

COMMERCIAL APPLICATIONS OF NEURAL NETWORKS

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Abstract

Direct your Research towards Promising Areas.

This work is directed to researching engineers, who are not only interested in pure research, but also in the question, how one's development can be applied in real-life - how it can be used. We want to direct our research towards promising areas. To do that three questions were answered: (1) What kind of tasks are our inventions supposed to fulfil in commercial applications? Numerous commercial applications were analysed for this work and eleven task-oriented areas of application identified. From those "classification" was twice as often carried out than any other task and it seems clear, that "interpretation of information" is what neural networks are mainly used in commercial applications. (2) But what are the general strengths and issues of neural networks in commercial applications? What are their successes? This work reveals, that neural networks have indeed been successful, but although they have a lot of unique strengths, their weaknesses have to be addressed to be successful in the future. (3) So what about the future of neural networks? This question will be answered, by looking into past and present research and identifying three major types of neural-network-research, each with different impact on commercial applications. We conclude by deriving guidelines, that can help the reader direct his further research towards promising areas.

Zusammenfassung

Lenken Sie Ihre Forschung in vielversprechende Bahnen.

Diese Arbeit richtet sich an forschende Ingenieure, die sich nicht nur für reine Forschung interessieren, sondern auch die Frage stellen, ob und wie ihre Arbeit in der realen Welt umgesetzt und verwendet werden kann. Schließlich wollen wir unsere Forschung in vielversprechende Bahnen lenken. Um dies tun zu können, sollen drei Fragen beantwortet werden: (1) Welche Aufgaben sollen unsere Entwicklungen in kommerziellen Anwendungen erfüllen? Zahlreiche kommerzielle Anwendungen wurden für diese Arbeit analysiert und elf aufgabenorientierte Anwendungsbereiche identifiziert. Mehr als doppelt so oft als jede andere Aufgabe wird "Klassifikation" ausgeführt und es scheint offensichtlich, dass Neuronale Netze in kommerziellen Anwendungen in erster Linie zur Interpretation von Information verwendet werden. (2) Doch was sind die grundsätzlichen Stärken, Schwächen Neuronaler Netze in kommerziellen Anwendungen? Wie groß ist ihr Erfolg? Diese Arbeit zeigt auf, dass Neuronale Netze in der Tat erfolgreich sind, aber obwohl sie einzigartige Stärken haben, müssen ihre Schwachstellen behoben werden, um in der Zukunft erfolgreich zu sein. (3) Wie also steht es um die Zukunft Neuronaler Netze? Diese Frage wird unter Beachtung der Vergangenheit und Gegenwart der Forschung beantwortet. Drei Forschungsrichtungen können identifiziert werden, jede mit unterschiedlicher Bedeutung für kommerzielle Anwendungen. Wir schließen diese Arbeit mit Richtlinien, die dem Leser helfen sollen seine weitere Forschung in vielversprechende Bahnen zu lenken.

Contents

1	Introduction	5
2	Task-Oriented Areas of Application	7
2.1	Idea, Method and Results	7
2.2	Details and Examples	8
2.2.1	Modelling	8
2.2.2	System Control	8
2.2.3	Optimisation	8
2.2.4	Analysis	9
2.2.5	Clustering	9
2.2.6	Classification	9
2.2.7	Evaluation	9
2.2.8	Scenario Prediction	10
2.2.9	Strategy Planning	10
2.2.10	Time Series Prediction	10
2.2.11	Signal Processing	10
3	Assessment of Neural Networks in Applications	11
3.1	Strengths and Issues of Neural Networks in Business Applications	11
3.2	Success of Neural Networks in Commercial Applications	12
4	Progress of Neural Networks in Research and Applications	15
4.1	Historiography of Research and Applications	15
4.2	Research Approaches and their Meaning for Applications	16
5	Discussion and Conclusions	17
	Appendix	19
I	SyNAPSE, the IBM Cognitive Computing Project - a short description	19
II	Commercial Neural Network Software Solutions	19
III	Examples of Applied Applications	20
III.i	Modelling	20
III.ii	System Control	20
III.iii	Optimisation	21

III.iv	Strategy Planning	21
III.v	Analysis	21
III.vi	Clustering	21
III.vii	Classification	22
III.viii	Scenario Prediction	23
III.ix	Time Series Prediction	24
III.x	Signal Processing	24
IV	Examples of Future Applications	24
IV.i	System Control	24
IV.ii	Classification	25
IV.iii	Scenario Prediction	26
V	Examples of Researched Applications	26
V.i	Modelling	26
V.ii	System Control	27
V.iii	Optimisation	27
V.iv	Strategy Planning	27
V.v	Clustering	28
V.vi	Classification	28
V.vii	Evaluation	30
V.viii	Scenario Prediction	30
V.ix	Time Series Prediction	31
V.x	Signal Processing	31
	List of Figures	33
	Bibliography	35

Chapter 1

Introduction

Besides pure research, engineers aim for applicable development. In order to invest time and money in promising areas, it is essential to know what others work on, what already works in real-life and where the journey might be going.

Reviewing neural network (NN) applications, one likely tries to answer one of the following questions.

- ▶ *Where* does the application come from (e.g. medical, productive, financial sector)?
↔ The answer is mainly interesting for professional from those sectors, less for the NN-engineer. Most reviews cover only one sector, trying to answer this question. Paplik et. al review NN applications in medicine ([PMS⁺98]), Haque et. al in power systems ([HK05]) and Vellido et al. in the business sector ([VLV99]).
- ▶ *How* does the NN work (e.g. supervised MLP or unsupervised Kohonen SOM)?
↔ Scientific books cover this topic pretty well.
- ▶ *What* task is the NN supposed to fulfil (e.g. evaluation or data compression)?
↔ This is most important in order to see ones work applied in real-life.

Besides answering this last question, the contributions of this work are:

- ▶ We identify in chapter 2 the tasks neural networks have been used for in commercial applications. For that we take different industry sectors into account. Examples of real-life applications of neural networks are given. This will help the reader to identify research directions, that are promising for commercial applications.
- ▶ We present some of the most mentioned strengths and issues of neural networks, refer to solutions given by various researchers and report of the success of neural networks in chapter 3. This will help the reader to intentionally use NN-strengths to his advantage on the one hand and address problems on the other hand.
- ▶ We give an historic overview of research and applications of neural networks in chapter 4, because “Those who cannot remember the past are condemned to repeat it.” [San06]. From the present research we derive three types of research and their meaning for commercial applications, enabling the reader to classify his work or to intentionally decide for a type.

Chapter 2

Task-Oriented Areas of Application

2.1 Idea, Method and Results

This paper aims to answer the question what kind of task a neural network application fulfils. For that several paper were read by the author and the function of the networks within the applications identified. From those functions task-oriented groups were defined. Within a group, the architectures of those networks are not necessarily the same, nor are they diverse between groups, but the distinction is the task they fulfil. The author of this work defines the groups as follows.

Modelling: NN models a complex system by samples.

System Control: NN controls a technical system.

Optimisation: NN minimises a cost functional respect to optimise parameters.

Analysis: NN breaks down a complex subject for better understanding.

Clustering: NN finds categories within a group of samples. Samples within a cluster a similar, samples between cluster unsimilar.

Classification: NN qualitatively identifies whether / to which category a sample belongs.

Evaluation: NN determines an object's quantitative properties.

Scenario Prediction: NN predicts a future scenario from a present scenario state.

Strategy Planning: NN recommends an action for a present scenario state.

Time Series Prediction: NN predicts a series of events from past series of events.

Signal Processing: NN converts signals or data.

Similar groups have been identified by other others: Paplik et. al defined (1)modelling, (2)signal processing, (3)system control and checking, (4)classification and (5)prediction for medical applications in [PMS⁺98]. Widrow et. al group in [WRL94] applications, that have been installed in various industry sectors, in (1)pattern classification, (2)prediction and financial analysis and (3)control and optimisation.

From figure 2.1, one is able to derive, that most applications are found in the area of classification and the related fields of prediction and strategy planning.

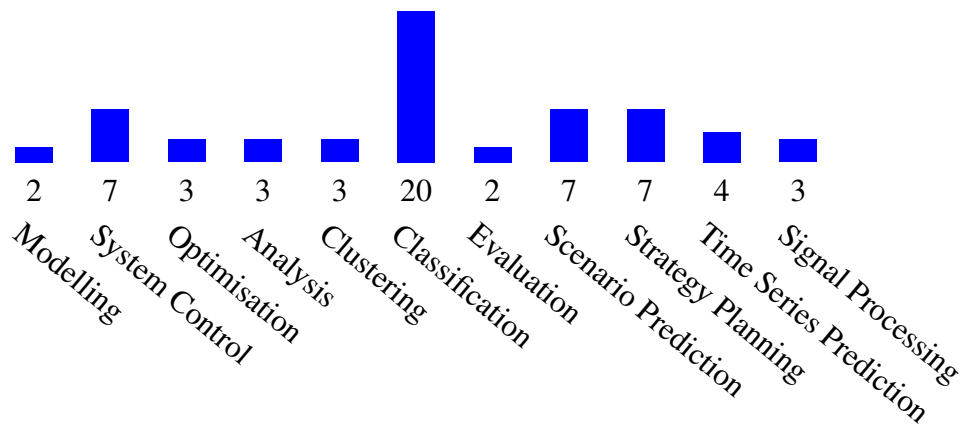


Figure 2.1: Number of the commercial applications found for this work. Not all are also mentioned as examples.

2.2 Details and Examples

2.2.1 Modelling

is used to represent a real-life system. The model can be used for example in a simulation or in a system controller.

Commercial Example: Aston Martin uses an adaptive neural network in their DB9's V-12 engines to prevent misfiring, which is common in those kinds of cars. [Blo04]

2.2.2 System Control

is about the control of technical systems as the subject of control systems engineering.

Commercial Example: For AEG's washing machines neurofuzzy control measures the load and controls the amount of water needed, saving about 20% water and energy [LVE00, chapter 11].

2.2.3 Optimisation

is the mathematical task to optimise parameters in respect to a given cost functional, that has to be minimised.

Commercial Example: Glidden Co. and other companies successfully optimised their chemical formulations with neural networks, formulating an adhesive product [WRL94, page 95].

2.2.4 Analysis

is the process of breaking a complex issue into smaller parts to gain a better understanding of it.

Commercial Example: PFC Energy performs quantitative analysis on the complex interactions in energy markets, including natural gas and oil prices - “making sense of a complex world” [Neu12d].

2.2.5 Clustering

is a type of unsupervised learning. It has the task to divide a set of objects into groups, so called clusters. In those clusters objects are supposed to be more similar to each other than to objects in other clusters. Criteria for the similarity are set by the architect of the system. Clustering is also called Cluster analysis. Data Mining falls in the same category.

Commercial Example: Megaputer build their TextAnalyst, which is able to cluster text by breaking links representing weak relations in the original Semantic Network [AK].

2.2.6 Classification

is the supervised method which identifies to which category or categories a new object belongs to. It is a qualitative analysis. Diagnostic is a form of Classification.

Commercial Example: Classification is the biggest neural network topic: Beer quality has been classified in some breweries, based on chemical readings [Pel04]. Homicide ([Cri12]) and drug crimes ([WRL94]) have been fought. Machine written, hand written and cursive identified, helping Wyoming to save 300,000\$ per year from late deposited checks [WRL94]. Sharp Corp. even managed to recognise Japanese characters [Ham93].

2.2.7 Evaluation

is the systematic determination of an object’s quantitative properties, as size, merit or significance, based on a set of standards and rules. While a classification determines the membership to a category, thus being foremost an qualitative analysis, an evaluation determines quantitative values of the object of interest.

Commercial Example: M P Murphy & Associates Pty Ltd evaluates athletes with neural networks in order to recommend selections based on required player or team composition to sport clubs, resulting in reportedly 57% less injured player [Neu12f].

2.2.8 Scenario Prediction

is about foreseeing what kind of scenario will be the outcome from a given situation. Scenario Prediction takes the state of a reference system in one point of time into account to foresee the future of a system which can be the reference system or a system that is depends on the reference system. Prognostics is a form of Scenario Prediction.

Commercial Example: Neural networked based financial forecasting and portfolio management enables many investment firms and banks to earn higher returns from their investments. Citibank's Andrew Colins claimed to have a 25% raise in return [WRL94].

2.2.9 Strategy Planning

is the task to give a recommendation what kind of strategy to choose in regard to the current situation. While Scenario Prediction is an instrument of observation, Strategy Planning anticipate an intervention into the system of interest.

Commercial Example: Alyuda (Tradecision) and NeuroDimension (TradingSolutions) developed software which helps traders to plan their stock trading strategy [Aly12] [Neu12a]. Reports¹ claim returns from 31% in six up to 120% in one month.

2.2.10 Time Series Prediction

is about foreseeing how a series of events will develop in the future. In opposite to Scenario Prediction, Time Series Prediction many previous system states into account to predict the same systems states in the future in one or more time steps.

Commercial Example: Neurobat has been building a system, that predicts the anticipates the temperature in building in order to control it ideally [Bar12]. The system won multiple prizes and reports² claim energy saving from 28% up to 65%.

2.2.11 Signal Processing

is about conversion signals or data into different formats, dimensions etc. to be further processed. Data Processing falls into the same category.

Commercial Example: Data Compression, especially image compression, has been one of the big topics of neural networks [HM10].

¹<http://www.tradingsolutions.com/news/interviews.html>

²<http://www.neurobat.net/de/produkte>

Chapter 3

Assessment of Neural Networks in Applications

3.1 Strengths and Issues of Neural Networks in Business Applications

Strengths and issues of neural networks have been collected by Vellido et al. in [VLV99] and summarised in figure 3.1. One may notice, that the number of quotes of strengths is 132 to 94 of the issues. To address the issues, several methods have been introduced. The numbers in the following list relate to the number of the according issue of figure 3.1.

1. In [LVE00, chapter 2] NeuroRule is introduced, which is able to derive rules from the trained neural network, that give an explanation how the neural network works. Using those rules, *instead* of the neural network, an accuracy very close to that of the network is reached, making the “black box” successfully transparent.
2. With pruning a deliberately too large chosen neural network is reduced to a network with far less neurons and synapses - see [Set97], [Tho], [Kar90] and [GT94] (improvement of [Kar90]). Another technique is to let genetic algorithms design both the network’s weights *and* architecture [Bra95], [LLLT03], [Kri07].
3. Most of the time Error-Back-Propagation is used to train neural networks, but as [Wil10] describes, other methods train neural networks up to 1000 times faster - for all kinds of neural network architectures.
3. One of the reasons of high training time is due to the von Neuman structure of conventional computers. For the completely different neural computing, Thakoor et al. examine in [TMLK87] different kinds of hardware implementations. More are presented in [MT98, section 11.7] and [Wil97, section 6.4]. Nevertheless, one has to admit their economical issues, see [Lin]. For a list of NN-chips see [Lin12].
4. To avoid this problem, not only the task, but also the amount of available training data has to be considered, when choosing the architecture: less weights are the key. To reduce weights, especially pruning (see above) is useful.

4. Often MLP are used, which often require considerably more weights than recurrent networks. Why and how later can be effectively trained is described in [Wil10].
6. In order to find out, which kind of input-data to choose, [BLS96] introduces and compares three methods. Genetic algorithm delivers the best results. However, the amount of data is indeed still a big issue. In the author's opinion it is actually the biggest problem in real-world settings.
7. In order not to converge into local minima, one can either use methods to get out of local minima - as simulated annealing ([Rut89], [KMR97, section 7.3]) or Mean Field Theory ([PA87]) / MFT Tunneling ([Gal12]), or one can search globally from the start with methods as genetic algorithms [Bra95], [LLLT03], [MD89].

3.2 Success of Neural Networks in Commercial Applications

As demonstrated in section 2.2 and at various parts in appendix III, neural networks have shown to be very useful in commercial applications: Several reports claim, they often perform better than conventional methods. They reduce costs and errors [WRL94] and increase returns¹. Up to 25% of project time and cost could be saved by METRIA Miljo-analys with neural networks in satellite imagery projects [Neu12e]. In medicine neural networks reduced cost and waiting time by reducing the response time for authorisations to minutes [Neu12h]. Students in risk of failing have been identified for further support. The overall success rate could be increased by 8% [Neu12c]. Neural Network have been predicting snow fall 75% to 183% better than the next best approach [Neu12g]. Local scour downstream of hydraulic structures have been predicted and explicitly formulated with neural networks, "saving a lot of time compared to other conventional numerical methods" and achieving 99% correlation with experimental results [Neu12b]. Neural networks helped reducing athletes' injuries [Neu12f] and even safe lives by preventing accidents ([Neu12i]).

Those reports however have to be treated with a little caution, since the failures of neural networks in commercial applications are not reported and the positive reports often have an advertising character.

¹<http://www.tradingsolutions.com/news/interviews.html>

Strength	Issue
(31) 1. NNs are able to learn any complex non-linear mapping / approximate any continuous function.	(28) 1. NNs lack theoretical background concerning explanatory capabilities / NNs as “black boxes”.
(30) 2. As non-parametric methods, NNs do not make a priori assumptions about the distribution of the data /input-output mapping function.	(21) 2. The selection of the network topology and its parameters lacks theoretical background. It is still a “trial and error” matter.
(29) 3. NNs are very flexible with respect to incomplete, missing and noisy data /NNs are “fault tolerant”.	(11) 3. NNs learning process can be very time-consuming.
(15) 4. NN models can be easily updated /are suitable for dynamic environments.	(10) 4. Neural networks can overfit the training data, becoming useless in terms of generalisation.
(15) 5. NNs overcome some limitations of other statistical methods, while generalizing them.	(8) 5. There is no explicit set of rules to select a suitable NN paradigm / learning algorithm.
(5) 6. Hidden nodes, in feed-forward supervised NN models can be regarded as latent / unobservable variables.	(6) 6. NNs are too dependant on the quality / amount of data available.
(4) 7. NNs can be implemented in parallel hardware, increasing their accuracy and learning speed.	(5) 7. NNs can get stuck in local minima /narrow valleys during the training process.
(3) 8. NNs performance can be highly automated, minimizing human involvement.	(3) 8. NN techniques are still rapidly evolving and they are not reliable / robust enough yet.
(3) 9. NNs are specially suited to tackle problems in non-conservative domains.	(2) 9. NNs lack classical statistical properties. Confidence intervals and hypothesis testing are not available.

Figure 3.1: Strengths and issues of neural networks according to [VLV99]. The number of quotations is given in brackets.

Chapter 4

Progress of Neural Networks in Research and Applications

4.1 Historiography of Research and Applications

In figure 4.1 the numbers of published papers from 1952 until 2012 are given, derived from Internet searches. One can notice, that the number of publications is rising roughly exponentially until 1997 for publications found with Google-Scholar (red) and stagnates since then. The publication from IEEE (blue) on the other hand have had two times of exponential rising - once until the 1960's and later during the 1980's. Otherwise they also stagnate. It seems, that the progress of neural networks is high during certain phases, but otherwise rather slow. The historiography of neural networks shows that those "high phases" and "low phases" have been triggered by influential discoveries: Though the story began with Bain 1873 [Bai73] and James 1890 [Jam90], who proposed the needed preliminary theoretical base, modern neural networks were first defined 1943 by McCulloch and Pitts in [MP43]. Hebb postulated 1949 his learning rule in [Heb49]. Those first steps became the first prosperity (1952-1969), in which the MIT developed a digit recognising one-layer perceptron and Widrow and Hoff presented 1960 ADALINE in [WH60] - the first neural network widely applied commercial. When 1969 Minsky and Papert showed limitations in [MP], research funds were drastically cut, resulting in less publication and no conferences. Research continued with little exchange, leading to a diversity of architectures, [Kri07]. Kohonen presented his maps in [Koh82], Hopfield his nets in [Hop], laying the theoretical foundation for the upcoming renaissance of neural networks. When 1986 Rumelhart et. al published the backpropagation algorithm, an explosive development, like a renaissance, took place. Until 1990, only the financial sector widely use neural networks as commercial application, [WRL94, abstract]. Since then more and more neural networks have been applied in the industry, but the adoption is going slow and cautious and rather conservative neural networks are used instead of the newer generations.

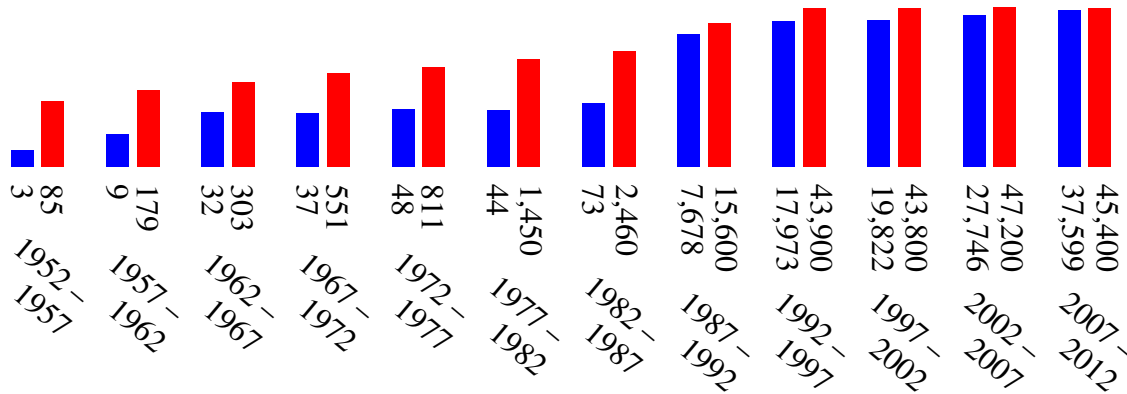


Figure 4.1: Statistical overview of the number of hits on IEEE for the search term “neural network” (blue) and on Google Scholar for the search term “artificial neural network” (red) for specific years of publication. The length of the graphs is displayed in the common logarithm of the hits.

4.2 Research Approaches and their Meaning for Applications

In the progress of neural networks, three different approaches have been applied and will be applied in the future.

1. The researcher tries to improve existing techniques from a practical angle.
2. The researcher tries to raise the level of biological realism of the network.
3. The researcher tries to combine the network with other techniques in a new way.

The first two are closer to development, while the third is mostly pure research. For the aspect of hardware implementations, the reader may be referred to [MT98, section 11.7], [Wil97, section 6.4], [Lin] and [Lin12]. The in chapter 3 described techniques belong into the category 1. Both the industry and provider of NN-software are rather conservative. For neural networks to be used, they need to reliably “get the job done”. Thus research that improves existing networks, is more likely to be used in real-life applications, than research from category 2. Raising biological realism, new generations of neurons and neural networks rose. The first generation had been McCulloch-Pitts threshold neurons [Maa97]. Depending on literature, the second generation have been neurons with continuous activation function or the Boltzmann machine. Spiking neurons [Vre03] are considered the third generation. Currently scientists at SyNAPSE, see appendix I, develop a neural network of such magnitude, that it itself might be considered a new generation. Though being important for progress, this type of research can not expect to be applied in the foreseeable future. Research of category 3 takes into account that, neural networks have always been combined with other technologies in applications, [Lin]. Thus it is most essential for the implementation of neural networks in applications. Examples are fuzzy logic, mentioned in section III.iv, or genetic algorithms, see [Bra95], [LLLT03], [MD89].

Chapter 5

Discussion and Conclusions

From the previous chapters, we draw conclusions (bold) for application-oriented research:

- ▶ While a lot of research has been done in the field of neural network, far **fewer commercial applications exist**¹. Nevertheless, where they have been applied they have been **proven to be useful**. To increase the usage of neural networks, developer need to **take user demands seriously**.
- ▶ From both the commercial applications and from the in II presented programs, it can be concluded, that mainly conservative systems are used, like MLP, and less newer generations. This shows how important it is to deliver systems that are **well-proven, stable and robust** for industry. Systems should **work in various situations** and not just in the lab under ideal conditions.
- ▶ The in chapter 3 mentioned mentioned **critics have to be addressed** thoroughly, instead of creating more complex networks, that increase issues like the “black box”-disadvantage and are even less robust. Already presented **solutions should be followed**, when useful.
- ▶ It seems that some developers on the science end miss to take industries demands into account, while some developers on the commercial end, do not consider implementing science good ideas. An **open mind to the new and open conversation should be encouraged**.
- ▶ Neural networks are great systems that can help save a lot of money, increase return, even safe lives by preventing prevent accidents ([Neu12i]), thus **worth researching**. But they are still **only tools**, that work only embedded in greater systems. Thus they should be researched that way and **not isolated developed**.
- ▶ From the eleven areas, presented in chapter 2, graphic 2.1 shows that classification is the task most often performed by neural networks. Taking the follower into account, it seems reasonable to conclude, that neural networks have been used mainly in **interpretation of information**, which might be worth putting emphasis on.

¹But one should take into account, that a lot of companies don't advertise their usage of neural networks, due to reasons of competition. Calera for example started using neural networks in 1986, but did not acknowledge the usage until 1992 [WRL94, page 94]

Appendix

I SyNAPSE, the IBM Cognitive Computing Project - a short description

In SyNAPSE, the IBM Cognitive Computing Project, the so far most impressive step is taken. Combining Neuroscience, Supercomputing and Nanotechnology, researchers from all different kind of field build a neural network exceeding the scale of a cat cortex [AESM09], with 10^9 neurons, 10^{13} synapses and a training algorithm that increases and decreases weights depending on the number of spikes, that went via that synapse and is far closer to the biological principle than any other training algorithm before [Pro12]. However, although the goal of the project is very ambitiously to create a computer that thinks like a human, applications are actually quite pragmatic. One of the key phrases is the “Smart Planet”, which refers to the idea of collecting all kind of scientific global data and draw conclusions with them with the “artificial brain”. An example for application is to measure temperature, wave height etc. on the ocean and calculate the risk and outcome of tsunamis.

II Commercial Neural Network Software Solutions

There are several commercial neural network software solutions. Some may be mentioned at this point. Links are provided.

Alyuda: <http://www.alyuda.com/neural-networks-software.htm>

Investox: <http://investox.de/Investox/InvestoxVersionen.htm>

Mathlab: <http://www.mathworks.com/products/neural-network/index.html>

NeuroSolutions: <http://www.neurosolutions.com/>

Palisade: <http://www.palisade.com/neuraltools/>

Peltarion: <http://www.peltarion.com/products/synapse/>

Tradecision: <http://www.tradecision.com/>

TradingSolutions: <http://www.tradingsolutions.com/>

Wardsystems: <http://www.wardsystems.com/>

III Examples of Applied Applications

III.i Modelling

Production Industry

General Motors successfully modelled subjective customer ratings of automobiles based on their dynamic characteristics, thus helping engineers to tailor cars to the market [WRL94, page 96].

III.ii System Control

Production Industry

Dopant concentration and deposition thickness errors of **semiconductor process control** were cut in less than half using neural networks in solar cell manufacturing [WRL94].

A software package of Pavilion Technologies is in **chemical process control** in use, that reduces waste, improve product quality, increases plant throughput [WRL94].

Also in **petroleum refinery process control**, product quality has been improved with a neural network, trained with about 1500 samples, by correcting errors in advance [WRL94, page 95].

Continuous-casting neural network control during **steel production** is implemented in Japan in order to reduce spillage of molten steel. The system reduced costs by several million dollar [WRL94, page 96].

Products

For AEG's **washing machines** neurofuzzy control measures the load and controls the amount of water needed [LVE00, chapter 11].

Automotive

Watching humans drive, ALVINN, the self-driving car, has been able to learn how to drive, thanks to an implemented single hidden layer back-propagation neural network. It is able to drive autonomously long distances at normal highway speed (up to 70 mph), negotiating through traffic without human interactions. The network was trained on images of the road under a variety of conditions and the appropriate steering modification for each condition. When driving an on-board camera provides the input for the neural network, which gives the steering command as output [WRL94, page 99], [Rob12].

III.iii Optimisation

Production Industry

In scrap steel melting **electric arc furnaces**, neural networks position electrodes, increasing furnace throughput and reducing electrode wear and electricity consumption [WRL94].

The **food and chemical formulation** was optimised successfully with neural networks, formulating a adhesive product [WRL94, page 95].

III.iv Strategy Planning

Financial Sector

As one of the most well know applications for neural networks, Banks and consumer credit reporting agency use all kinds of **loan approval** systems, for some time also neural networks have become a compatible method. Equifax for example build a radial basis function and ridge polynomial network using a genetic algorithm. Npower Ltd. build a neurofuzzy system with Inform GmbH's fuzzyTECH², implemented amongst others at BMW bank [LVE00, chapter 6, 7, 11], [WRL94], [Rob12].

III.v Analysis

Natural Language Processing

In order to process natural language, the company Megaputer developed a system using artificial intelligence and dynamically growing recurrent neural networks and Hopefield networks [AK].

III.vi Clustering

Marketing

In their marketing, British Airways, as well as other airlines, try to use customer data to increase their understanding of the customer's requirements, in order to tailor their products to them in and thus being strengthen the customer-airline relationship. To do so 260,000 customers where asked over 150 questions, from which 12,000 records and 60 questions were used to train a Kohonen self-organising map, which clustered the customers into 16 groups. In conjunction with additional knowledge a personalise mailing list could be derived. [LVE00, chapter 1].

²<http://www.fuzzytech.com>

III.vii Classification

Medicine

Neuromedical Systems Inc. uses neural networks in electrocardiographs and pap smear systems, used in **cancer recognition** [WRL94].

Production Industry

Fault detection with neural networks has also been done in the **chemical processes industry** [WRL94, page 95].

Human Sensory Simulation: Character, Speech, Smell Recognition

Machine-printed character recognition has been implemented by various companies and been described a lot in literature, both for Latin and Asian letters, as for example Japanese characters from Sharp Corp. [Ham93], for which a network with about 10 million weights was used in a variant of a Kohonen's LVQ algorithm was used. An example is an application which transforms faxes into software documents. Apparently the neural network has outperformed conventional methods. [WRL94].

Since handheld devices like Palm Pilot or smart phones became popular, the need for **handwritten characters recognition** got immanent, for which neural networks can be trained. Thanks to handwritten character recognition Wyoming saves 300.000 dollar per year [WRL94], [Rob12].

Financial Sector

Credit card fraud detection is one of the earliest applications of neural networks and since it is a still growing threat to industry, it is not likely to decrease in importance. [WRL94], [LVE00, chapter 7, 9].

In order to **detect different kinds of fraud in mobile telecommunications**, a consortium of well-know organisations build the neural network system ASPeCT [LVE00, chapter 8]. Nestor Inc. developed a system based on a radial function neural network to **detect money laundering** [LVE00, chapter 10].

Production Industry

Neural networks have been used for **quality control** in large number as for detecting contaminant-level from spectroscopy data in chemical plants, to classify defects in loud-speakers, to evaluate orange juice purity or in vision computers neural recognition features in factories. [WRL94].

Research Facilities

In CERN, neural networks have been used to detect interesting events in **particle accelerators**, thus letting scientists concentrate on those events instead wasting time on meaningless events [WRL94].

Oil and Gas exploration

Oil companies use neural networks in **petroleum exploration** to determine the locations of underground oil and gas deposits [WRL94].

Crime Fighting

In the US-Government's war on drugs, neural networks are used for **drug identification**. The system is even able to recognise the batch a sample of cocaine is originates from [WRL94].

The CATCH (Computer Aided Tracking and Characterisation of Homicides) program is able to learn from information of existing crimes, as the location and characteristics of the offence and is able to give support for the investigators in order to catch the killer [Cri12].

Financial Sector

Foster Ousley Conley evaluates the value of **real estates** in California with neural networks [WRL94].

III.viii Scenario Prediction

Financial Sector

Used by many investment firms, neural network based **financial forecasting and portfolio management** enables investment firms and banks to earn higher returns per year from their investments [WRL94].

Marketing

In **marketing analysis**, the neural networks are used to determine which unlikely future customers to remove from a list of potential customers or who to send mail order catalogues. Spiegel's director of market research expected to save that way at least 1 million dollar per year [WRL94].

Neural networks are used to to allocate **airline seating** fro carriers including Nationair Canada and USAir [WRL94].

Chemical Processes Industry

In chemical processes industry, process performance has been predicted [WRL94, page 95].

Whether forecasting

At the National Wether Service in the USA, a neural network has been implemented, which is 75% to 183% better than the next best approach [Neu12g].

III.ix Time Series Prediction

Financial Sector

Since **stock market prediction** can not follow a set of simple rules, neural networks seem a good choice of tool. In fact they have been successfully trained to examine and sort out lot of information, predicting the stock market's movements to a certain degree [Aly12], [Rob12].

Aircraft performace

Npower Ltd. developed a system for the UK National Air Traffic Control to predict **aircraft track performances**, given a current height [LVE00, chapter 11].

III.x Signal Processing

Data Compression

Data Compression, especially **image compression**, has been one of the big topics of neural networks [HM10], [LVE00, chapter 5], [Rob12].

IV Examples of Future Applications

IV.i System Control

Military

In **missile guidance and detonation** as well as other military applications, neural networks have shown to have an enormous advantage towards conventional methods, when fast decisions are required [WRL94, page 96].

It is not clear whether a system for **fighter flight and battle pattern guidance** based on neural networks is already operational, however advanced tactical fighter based on real-time predictions of the immanent actions of an enemy aircraft are claimed to be developed [WRL94, page 96].

Products

Controlling 69 piezoelectric actuators with a neural network, **optical telescope focusing** improves vision of small telescopes to rival big ones by compensating atmospheric disturbances [WRL94, page 96].

The **voltage control of copiers** could be successfully improved with neural networks in order to preserve uniform copy quality. Temperature, humidity, time since last copy, time since change in toner cartridge and other variables have been taken into account [WRL94, page 96].

Automotive

Neural network based **vehicular trajectory control** has been applied to back up a computer-simulated trailer truck. Regardless from initial conditions, the truck is able to learn of its own accord. [WRL94, page 96].

Ford Motor Co., General Motors and other automobile manufactures are researching neural network application in various areas as anti-lock brake control, active-suspension control and idle speed control [WRL94, page 96].

IV.ii Classification

Medicine

According to Professor Roberts from Stanford University, neural networks have gained attention in the area of **cardiopulmonary diagnostics**. Data as heart rate, blood pressure, breathing rate, etc. are included into models. The neural network merges the different model into a complete conceptual picture and diagnoses the patient's condition based upon the models. However this seems to be in a proof-of-concept stage [Rob12].

Production Industry

Engine fault detection and diagnosis in the **automotive industry** is researched [WRL94, page 96].

Human Sensory Simulation: Character, Speech, Smell Recognition

Speech recognition has been on the market for quite a while. At Stanford Research Institute a neural network combined with hidden Markov models and other technologies was highly successfully designed, recognising different speakers. [WRL94, page 96].

Inspired by the idea of an **artificial nose**, a chemical sensing system, such as a spectrometer, translates an odour that can be used as an input for an neural network, which identifies the chemical. Several applications were listed by the Pacific Northwest Laboratory: In the environment, toxic waste or household odours can be identified, fuel mixtures analysed, oil leaks detected, air quality or factory emission monitored and ground water

for odours tested. In medicine odours can be examined for diagnosis, as to detect tuberculosis. In the food industry, perhaps the biggest practical market, food and fish can be inspected and it's quality graded, fermentation or flavors controlled, mayonnaise for rancidity checked, cheese ripening monitored, verified if orange juice is natural, beverage containers inspected and whiskey graded [Rob12].

Research Facilities

The neural network MSnet was trained for **mass spectra classification** and is able to classify mass spectra more reliably than other methods reported in the literature, is faster than nearest-neighbour techniques and it's output can easily be combined with other information sources [WRL94].

IV.iii Scenario Prediction

Medicine

An especially promising application area of neural network based prediction is **drug development**. Here the medicinal properties of substances are to be predicting without expensive, time-consuming and often inhumane animal testing. For cancer drug testing this has already been successfully applied [WRL94].

Patience mortality prediction has been done with neural networks [WRL94].

Production Industry

Neural network based **electric motor failure prediction** developed by Siemens showed a 80% to 90% accuracy, compared to 30% accuracy of conventional methods. [WRL94].

V Examples of Researched Applications

V.i Modelling

Medicine

Since neural networks are a bionic technology that is modelled after the nerve system of mammals, nothing comes more natural than to use neural networks to simulate and model the functions of the brain and neurosensory organs [PMS⁺98, table 1].

But also other physical mechanism were modelled [PMS⁺98]: In **Cardiology**, heart rate regulations were modelled with neural networks.

In **Otorhinolaryngology**, hearing was effectively modelled with neural networks, thus helping to understand, model and treat speech and hearing impairments.

In **Biochemistry**, the laws of the mechanism to structure relationship of primary protein structure to the features of complex organisation are unknown. However it was possible to represent amino acid sequences with neural networks.

V.ii System Control

V.iii Optimisation

Power Systems

The main goal of **economic dispatch** is to minimise the non-convex operating costs depending on demand and subject to constraints. Various methods have been applied so far, but methods as the Lagrangian multiplier method can not be directly applied any longer. For practical-size systems methods as dynamic programming became unpractical due to the curse of dimensionality. For genetic algorithms and tabu search, it is difficult to define a proper fitness function, one has the risk of ending up in a local minimum and the search time is considerable long. Neural networks, especially Hopfield networks, are capable of solving such a combinational optimisation problem, though Hopfield networks have the drawback of a low converging speed. Especially neural networks based on genetic algorithm and fuzzy systems became attractive recently [HK05].

Production Industry

Since identification and classification of geometrical features is not enough to successfully predict a suitable milling path strategy, an the technological parameters of **milling machines** need to be optimised. This is done in [Bal04] by a multilayer neural network.

V.iv Strategy Planning

Medicine

In Medicine, neural networks have been used to intelligently control and check machines based on responses of biological or technical systems given to any signals [PMS⁺98, table 1].

In **Oncology** therapeutic strategies have been selected for breast cancer treatment [PMS⁺98].

In **Otorhinolaryngology** the parameter settings of hearing aids have been optimised [PMS⁺98].

Production Industry

To predict a suitable milling strategy for **milling machines**, [Bal04] introduces a self-organising model (SOM), which learns from cases. The output of the SOM is a probabilistic value which indicates the milling strategy that fits best to the constraints. The input layer of the neural network receives the coordinates of points obtained from the CAD model for individual types of machining operation, while the output layer of the neural network (not yet the whole SOM) are new points, representing the tool path for each machining operation.

V.v Clustering

Marketing

The **segmentation of the e-commerce consumer market** with a Generative Topographic Mapping is discussed in [LVE00, chapter 3].

V.vi Classification

Medicine

The general goal of neural networks in medicine is to interpret physical and instrumental findings to achieve more accurate diagnosis [PMS⁺98, table 1].

In **cardiology**, serum enzyme level need to be analysed as a bases of acute myocardial infarction diagnosis. To do so neural networks have been trained by enzymatic data, EKG-phenomena, subjective symptoms and changes after administration of nitroglycerin. First the neural network was trained on 351 patients, likely to have myocardial infarction, afterwards 331 other patients were classified and the results compared with an experts opinion. The conclusion was that a system like that might be useful, but more tests are necessary [Bax91], [PMS⁺98].

One of the main challenges in **radiology** is the interpretation of the images made. Neural networks have helped to recognise alterations in during cold lesion detection. Another neural network system was able to detect one of seven coronary artery disorders, yet another one micro-classification on digital mammograms [PMS⁺98].

In **EEG analysis**, spontaneously occurring HVS-patterns and EEG patterns have been recognised with neural networks [PMS⁺98].

In **ophthalmology**, shape abnormalities of the cornea were diagnosed [PMS⁺98].

In **oncology and pathology** breast cancer was diagnosed [PMS⁺98].

Also in **pathology** tubular carcinoma from sclerosing adenosis are differentiated [PMS⁺98].

In **neurology**, neural networks assisted in diagnosing between Alzheimer disease and vascular dementia.

Images of **radiology** have been interpreted by neural networks, which is impossible for conventional rule based systems. The neural networks were used in noise filtering and recognition of unusual images. Newer decision supporting systems pre-process features of the image. The derived parameters are fed into the neural networks. Similar like expert systems, neural networks differentiate between leaver diseases based on ultrasonographic and laboratory findings, without the help of the networks the data would not be enough for a diagnosis [PMS⁺98]. Another example for classification in radiology is the classification of mammographic images.

In **pulmonology** neural networks have been proven to be less successful than conventional methods to classify solitary pulmonary nodules, but more successful than two well-trained experts [PMS⁺98].

In **cytology** cervical smears are automatically cytologically screened. Neural networks were implemented to recognise malignant cervical cells [PMS⁺98].

In **genetics**, chromosomes are classified with neural networks, and in **Biochemistry** superfamilies of proteins with ProCANS system [PMS⁺98].

Monitoring glaucoma by means of a neurofuzzy classifier is done by Npower Ltd. with fuzzyTECH in [LVE00, chapter 11].

Production Industry

A Kohonen self-organising map (SOM) was used in [Bal04] to connect surface patches into a grid to be able to configure the topology of the machining surface. Since this SOM has only one layer and predefined weights, no training is needed.

Power Systems

During a fault in power systems a lot of flags are raised and huge amount of data is produced, giving birth to the question where the original fault is and thus to **fault diagnosis / fault localisation**. To identify the event that causes the sequence of alarms, the operator needs help. Since the reasoning is of heuristic nature, artificial intelligence techniques as expert systems, fuzzy logic, genetic algorithms, petri nets and neural networks are considered. In the 90's the main attention was given to expert system, but they are not able to generalise and have the difficulty of validating and maintaining large rule-bases. The main advantage of neural networks for fault diagnosis is their flexibility with noisy data, their main drawback the long time that is required for training. To shorten the training time, general regression neural network, probabilistic neural network, adaptive neuro-fuzzy methods and selective back propagation algorithm were introduced [HK05].

For **security assessment** in power systems, real-time measurements are stored in a database and a security level (normal or secure state, alert or critical state, emergency or insecure state) is determined based on simulation. Due to the nature of the task, the system has the problem is subject to the curse of high dimensionality. To tackle this problem, either the number of contingencies and characterisation of the security boundaries is restricted (e.g. in supervised neural networks like MLP) or the dimension of the operating vector (e.g. in unsupervised NNs like Oja-Sanger networks) is reduced or the operating point into a reduced number of classes are quantified (e.g. with clustering algorithms like nearest neighbour or k-means). Since MLP with backpropagation are able to learn on-line, their training algorithm satisfies these conditions, but it has the two problems of which input data to choose and over-training. The first is solved by calculating the security indicator by the energy management system (EMS) as inputs to the NN. The second is solved through backpropagation with selective training algorithm. The main reason to use neural networks is the high dimensionality of the problems with many limitations and constraints, which is caused by growing power systems, energy demand and demand for reliable and secure energy. For faster calculation, often Hopfield networks are used in addition to MLPs [HK05].

V.vii Evaluation

Medicine

To improve **Intensive care**, alarm systems contain neural networks that simultaneously evaluate changes and interactions of physical, chemical and thermodynamical parameters. While the relations of these factors are incompletely unknown, the neural networks is able to indicate the necessity to react for caretaker [PMS⁺98]. In Anaesthetic Practice, neural networks support clinicians, making response much faster (17 sec. instead of 45 sec.), especially for less experienced and skilled clinicians [PMS⁺98].

During the **Analysis of ECGs** long term ECG recordings are evaluated in order to improve diagnostic accuracy. It was possible to achieve more faultless operation even in the presence of complicating factors [PMS⁺98].

In **Pathology**, breast carcinoma and astrocytomas are graded and prostate cancer spread evaluated [PMS⁺98].

In **Clinical chemistry**, results of chemistry analysers are evaluated and answers for unexpected events programmed [PMS⁺98].

V.viii Scenario Prediction

Medicine

In medicine neural network provide prognostic information based on retrospective parameter analysis [PMS⁺98, table 1].

In **gastroenterology**, the prognosis for hepatectomy was with a 100% accuracy determined. Here the patients' data was split into 54 training and 11 testing samples [PMS⁺98].

In **obstetrics and gynaecology** the teratogenicity of perinatal administered drugs has been determined with neural networks [PMS⁺98]. Lapeer et al. designed a networks that picks out perinatal parameters influencing birth weight [PMS⁺98].

Financial Sector

To predict **business bankruptcy**, a neurofuzzy model was used in [LVE00, chapter 4] and in [BLS96] it is claimed that bankruptcy prediction has been researched a lot since 1932.

Marketing

In order to **predict the propensity to buy** from the Internet channel, a Bayesian neural network was trained. The goal was to predict the propensity only by knowing little information about the consumer. The results of the neural network were not exhilarating but decent [LVE00, chapter 3].

Production Industry

For **milling machines** both tool path strategies and surface quality have been predicted in [Bal04].

V.ix Time Series Prediction

Power Systems

Load forecasting plays an important role in power system for development, expansion and planning as well as on an economic and financial level. Short-Term load forecasting (about 1 hour to 1 week) is needed to commit units efficiently, for economic dispatch, energy transfer scheduling and real time control. Methods so far included regression model, Kalman filtering, Box & Jenkins model, expert systems, fuzzy inference, neurofuzzy models and chaos time series analysis. Main limitations of some of those methods are, that they neglect some forecasting attribute conditions, it is difficult to find functional relationships between all attribute variables and instantaneous load demands as well as to upgrade the set of rules that govern at expert system and they are not able to adjust themselves to rapid nonlinear system-load changes. Neural networks solve those problem and take parameters as weather conditions, holidays, weekends, special sport matches days etc. into account. Mid-term load forecasting (about 1 month to 5 year) is needed to purchase the right amount of fuel for power plants after electricity tariffs are calculated. Long-term load forecasting (about 5 to 20 years) is needed to determine the right type and size of generating plants, minimising fixed and variable costs. The main advantages of neural networks are, that they are, firstly, conducted offline without time constraints and secondly without direct coupling to power system for data acquisition. Thirdly, they have the ability to adjust to inputs that have no functional relationship between them such as weather conditions [HK05].

V.x Signal Processing

Medical Filter

According to [PMS⁺98, table 1], neural networks have been used in **bio-electric signal processing** for bio-electric signal filtering and evaluation.

In **Otorhinolaryngology**, neural networks have been used for noise filtering, thus improving hearing aids [PMS⁺98].

Dimension Reduction and Data Visualisation

In order to be able to visualise high dimensional data, Kiviluoto et al. use Self-Organising Maps to break high dimensional data of **financial statements** into two or three dimensional space and visualise it afterwards [LVE00, chapter 5].

List of Figures

- | | | |
|-----|--|----|
| 2.1 | Number of the commercial applications found for this work. Not all are also mentioned as examples. | 8 |
| 3.1 | Strengths and issues of neural networks according to [VLV99]. The number of quotations is given in brackets. | 13 |
| 4.1 | Statistical overview of the number of hits on IEEE for the search term “neural network” (blue) and on Google Scholar for the search term “artificial neural network” (red) for specific years of publication. The length of the graphs is displayed in the common logarithm of the hits. | 16 |

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