Binary coding. Varying scaling factor.

Table 9: Impact of Encoding Bits and Range of Weights

	3 bits (-4, +4)	5 bits (-16, +16)	7 bits (-64, +64)	9 bits (-256, +256)
factor 1.0	0.153030 0.153030 0.153030 0.165535 0.167299 0.167299 0.167299 0.167299 0.167299 **0.167299** 0.167299 0.181069 0.181069 0.181457 0.181457 0.181734 0.184193 0.192114 0.192114 0.203813	0.044309 0.045748 0.045926 0.046576 0.049201 0.059204 0.059749 0.059842 0.060958 **0.071386** 0.071605 0.079629 0.093596 0.094930 0.108731 0.109770 0.115010 0.126416 0.146723 0.150069	0.052438 0.067474 0.069318 0.073104 0.076985 0.107452 0.116326 0.121792 0.136346 **0.136933** 0.139090 0.139795 0.149087 0.149235 0.151369 0.151847 0.155842 0.156825 0.159297 0.165454	0.0661776 0.101586 0.133243 0.135788 0.138132 0.150616 0.150978 0.151314 0.151638 **0.157729** 0.159126 0.170319 0.174345 0.183583 0.187701 0.189298 0.192337 0.201894 0.206178 0.227227

Table 9: Impact of Encoding Bits and Range of Weights

	3 bits (-4, +4)	5 bits (-16, +16)	7 bits (-64, +64)	9 bits (-256, +256)
factor 0.3	0.248386	0.118632	0.0295233	0.0498435
	0.248386	0.118632	0.0316353	0.0704057
	0.248386	0.118865	0.0334778	0.0714226
	0.248386	0.119028	0.0368493	0.0716892
	0.248386	0.119028	0.040791	0.0766553
	0.253577	0.120198	0.0488674	0.0917237
	0.253577	0.120619	0.050332	0.106842
	0.253577	0.124684	0.0535794	0.119931
	0.253577	0.145036	0.0539525	0.130911
	0.253577	**0.145036**	**0.0562101**	**0.144254**
	0.253577	0.145088	0.0672379	0.146182
	0.253577	0.145185	0.0679378	0.148769
	0.254062	0.160298	0.0688299	0.149224
	0.254062	0.160930	0.0715112	0.150575
	0.255607	0.163454	0.0799214	0.152315
	0.255607	0.165005	0.0885259	0.15547
	0.255607	0.166743	0.0974661	0.161709
	0.255607	0.175946	0.0989347	0.169699
	0.255607	0.185054	0.103806	0.1777
	0.255607	0.185305	0.144998	0.191477
factor 0.1	0.313010	0.227216	0.084543	0.032426
	0.313010	0.227216	0.087498	0.036018
	0.313010	0.227216	0.087849	0.046769
	0.313010	0.227256	0.089561	0.049013
	0.313010	0.227256	0.101269	0.049217
	0.313010	0.232908	0.114790	0.055787
	0.313010	0.232949	0.115402	0.057749
	0.313010	0.232949	0.118045	0.058833
	0.313213	0.232949	0.119068	0.066740
	0.313213	**0.233084**	**0.119340**	**0.070743**
	0.313213	0.234149	0.121218	0.073356
	0.313264	0.234178	0.122774	0.075433
	0.313264	0.234178	0.124372	0.082707
	0.313365	0.234178	0.124788	0.126809
	0.313365	0.234184	0.126510	0.136825
	0.313365	0.234211	0.137003	0.138920
	0.313365	0.234226	0.141770	0.146683
	0.313365	0.234226	0.148802	0.147172
	0.313365	0.234298	0.155459	0.148235
	0.313365	0.234666	0.156998	0.150765

Table 9: Impact of Encoding Bits and Range of Weights

	3 bits (-4, +4)	5 bits (-16, +16)	7 bits (-64, +64)	9 bits (-256, +256)
factor 0.03	0.330737 0.330737 0.330737 0.330737 0.330737 0.330737 0.330737 0.330737 0.330737 **0.330737** 0.330737 0.330737 0.330737 0.330737 0.330737 0.330737 0.330737 0.330737 0.330737 0.330737	0.307095 0.307095 0.307095 0.307095 0.307095 0.307095 0.307095 0.307095 0.307249 **0.307249** 0.307249 0.307249 0.307249 0.307249 0.307249 0.307251 0.307404 0.307649 0.307649 0.307649	0.215711 0.215711 0.215713 0.215721 0.215725 0.215938 0.22262 0.222724 0.222724 **0.222725** 0.222729 0.222729 0.222739 0.222744 0.222765 0.222796 0.222944 0.222996 0.222996 0.223004	0.0727724 0.0739605 0.0761268 0.0780194 0.0835465 0.0989931 0.0996362 0.0996622 0.0999415 **0.102609** 0.104635 0.105248 0.108213 0.108351 0.108464 0.128752 0.134128 0.143609 0.154041 0.165353

Clearly , both the number of encoding bits and the range of weights have high impact on the efficiency of the GANN system. The influence of the scaling factor on the performance of the neural network depends on number of bits: For the 3-bit encoding the factor 1 worked the best, whereas for the 9-bit encoding the factor 0.1 resulted in the lowest terminal error .

To localize the optimal scaling factor , we ran additional variations of experiment 7 for the 7-bit and 9-bit encoding schemes. The results are shown in T able 10 and 1 1, only the median (the 10th best out of 20 runs) is displayed.

Table 10: Search for the Best Weight Range Using 7 Encoding Bits

factor 0.20 max. 12.8	factor 0.25 max. 16.0	factor 0.30 max. 19.2	factor 0.40 max. 25.6	factor 0.50 max. 32.0
0.072611	0.068293	0.0562101	0.064460	0.088252

The results are quite interesting. Although a different optimal scaling factor for both cases has been found - 0.3 for 7-bit and 0.08 for 9-bit - the actual optimal range of the weights is quite similar . The GANN system seems to find the best networks, if the weights are limited to values in the interval (-20,20).

Table 11: Search for the Best Weight Range Using 9 Encoding Bits

fact. 0.05 rng. 12.80	fact. 0.06 rng. 15.36	fact. 0.07 rng. 17.92	fact. 0.08 rng. 20.48	fact. 0.10 rng. 2.560	fact. 0.15 rng. 38.40	fact. 0.20 rng. 51.20
0.072213	0.075602	0.060600	0.053783	0.070743	0.084441	0.071368

Using this range for 3-bit and 5-bit encoding (using scaling factors of 4 and 1.25 respectively) enhances the impression that this is the optimal range, independent from the number of encoding bits: Also here, better results than with other scaling factors can be achieved. Table 12 presents the terminal error of the median run in all four encoding cases.

Table 12: Quality of n-Bit Encoding Using Optimal Range

3-node range 20	5-node range 20	7-node range 19.2	9-node range 20.48
0.083744	0.064960	0.0562101	0.053783

The more encoding bits are used, the better the results. A higher number of encoding bits slightly increases the computation time: The computation time for a single run of the experiments varies from 9.7 minutes for 3-bit encoding to 11.2 minutes for 9-bit encoding on a SUN IPX. A much higher number of encoding bits, however, would result in a relatively stronger slowdown, since different data types than 16-bit integers for the weight storage have to be used.

Population Size

In all our experiments so far, a population size of 30 has been used. Since in each generations 10 GA operators were applied to the individuals, up to 10 new individuals replaced the worst individuals, while at least two thirds of old individuals remained in the population.

In experiment 8, we examine how different population sizes effect the performance of the GANN system. To achieve comparable results the number of generations was adapted to the population size, so that always 100,000 individuals were generated.

Experiment 8: Varying number of generations, 1 population with varying number of individuals, 5 mutations and 5 crossovers with crossover-mutation rate 20. 1 epoch, learning rate 0.8. Sine with 17 training patterns. Weight-based encoding: 5 total nodes, 7 bits/weight (no index), mutation rate 20. Two-point-crossover. Binary coding. Scaling factor 0.08.

Table 13 reports the results. Again, the rms error of the median (10th best run out of 20) is displayed. Clearly, a larger population yields to better performance: the empirical data favors the size 100, although this may be based on the error of the measurement. However, population sizes smaller than 30 rank certainly last.

Table 13: The Impact of Generation Size

10	20	30	50	100	200
0.079219	0.077692	0.060396	0.069216	0.048445	0.059918

Distributed Genetic Algorithm

In experiment 9 we examine, if the use of a distributed genetic algorithm improves the evolution of good weight settings. Distributed GA were introduced in [T anese, 1989], and are discussed in section 1.3 of this thesis. In the experiment, 10 subpopulations with 30 individuals each are used. Again, 100,000 individuals are generated during one run of the experiment.

In three different versions of the experiment, the distribution cycle is varied. The distribution cycle is the number of generations, after which the best individuals of each generation are exchanged.

Experiment 9: 970 generations, 10 population with 30 individuals, 5 mutations and 5 crossovers with crossover -mutation rate 20. 1 epoch, learning rate 0.8. Sine with 17 training patterns. W eight-based encoding: 5 total nodes, 7 bits/weight (no index), mutation rate 20. T wo-point-crossover . Binary coding. Scaling factor 0.08.

Table 14 presents the results of the three different versions of the experiment in the usual fashion - the fitness value 10th best run out of 20 is displayed. Three different distribution cycles are used. The results indicate that the distributed GA shows superior performance compared to the standard GA. Also, a high distribution cycle is the best choice.

Table 14: Distributed GA

Cycle 10	Cycle 50	Cycle 200
0.045303	0.039761	0.038429

Crossover T ype and Gray Coding

In Experiment 10 we investigate, if the three standard crossover operators differ in their performance on the task of evolving weights for the sine function. The best design of the population that was found in the experiment 9 is used: 10 subpopulations with 30 individuals each and distribution cycle of 200.

Experiment 10: 970 generations, 10 population with 30 individuals, distribution cycle 200, 5 mutations and 5 crossovers with crossover -mutation rate 20. 1 epoch, learning rate 0.8. Sine with 17 training patterns. W eight-based encoding: 5 total nodes, 7 bits/weight (no index), mutation rate 20. V arying types of crossover . Binary ands gray coding. Scaling factor 0.08.

The results are reported in table 15 in the usual fashion. Uniform crossover seems to be superior to one- and two-point crossover . However , the difference is not large and may be even in the range of measurement error . Also, no significant difference between gray and binary coding can be observed, although the results suggest that gray coding is a bad choice for two-point crossover .

Table 15: The Impact of Crossover Type and Gray vs. Binary Coding

	One-Point	Two-Point	Uniform
Binary	0.036879	0.036089	0.035413
Gray	0.034778	0.041122	0.034802

Application to Other Tasks

After optimizing all the parameters of the GANN system, we finally examine in experiment 11, 12 and 13, how the its performance compares to backpropagation. Three real-valued functions are examined: 4-period sinus, the Gaussian bell curve and a two-dimensional Gaussian bell curve. The functions are trained to a fully connected 7-node, 5-node and 7-node architecture respectively.

Experiment 11: 970 generations, 10 population with 30 individuals, distribution cycle 200, 5 mutations and 5 crossovers with crossover-mutation rate 20. 1 epoch, learning rate 0.8. 4-period sine with 17 training patterns. Weight-based encoding: 7 total nodes, 7 bits/weight (no index), mutation rate 20. Varying types of crossover. Binary ands gray coding. Scaling factor 0.08.

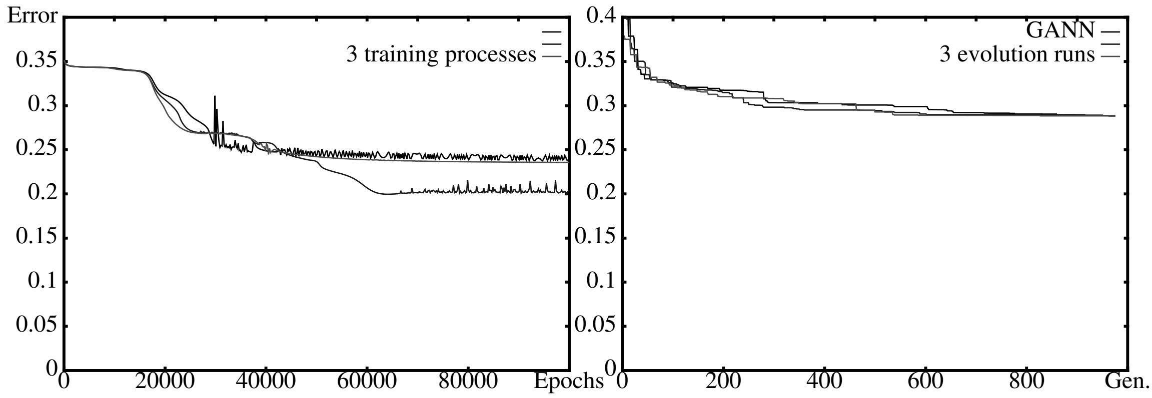


Figure 3.7: Backprop. vs GANN and the 4-Period Sine Function

For each experiment, a figure (3.7, 3.8, and 3.9) displays three runs of the experiment in its right graph. As a comparison, three training processes of backpropagation are displayed in the left half of the figure. The backpropagation algorithm ran for each training process over 100,000 epochs. The GANN system generated 100,000 individuals.

Although this is a quite crude comparison, we have to observe that back-propagation shows similar results to the genetic weight evolution.

Experiment 12: 970 generations, 10 population with 30 individuals, distribution cycle 200, 5 mutations and 5 crossovers with crossover-mutation rate 20. 1 epoch, learning rate 0.8. Gaussian bell curve with 17 training patterns. Weight-based encoding: 5 total nodes, 7 bits/weight (no index), mutation rate 20. Varying types of crossover. Binary ands gray coding. Scaling factor 0.08.

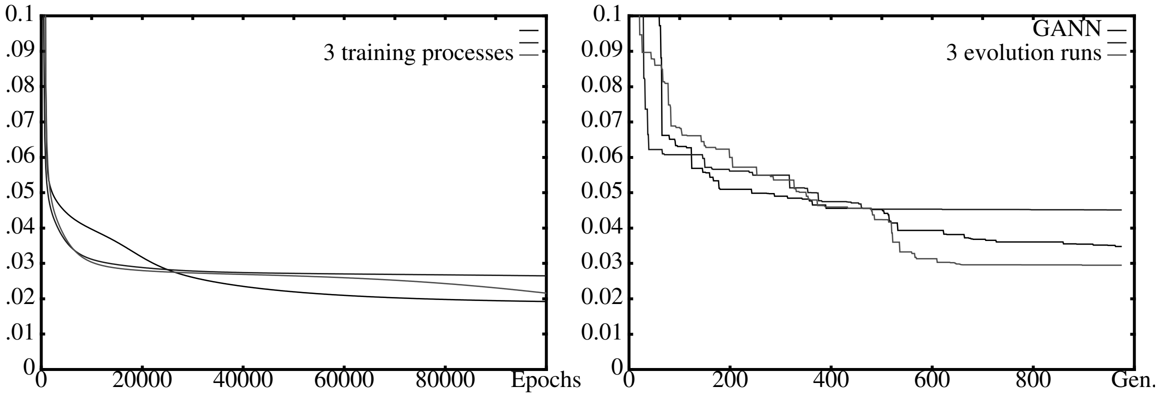


Figure 3.8: Backprop vs. GANN and the Gaussian Bell Curve

Experiment 13: 970 generations, 10 population with 30 individuals, distribution cycle 200, 5 mutations and 5 crossovers with crossover-mutation rate 20. 1 epoch, learning rate 0.8. 2-dimensional gaussian bell curve with 25 training patterns. Weight-based encoding: 7 total nodes, 7 bits/weight (no index), mutation rate 20. Varying types of crossover. Binary ands gray coding. Scaling factor 0.08.

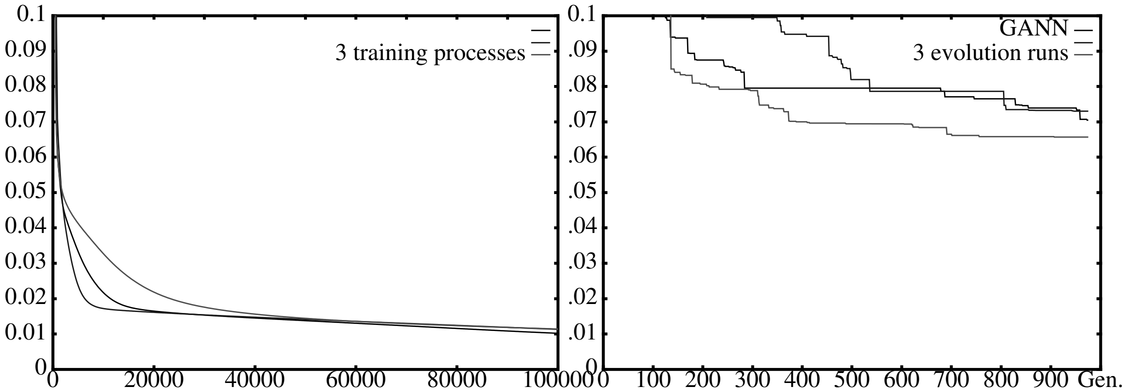


Figure 3.9: Backprop. vs GANN and the 2D Gaussian Bell Curve

3.4 Experiments on Architecture Optimization

The optimization of the architecture of neural networks is a completely different task from weight optimization. While for the later, the GANN system has to compete with back-propagation, no generally accepted strategy exists to find a good architecture for an arbitrary task.

Traditionally, a standard topology is selected and the number of nodes follow rules of thumb. Standard topologies are for instance layered networks with a small number of hidden layers or fully connected networks.

Optimal Topology for XOR

First, we examine how much the choice of architecture influences the training process, and how we can evaluate a certain architecture. We investigated the performance of different architectures for the XOR function. The performance is measured by the error of the network after training. The network is initialized to random weights. Since the training of large networks, the number of epochs depends on the number of connection of each network:

$$epochs = \frac{E}{connections}$$

Table 16 gives the evaluation of different architectures for the XOR problem. The displayed fitness is the average error of 10 evaluations. Three different topology classes are investigated: fully connected feed-forward networks, layered architectures and layered architectures with a bias unit in the input layer . A bias unit is a hidden node that has the constant activation 1. The results suggest that the 6-node fully connected network is the best competitor for the longest training period.

Table 16: Performance Evaluation of Various Network Architectures for XOR

E	1000	2000	5,000	10,000	20,000	100,000
4 node fully-c	0.515437	0.513334	0.484624	0.453512	0.451519	0.450719
5 node fully-c	0.518312	0.509715	0.389778	0.137291	0.053577	0.018675
6 node fully-c	0.520498	0.510036	0.432788	0.140613	0.056107	0.017559
7 node fully-c	0.525658	0.519585	0.408227	0.149738	0.060961	0.019101
8 node fully-c	0.529587	0.524147	0.466310	0.292121	0.085560	0.019935
9 node fully-c	0.534662	0.530759	0.510064	0.363000	0.131906	0.021986
10 node fully-c	0.536131	0.532083	0.507876	0.353022	0.110811	0.023429
11 node fully-c	0.542059	0.536737	0.514340	0.380702	0.152209	0.027108
2-2-1	0.500000	0.500000	0.500000	0.500000	0.500000	0.500000
2-3-1	0.503402	0.496261	0.426042	0.293187	0.258096	0.250959
2-4-1	0.515189	0.508591	0.471117	0.293429	0.132421	0.025543
2-5-1	0.514120	0.512444	0.474998	0.255315	0.097225	0.025024
2-6-1	0.521576	0.512424	0.459168	0.264913	0.102529	0.025856
2-7-1	0.528192	0.520914	0.487832	0.325130	0.102028	0.026940
2-8-1	0.526797	0.523003	0.490040	0.331040	0.146517	0.030287
3-3-1 incl. bias	0.507148	0.501188	0.411446	0.224329	0.191503	0.217216
3-4-1 incl. bias	0.509988	0.502421	0.421896	0.180641	0.091618	0.015099

Table 16: Performance Evaluation of Various Network Architectures for XOR

E	1000	2000	5,000	10,000	20,000	100,000
3-5-1 incl. bias	0.517983	0.513984	0.481745	0.272044	0.108480	0.018168
3-6-1 incl. bias	0.524419	0.519634	0.480121	0.251478	0.073099	0.018310
3-7-1 incl. bias	0.524781	0.519920	0.499058	0.311401	0.079394	0.019666
3-8-1 incl. bias	0.526714	0.521591	0.496229	0.312837	0.113252	0.021580

The table illustrates the problems that come along with the fitness evaluation of architectures that are generated by the GA. In order to achieve the best possible evaluation, training over a high number of epochs has to be performed. Also, error evaluation based on random weights is a noisy fitness function. the more training processes performed, the more representative the resulting evaluation value.

Figure 3.10 displays some of the data of table 16: For the longest training process, the 3-4-1 layered ranks the best among the four displayed architectures. However , it is ranked second after E = 5,000 and third after E = 10,000 and 20,000. So, the short term convergence does not predict long term convergence, even within the same topology class. The 5-node fully connected network seems to superior to its 6-node competitor up to E = 20,000, until it is ultimately outperformed.

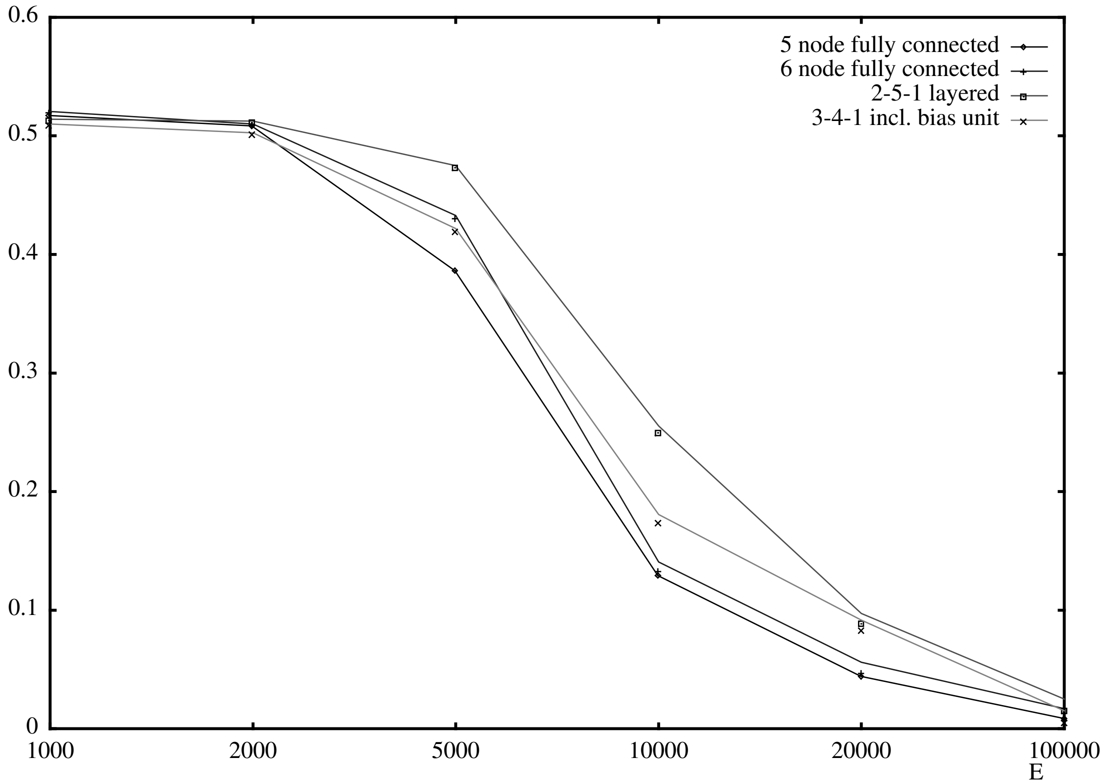


Figure 3.10: Error Development for Standard Architectures

The other problem for defining the fitness of an architecture lies in the fact that the success of training depends on the initial weight values. Since, we merely optimize the architecture, the weights are initially set to random values. So, if we repeat training evaluations with different initial weight, we get different results.

Figure 3.1 1 displays how much the results vary for the 5-node fully connected network. 100 samples of 1,1 11 epoch (E/cc = 10,000/9) training are shown. 7% of the cases are complete failures with a rms-error of about 0.5. Figure 3.12 shows the same picture for the 6-node network. For E = 100,000, the results vary merely between 0.01 and 0.03 (see figure 3.13).

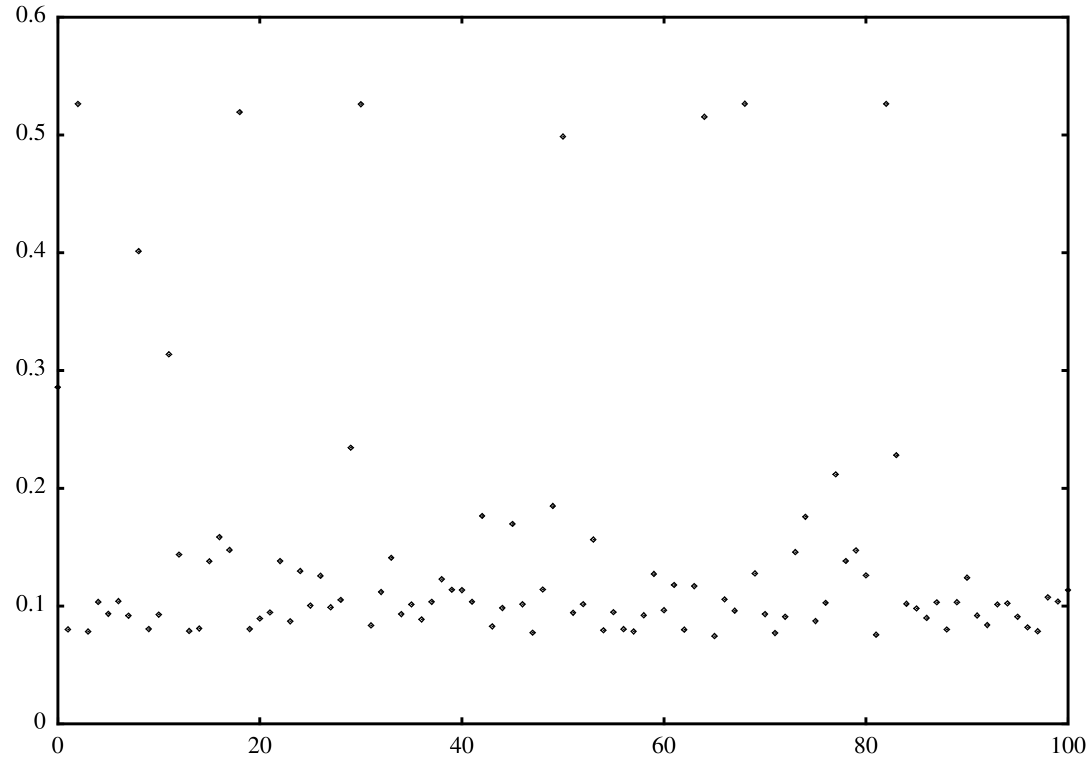


Figure 3.11: Evaluations after 10,000 E for 5-node Fully-Connected Net

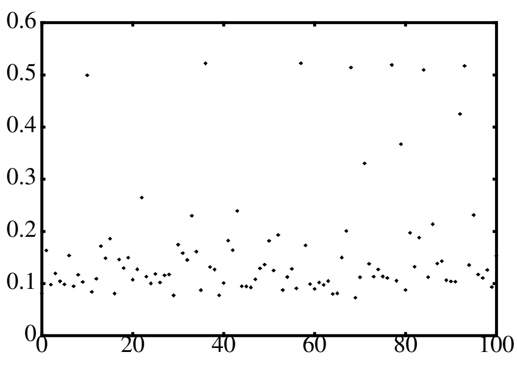


Figure 3.12: Error Sampling for 6-node (E =10,000)

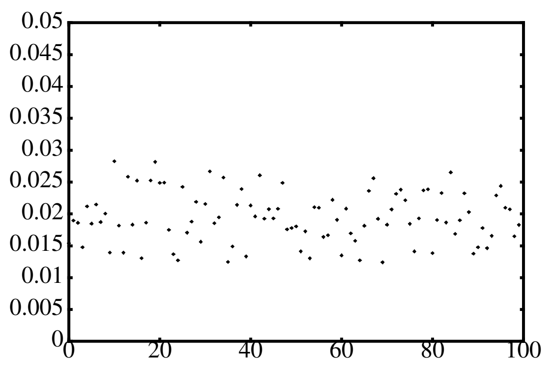


Figure 3.13: Error Sampling for 6-node (E=100,000)

These considerations urge for a high value of E and a high number of training processes. However , repeated long training processes are very time consuming. One training process for

E=100,000 takes about 3 seconds computation time, when using the research tool on a SUN SPARC 5m70. For E=10,000, only 0.3 seconds are required.

Optimizing NN Architectures Using Weight-Based Encoding

In weight-based encoding of an architecture, each connection of a fully connected architecture is encoded by one bit: the index bit. If it is set, the connection exists, otherwise not. Each network can be represented by a string of these index bits. Thus, the original GA operators can be applied.

Since each weight has a fixed interpretation in a given fully connected architecture, we have to restrict the search initially to architectures with a maximum number of nodes.

> **Experiment 14:** 100 generations, 1 population with 30 individuals, 5 mutations and 5 crossovers with crossover-mutation rate 20. Epochs = 100,000 divided by connection count, 10 evaluations, learning rate 0.8. XOR. Weight-based encoding: 11 total nodes, 1 index bit, mutation rate 20. Two-point-crossover.

In experiment 14 we investigate, how efficient the genetic algorithm finds a good network architecture using weight-based encoding. A run of the experiment with E=100,000 over 100 generations takes about ten hours computation time on the mentioned machine.

Figure 3.14 displays a typical run of the experiment. It illustrates the impact of the noisy fitness function quite well. Two lines are displayed: The "noisy" line displays fitness evaluations of the best individual, that are computed at the end of each generation. The other line displays the fitness value of the best individual: This fitness value was generated after the creation of the individual and is used by the genetic algorithm.

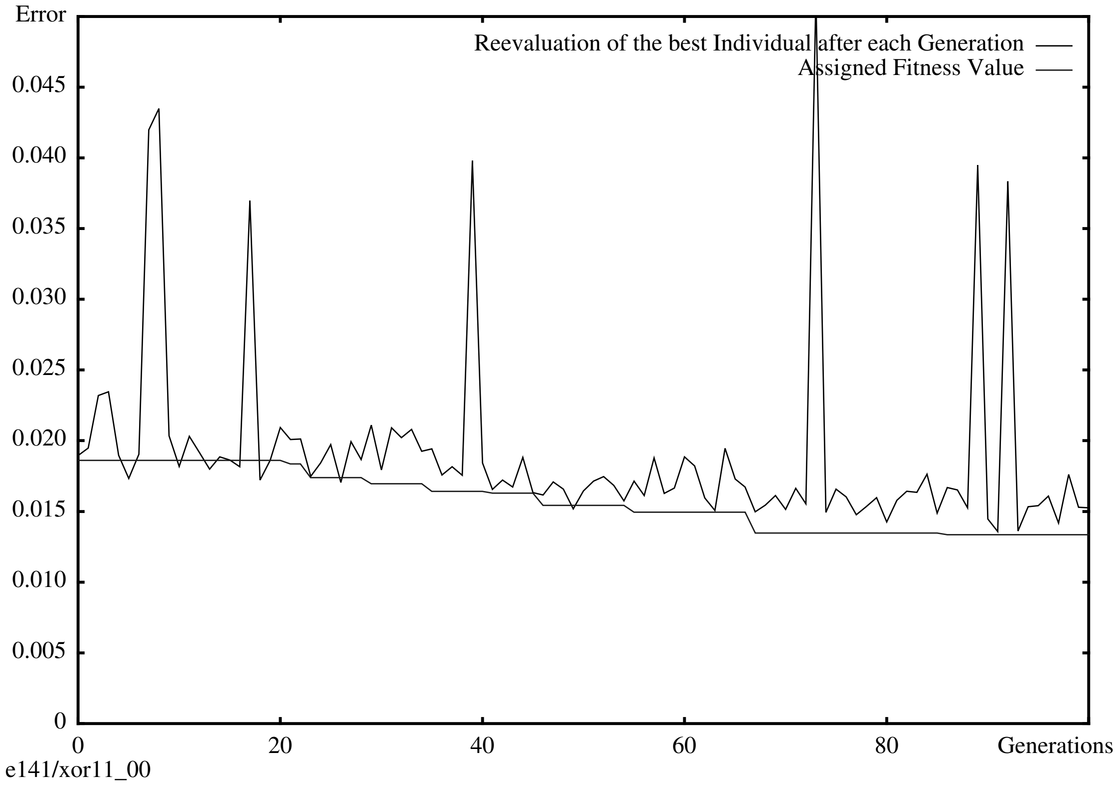


Figure 3.14: Fitness Evolution of Optimizing XOR-Architecture (E=100,000; 10 Evaluations)

Both lines show continuous progress towards a fast learning architecture: Beginning with a best individual with fitness 0.0186142, finally an fitness of 0.0133564 is reached. However, these good values do not neccessarily represent the quality of the architecture. They also profit from accidentally good random initial weights during the evaluations. A more accurate measurement is displayed in the "noisy" line. It represents the reevaluation of the best individual after each generation. Its average also improves from circa 0.02 to circa 0.015.

So, the genetic algorithm was able to find an good architecture and made consistent progress in this task until it was stopped after 100 generations. The resulting network is comparable with the best of the standard architectures.

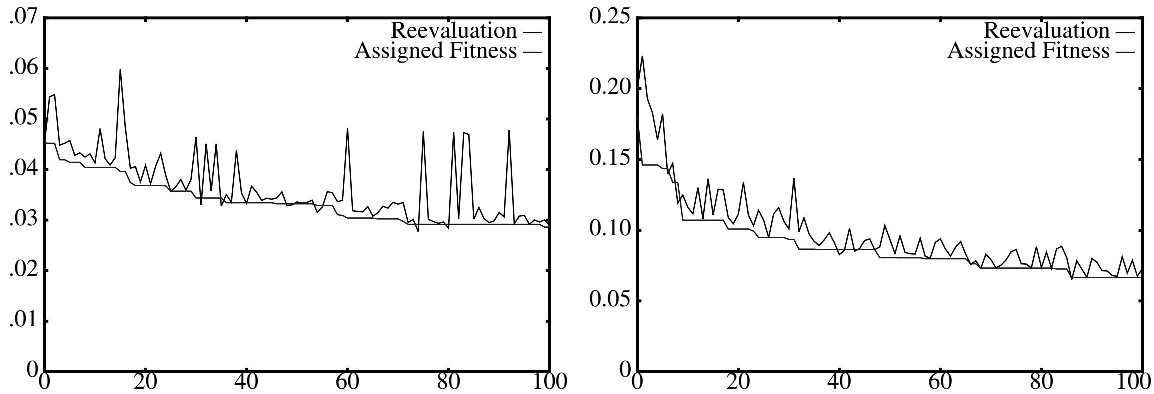
Impact of Training Length and Number of Evaluations

In experiment 15 and 16 we investigate, if the genetic algorithm can be improved by more accurate fitness evaluations. We train each generated architecture 20 times, and in the 13th experiment 50 times in order to get an adequate average error. On the other hand, the training length is decreased to E=50,000 and E=20,000. So, the run of these experiment variations takes about the same computation time as a run of experiment 14.

> **Experiment 15:** 100 generations, 1 population with 30 individuals, 5 mutations and 5 crossovers with crossover-mutation rate 20. Epochs = 50,000 divided by connection count, 20 evaluations, learning rate 0.8. XOR. Weight-based encoding: 11 total nodes, 1 index bit, mutation rate 20. Two-point-crossover.

> **Experiment 16:** 100 generations, 1 population with 30 individuals, 5 mutations and 5 crossovers with crossover-mutation rate 20. Epochs = 20,000 divided by connection count, 50 evaluations, learning rate 0.8. XOR. Weight-based encoding: 11 total nodes, 1 index bit, mutation rate 20. Two-point-crossover.

The results are shown in Figure 3.15. The performance of the GANN system using this parameter setting is similar to experiment 14. However, especially in the setting with 50 evaluations, a much smoother and more consistent progress can be observed.



11a_01 E= 50,000 - 20 Evaluations 11b__10 E = 20,000 - 50 Evaluations

Figure 3.15: Variation of Training Length and Number of Evaluations

Table 17 compares the performance of the best architectures found by the genetic algorithm and the best standard architectures. The performance of the found architectures is comparable with best instances of standard topologies. In nearly all cases, a better fitness than the layered 2-5-1 architecture could be achieved

The results also illustrates that the networks were trained for a specific purpose: The net that was evolved for E=20,000 is the best net for E=20,000 among the evolved networks and beats also two standard architectures, but it ranks second to last for E=100,000. On the other hand, the net that was trained for E=100,000 is the overall third best net for this task, but shows poor performance for E=20,000.

Table 17: Performance of Evolved and Standard Architectures

Architecture	E=20,000	E=100,000
Trained for E=20,000	0.07853	0.019189
Trained for E=50,000	0.093884	0.018650
Trained for E=100,000	0.218535	0.017688
6 node fully-connected	0.056107	0.017559
2-5-1 layered	0.097225	0.025024
3-4-1 incl. bias unit	0.091618	0.015099

Notice that the genetic algorithm is restricted to only 100 generations. The graphs of figure 3.14 and 3.15 suggest that a longer run of the experiments beyond 100 generations will resulted in even better architectures.

Bias towards "noisy" Architectures

Figure 3.16 illustrates how the problem of a "noisy" fitness function may significantly influence the performance of the GANN system. A run of experiment 12 is displayed. At generation 58 an architecture becomes the best individual, whose performance depends on a much larger scale on the initial weight setting. This results into reevaluation values between 0.0246553 and 0.061286.

Since the genetic algorithm only uses one of these evaluations - the first - an accidentally good static fitness evaluation will give such a "noisy" architecture a high ranking. Noisy architectures are a problem, since their quality can not be adequately assessed: Their fitness value is much more influenced by the random initial weights. This contradicts our goal to find good architectures independent from initial weights.

Size of the Networks

Randomly generated networks with 1 1 nodes have an average of 27 connections. However , the best standard architectures use a much lower number of nodes and connections. For instance, the 6-node fully connected network has 15 connections.

Figure 3.17 illustrates that the genetic algorithm is able to reduce the number of connections from the initial 27 down to around 20. The figure displays the network sizes of the same best individuals, whose fitness values are discussed in figure 3.14 and 3.15.

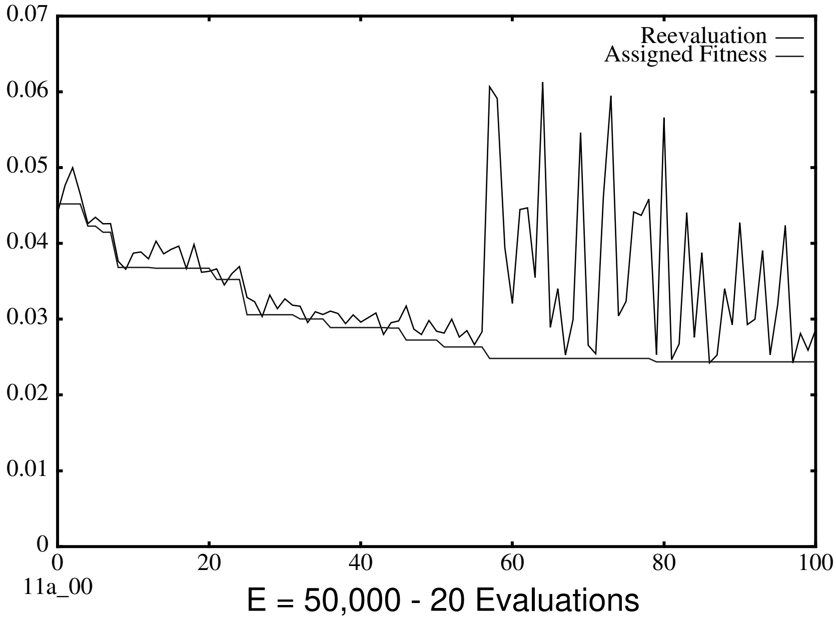


Figure 3.16: Problem of Bias towards “noisy” Architectures

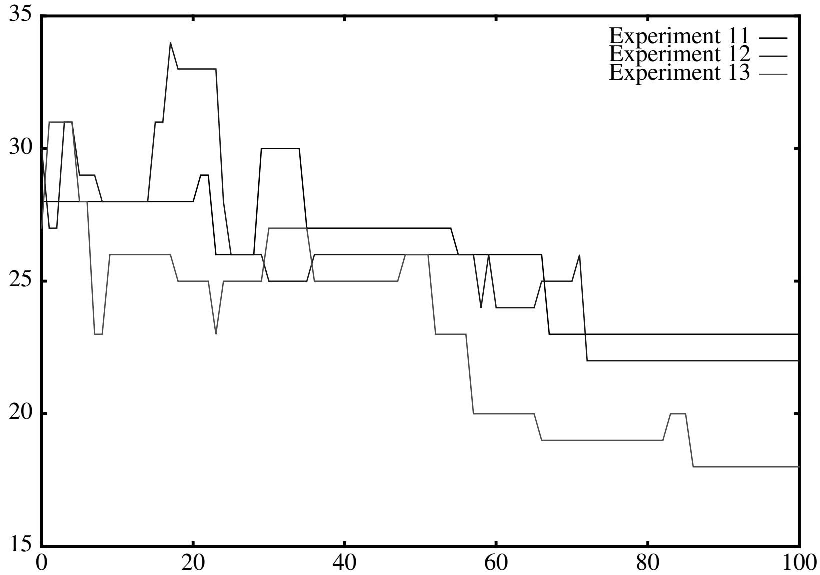


Figure 3.17: The Reduction of Network Size

The Architecture of Evolved Networks

Figure 3.18 and 3.19 give an impression of the topology of the evolved neural networks. Apparently , the GA reduced the number of effectively used nodes: In Figure 3.18, node 5 is not used anymore at all, and the nodes 2, 4, and 6 are reduced to a system of connected bias units. The core of the network is a layered 2-4-1 network with interior nodes 7, 8, 9 and 3.

Figure 3.19 displays a network that was generated in a E=100,000 run. It has a more complicated structure. But also here, unit 3 is almost abolished and the nodes 5 and 2 are merely bias units.

The shown architectures enhance the impression that a higher number of generations would result in even better networks. In case of the last architecture, a simple pruning of the connection from node 1 to 3 would help.

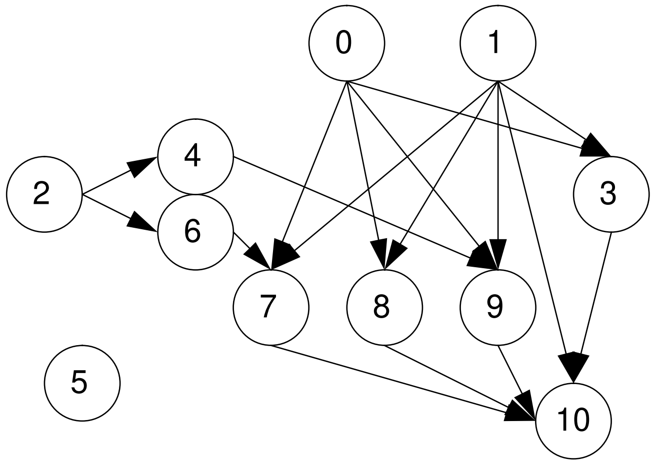


Figure 3.18: Network generated during a E=50,000 run

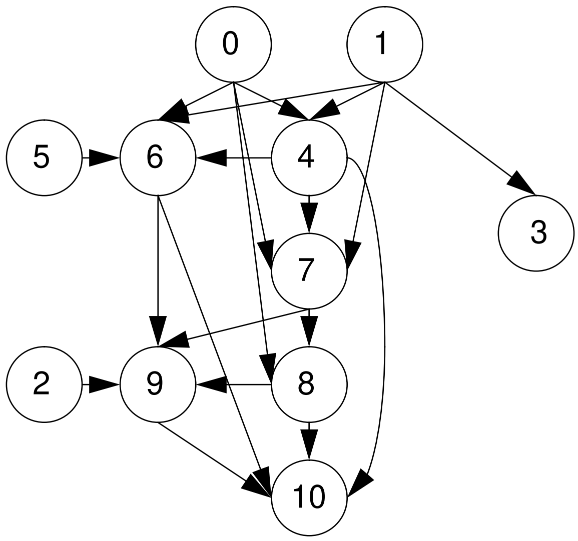


Figure 3.19: Network generated during a E=100,000 run

1-Bit Adder

In experiment 17 we evolve networks for the 1-bit adder . The evolution of the fitness values of the best individuals are plotted in figure 3.20. For each of the three different parameter settings for E and for the number of training processes, a typical run is displayed.

The results indicate that also for the 1-bit adder , progress towards improved architectures is smooth is consistent.

Experiment 17: 100 generations, 1 population with 30 individuals, 5 mutations and 5 crossovers with crossover-mutation rate 20. Varying number of epochs, varying number of evaluations, learning rate 0.8. 1-bit adder. Weight-based encoding: 13 total nodes, 1 index bit, mutation rate 20. Two-point-crossover.

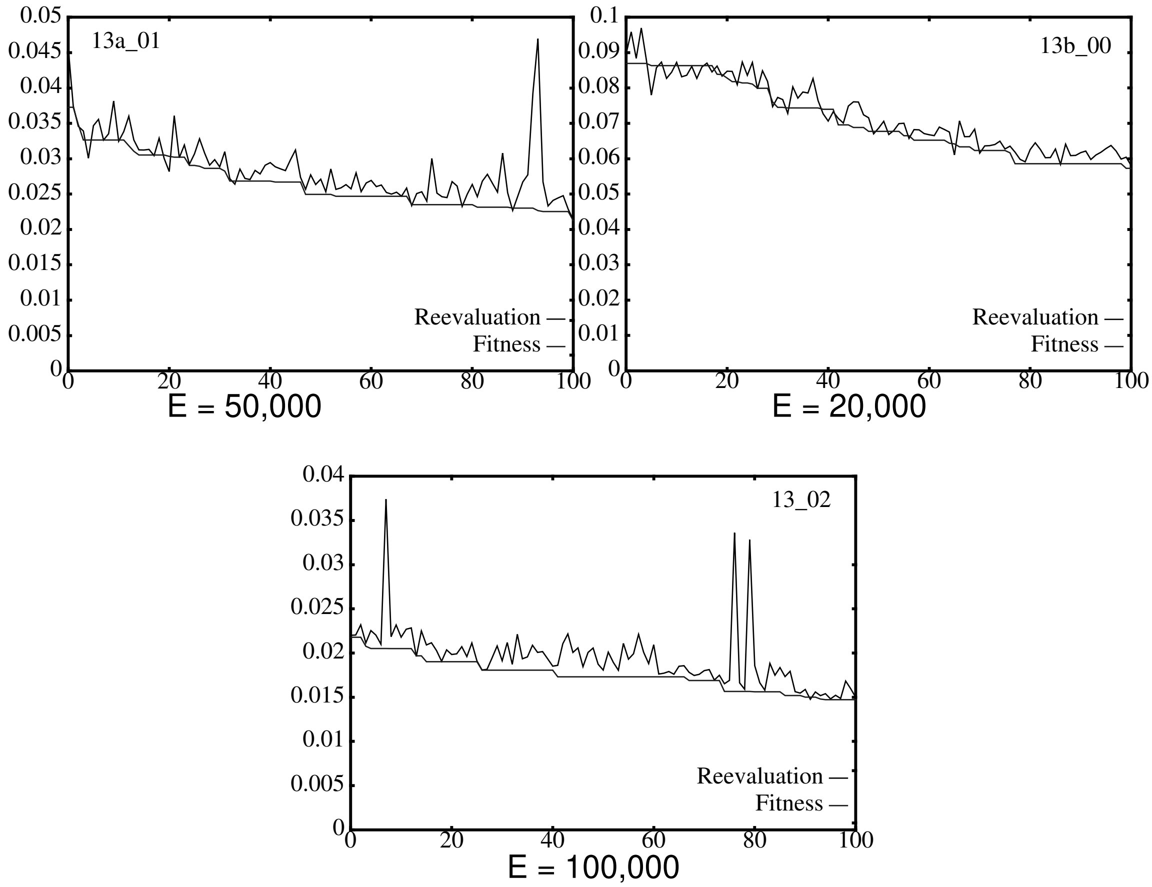


Figure 3.20: Architecture Optimization for the 1-Bit Adder

Sine

Finally, in experiment 18, we treat the sine function. Since 17 training patterns are involved, a run of experiment 18 takes about two days computation time on a SUN SPARC5m70.

Experiment 18: 100 generations, 1 population with 30 individuals, 5 mutations and 5 crossovers with crossover-mutation rate 20. Varying number of epochs, varying number of evaluations, learning rate 0.8. Sine with 17 training patterns. Weight-based encoding: 13 total nodes, 1 index bit, mutation rate 20. Two-point-crossover.

The results of runs for E=50,000 and E=100,000 are displayed in figure 3.21 in the usual fashion. The run for 100,000 suffers from noisy architectures. The assigned fitness for the best individuals fall remarkably below their actual fitness, which is indicated by the reevaluations. Better results could be achieved with 20 training processes and E=50,000. The evolved architectures reach error that even come very close to the ones in the E=100,000 run, although only half the number of training epochs are used.

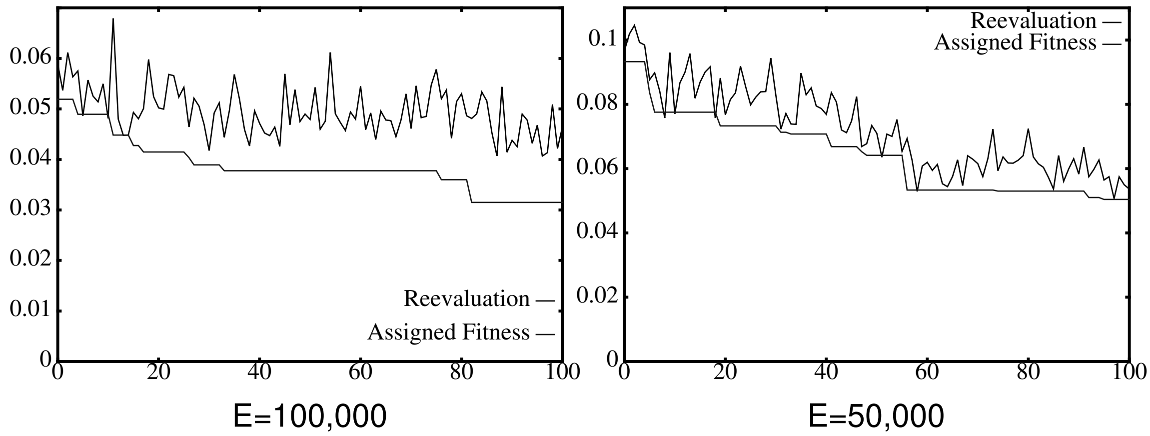


Figure 3.21: Architecture Optimization for Sine

3.5 Conclusions

We successfully applied the genetic algorithm paradigm to neural networks in the task of weight as well as architecture optimization.

Weight Optimization

For weight optimization, the GANN systems outperforms traditional neural network training, when small networks were used. In these small search spaces, the global approach of genetic algorithms proves to be roughly comparable to the local back-propagation. We also showed that genetic algorithms do considerably better than random search for weight values.

A mix of mutation and crossover operators proves to be most successful. Especially the crossover operator alone is not able to find good weight settings as fast as in combination with mutation.

The high number of encoding bits increases the performance considerably with hardly any increase of computational cost. An optimal range of weights is $(-20, 20)$ for the sine function, independent from the number of encoding bits. This range also resulted in good performance on other problems.

A large generation size and the use of a distributed genetic algorithm has also shown success. These strategies decrease the possibility of getting stuck in local minima and preserve the diversity among the individuals of the population.

However, the introduction of gray coding was not satisafactory, since no performance improvement could be observed for neither boolean nor real-valued functions.

Also, the Baldwin effect has no significant impact on the genetic search. The search space seems to be continuous enough, so that no further guidance by NN training is required. Hence back-propagation learning during the run of the genetic algorithm can not be considered as a reasonable strategy. However, back-propagation may be used to fine tune a weight setting that was evolved by the genetic algorithm, after it finished.

Genetic weight evolution does not scale up. Also, the preferred use of the mutation operator in small networks suggests that the genetic algorithm is not able to profit from its ability of parallel hyperplane sampling. Obviously, the sequential coding of weights does not sufficiently provide bit patterns, that can be exploited by the GA. There are multiple ways the weights can be set in order to solve a given problem. So, the genetic algorithm rather works as a genetic hillclimber.

In conclusion, the application of GANN systems for weight Optimization is reduced to the field of small networks, especially for control or other tasks, for which no error feedback exists. Since genetic algorithms operate on simple fitness, i.e. quality evaluations, they can be applied to a larger class of problems. Back-propagation training requires the information of a target output and cannot be used in a couple of control tasks.

Architecture Optimization

Even simple weight-based encoding shows promising results for the task of architecture optimization. Consistent progress can be observed in a small number of generations, when the problem of a noisy fitness function was able to be overcome by a sufficient number of training processes.

However, architecture optimization by a GANN system comes with a extremely high computational cost. If only one specific problem has to be examined, the search for a good architecture using a genetic algorithm can hardly be justified. Using a relatively bad architecture and spending computation time on excessive training will yield better results.

The application of GANN architecture optimization is feasible, if the goal is a good topology for a large class of similar problems. In these cases, the high computation time is justified, since it has to be performed only once. Then, for a particular instance of the problem the optimized architecture can be used.

Outlook

So far, many ideas regarding encoding strategies have been published. Also, a couple of empirical studies have produced intuition for the application of genetic algorithms to neural networks. This field, however, lacks attempts to create a theoretical account. A few principal properties - such as the structural-functional mapping problem - have been proposed, but the discussion of these is purely based on the interpretation of different empirical results.

GANN systems have already been applied to a couple of real world tasks. Future work should focus on robust GANN systems that can be used for commercial applications. The range of applications has been outlined.

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The symbol * indicates that I did not use these sources for this thesis, although I refer to them in the text.