Utilisation of embedded information devices to support a sustainable approach to product life-cycle management

UTILISATION OF EMBEDDED INFORMATION DEVICES TO SUPPORT A SUSTAINABLE APPROACH TO PRODUCT LIFECYCLE MANAGEMENT

by

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ABSTRACT

The huge landfills from solid waste generated by the massive utilisation of different products from domestic sources are badly affecting the environment. About 70% of the solid municipal waste, two thirds of which comprises of household waste, is dumped as landfill all over the world. For efficient product lifecycle management via upgrade, maintenance, reuse, refurbishment, and reclamation of components etc., storage of product related information throughout its lifecycle is indispensable. Efficient use of information technology integrated with product design can enable products to manage themselves in a semiautomatic and intelligent manner. It means that products themselves should contain information that what to do with them when they are of no use. More advanced products may locate themselves and communicate with their recyclers through internet or some other communication technology. This thesis investigates the possible technologies that can be used to store product lifecycle data; however, the main question that is addressed in this thesis is the possibility of deployment of an on-chip intelligent logic that can make product intelligent in the sense to predict its own lifetime against different usage modes. The other issue that is investigated in this thesis is the bi-directional communication between the product and its external environment in terms of information exchange. In addition to this, possibility of storing detailed maintenance logs into the product itself throughout its whole lifecycle has also been investigated. Different types of embedded information technologies are described in this thesis. These technologies are broadly classified as passive embedded information devices and active embedded information devices. Methods of automatic identification in combination with information technology can act as passive Embedded Information Devices (EID) to make products intelligent enough in order to manage associated information throughout their life cycles. Barcodes, Radio Frequency Identification tags, and a new technology called i-button technology are investigated as possible candidates for passive EIDs. The i-button technology from the perspective of product lifecycle management is presented for the very first time in the literature. Experiments demonstrated that RFID and i-button technologies have potential to store not only the static but dynamic data up to some extent, such as small maintenance logs. As passive EIDs are unable to store the sensory data and detailed maintenance logs regarding a product, therefore, in addition to these demonstrators for passive EIDs, an advanced active EID demonstrator for lifecycle management of products with high functional complexity is also presented. Initially, the idea is presented as smart EID system that records the sensory data of a refrigerator compressor and stores the detailed maintenance logs into the product itself. The idea of smart EID has successfully demonstrated the concept that detailed maintenance logs can be stored into the product itself. This idea is then extended as intelligent EID that is implemented on a gearbox in order to predict the gearbox lifetime under an accelerated life test. For this purpose, a gearbox test rig is explained that is used to conduct an accelerated life test of a gearbox by overloading a gearbox with the help of an electromagnetic powder brake. Further, it involves development of a novel on-chip life prediction algorithm to predict the gearbox lifetime under accelerated life testing scenario. The algorithm involves a combination of artificial neural networks and an appropriate reliability distribution. Results of accelerated life testing, simulation for the choice of appropriate reliability distribution and the life prediction algorithm are presented. The results prove that implementation of an efficient on-chip life prediction algorithm is possible with an averaged output error of 0.37%. Bi-directional communication software that is developed in order to retrieve lifecycle data from the intelligent EID and to keep intelligent EID updated is also explained. The developed software has successfully demonstrated the idea of bi-directional communication between the product and its external environment. Intelligent embedded information devices can be used to increase the lifetime of high cost industrial equipment e.g. machine tool, through predictive maintenance. Smart embedded information devices can be used to store product lifecycle data of white goods that are main source of end of life waste generation. Overall, embedded information devices can be proposed as a good solution to support a sustainable approach to lifecycle management.

Keywords: Embedded information devices, sustainability, product lifecycle management, artificial intelligence, life prediction.

"O my Lord! advance me in knowledge."

(Quran: Chapter 20: Verse 114)

To my parents Dr. Rashid Kamal and Farzana Kamal.

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GLOSSARY

ACA	Anisotropically Conductive Adhesives
ACSII	American Standard Code for Information Interchange
ANN	Artificial Neural Networks
ANSI	American National Standard Institute
API	Application Programming Interface
BOL	Beginning Of Life
BOM	Bill Of Materials
BSI	British Standard Institute
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
CAN	Controller Area Network
CART Analysis	Classification And Regression Tree
CCD	Charged Coupled Device
CDF	Cumulative Distribution Function
CMAC	Cerebellar Model Articulation Controller
CMMS System	Computerised Maintenance Management
CPI	Character Per Inch
CRC	Cyclic Redundancy Check
DBMS	Database Management system
EAN	European Article Number
EAS	Electronic Article Surveillance
EEPROM	Electrically Erasable Programmable Read Only Memory
EID	Embedded Information Device
ELDA	End of Lifecycle Design Advisor
ELIMA	Environmental Lifecycle Information Management and Acquisition
EOL	End Of Life
EPC	Electronic Product Code
ETSI	European Telecommunications Standards Institute
GLN	Global Location Number
GSM	Global System for Mobile communication
IMEI	International Mobile Equipment Identity
LCD	Liquid Crystal Display
LCDA	Life Cycle Data Acquisition
LED	Light Emitting Diode
MIPS	Millions of Instruction Per Second
MIS	Management Information System

MOL	Middle Of Life
MTBF	Mean Time Between Failure
MTTF	Mean Time To Failure
ONS	Object Name Service
OEM	Original Equipment Manufacturer
PDA	Personal Digital Assistant
PET	Polethylene Terphathalate
PML	Physical Markup Language
RAM	Random Access Memory
RFID	Radio Frequency Identification
RMS	Root Mean Square
ROM	Read Only Memory
RSS	Reduce Space Symbol
SAW	Surface Acoustic Wave
UCC	Uniform Code Council
UPC	Universal Product Code
WEEE	Waste Electrical and Electronics Equipment
WORM	Write Once Read Many
XML	Extensible Markup Language

Chapter 1

INTRODUCTION

1.1 Background and motivation for research

Heavy industrialisation in the past century has created negative impacts for the environment. This results in nature becoming unbalanced due to massive utilisation of resources and energy. The huge landfills of solid waste generated by the massive utilisation of different products from domestic sources are badly affecting the environment. About 70% of the solid municipal waste, two thirds of which consists of household waste, is dumped as landfill all over the world [1]. This waste includes various products like batteries, waste electrical and electronic equipment, chemicals, vehicle maintenance items, etc. It is reported that about 6 million tonnes/year of end-of-life electronic waste is disposed of by the European Union countries [2], with Nagel and Meyer [3] mentioning figures of between 6.5 to 7.5 million tonnes/year. This domestic waste, when disposed to landfill with the municipal solid waste, gives rise to various hazardous emissions like volatile organic compounds (VOCs) and liquid solutions of landfill called leachates. These leachates and VOCs are affecting underground water and air thus disturbing the overall ecosystem. This has resulted in the world being given new concepts of green design, eco-design [4], lifecycle design (LCD) or sustainable design. This involves design strategies for the whole lifecycle of the product by considering its impacts upon the environment involving various issues from acquiring raw material, manufacturing, utilisation, refurbishment or reuse to the final disposal of the product. Briefly, we can say that this involves design considerations with respect to the environment from 'the cradle to the grave' point of view. The concept of eco-design is welcomed by various companies, mainly electronics and domestic items manufacturers like Electrolux, Philips and AT&T [5].

The need to investigate the utilisation of embedded information devices for a sustainable approach towards lifecycle management is motivated by a number of factors. Constantly increasing legislative pressures from governments, customers and marketing demands are the main factors that are forcing the OEMs (original equipment manufacturers) to treat environmental considerations for product design not as constraints but as goals. These factors, especially the legislative pressures and marketing demands, are forcing the manufacturers to take back their end-of-life products [2]. According to the WEEE directive (Waste Electronics and Electrical Equipment), the manufacturers or producers will be responsible for taking back the used products at the end of their useful lives.

In addition to recovery, manufacturers will also be responsible for setting up systems for the treatment and recycling of the returned waste [6]. Customers and marketing demands are also forcing the manufacturers to make environmentally-friendly products that can be recycled or reused at the end of their useful lives. The awareness created by the media regarding environmental damage, global warming, landfill dumping, etc., among the masses has influenced customers to buy environmentally friendly or green products. However, this awareness is still limited to European countries and the USA. Obviously, business is also influenced by the customers' demands and nowadays companies are taking environmental considerations as the basic element of their business strategy and using green marketing as a tool as they seek to retain their customers [7]. That is why OEMs, especially electrical and electronics equipment manufacturers, are finding new ways for taking products back, developing new, longer-life, products with lower environmental burdens and using increasingly effective lifecycle management systems.

This motivates the need to investigate the utilisation of embedded information devices to attain a sustainable approach towards product lifecycle management. As the title of this thesis reveals, it is concerned with the usage of embedded information devices in order to support a sustainable approach to product lifecycle management. However, this project mainly highlights the management of the product use phase through embedded information devices for products with high functional complexity. Therefore, besides exploring the possible technologies that can be used as embedded information devices for lifecycle management of products with low functionality, this thesis also explains how the application of these technologies can make a functionally-complex product intelligent in the sense that it can predict its own life during its use phase. As explained above, the problem of waste generation is serious, therefore, some figures are provided in the next section to highlight the importance of the problem.

Figures 1.1 and 1.2 also highlight the problem of end-of-life waste generation from domestic and other sources. Figure 1.1 shows a huge collection of end-of-life white goods; whereas, figure 1.2 shows a snapshot of end-of-life IT equipment. Some facts and figures are explained in the next section.

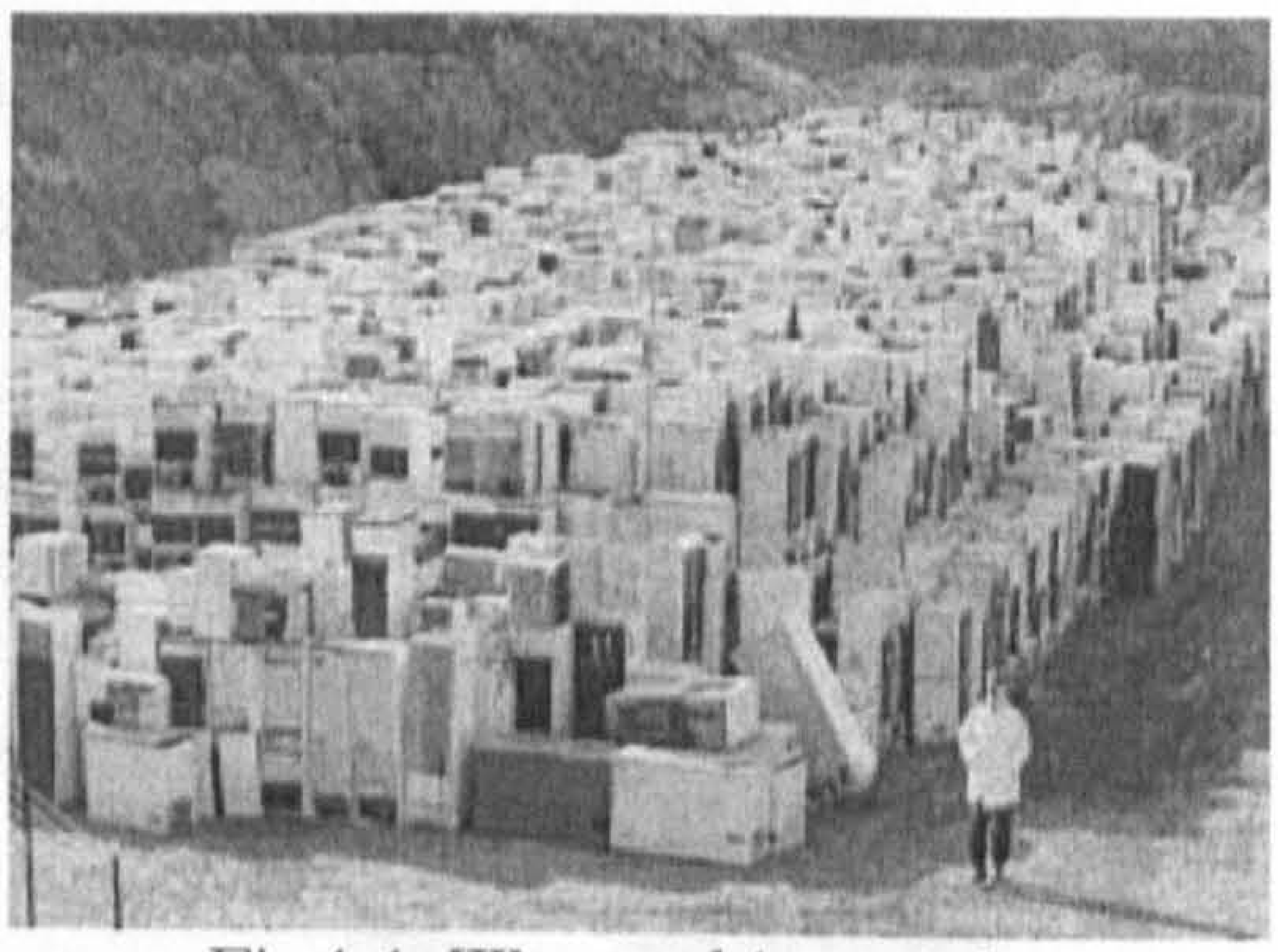


Fig.1.1. Waste white goods

Fig.1.2. Waste IT equipment

1.2 Facts and figures

Some facts and figures are presented here to highlight the severity of the problem. These facts and figures were obtained from different sources **[8-10]**. The problem of waste generation is increasing globally day-by-day, for the year 2000 the total electrical and electronic waste generated by the US was reported to be 2,124,400 tonnes. The situation of electronic waste generation is not very good in the UK as well. In the year 1998, the total electrical and electronic waste generated by the UK was reported to be 915,000 tonnes. The reported electronic waste mainly consists of large and small household appliances, telecommunication equipment, audio and video electronics, etc. According to the statistics, 43% (392,000 tonnes) of this waste consists of only large household appliances, whereas, waste IT equipment seems to be the 2nd biggest source of waste generation in the UK with about 39% (357,000 tonnes) of the total electronic waste generated. Waste television sets and other audio and video equipment contribute about 8% (72000 tonnes) of the total electronic waste, while 10% (94,000 tonnes) of the electronic waste consists of miscellaneous items like small household appliances, telecommunication equipment, toys, lamps, monitoring and control equipment, electronic and electrical tools, etc. This situation is represented in the Pie chart in Figure 1.3:

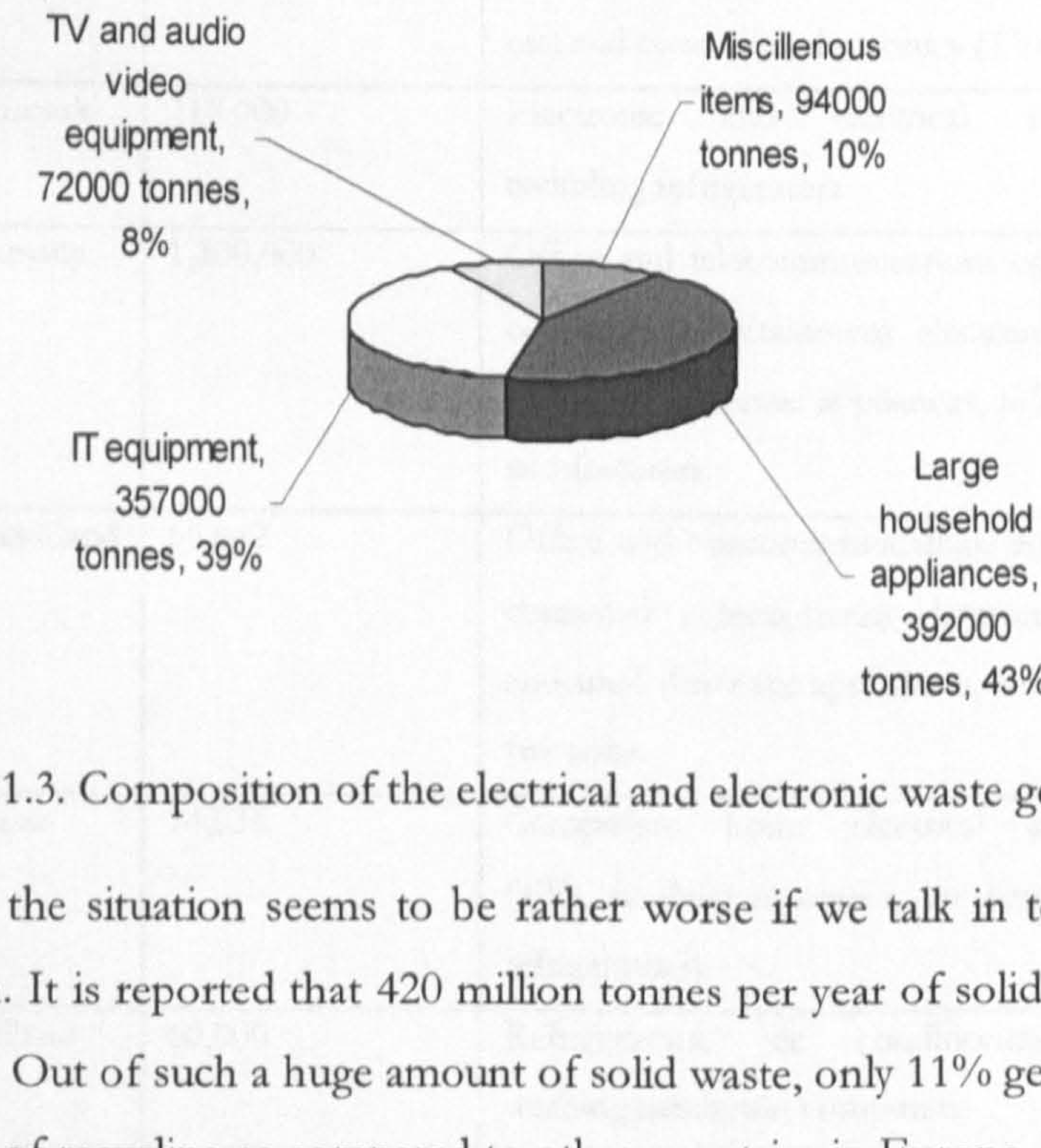


Fig.1.3. Composition of the electrical and electronic waste generated in the UK

However, the situation seems to be rather worse if we talk in terms of total solid waste generation. It is reported that 420 million tonnes per year of solid waste is generated in the UK alone. Out of such a huge amount of solid waste, only 11% gets recycled, which is quite a low rate of recycling as compared to other countries in Europe. For example, Switzerland has achieved a 52% recycling rate and Austria 50%, whereas Germany and the Netherlands have 48% and 46% respectively. About 5 million tonnes/year of paper is dumped as landfill all around the UK. 12 billion tonnes per year of cans are thrown away in the UK, whereas, 6 billion bottles per year that could be recycled are dumped as landfill. However, electronic and electrical waste generation in Europe and other countries is high as well. According to a recent estimate, Germany is producing 1,100,000 tonnes/year of electronic and electrical waste, which contains mostly office and telecomm equipment, large and small domestic appliances, especially refrigerators and consumer entertainment electronics. According to the figures for 1997, Denmark produced 118,000 tonnes of electronic and electrical waste. Other countries such as Canada produced 67,000 tonnes of IT and consumer electronics waste in the year 2005, Taiwan produced 14,036 tonnes of waste computers and domestic electrical appliances such as televisions, refrigerators and washing machines. This is summarised in table 1.1.

Country	Total waste generated tonnes/year	Waste items	Year
Canada	67,000	Computer equipment (computers, printers, etc) and consumer electronics (TVs).	2005
Denmark	118,000	Electronic and electrical appliances including refrigerators.	1997
Germany	1,100,000	Office and telecommunications equipment, consumer entertainment electronics, large and small domestic appliances, refrigerators and fractions.	2005
Switzerland	66,042	Office and telecommunications equipment, consumer entertainment electronics, large and small domestic appliances, refrigerators, fractions.	2003
Taiwan	14,036	Computers, home electrical appliances (TVs, washing machines, air conditioners, refrigerators).	2003
Thailand	60,000	Refrigerators, air conditioners, TVs, washing machines, computers.	2003
UK	915,000	Office and telecommunications equipment, consumer entertainment electronics, large and small domestic appliances, refrigerators, fractions.	1998
USA	2,124,400	IT and telecommunications equipment, consumer entertainment electronics, large and small domestic appliances, refrigerators, fractions.	2000

Table 1.1. figures for electrical and electronic waste generation[8]

This problem of huge waste generation can be minimised by reducing the effect of frequent product replacement by increasing useful lives of products through predictive and proactive maintenance. If products are designed in a modular manner, with some flavour of intelligence so that products can predict their own lifetime against different usage profiles then this will ultimately result in reduction of waste generation, as products then will be able to assist their users in order to increase their useful lifetime. In addition to this, adding features of predictive and proactive maintenance will increase the trend of reusing the useful components of products into new products. This will also result in reduction of waste generation. Adding features like storage of lifecycle data into future products can aid in making suitable decision regarding product end of life treatment. Next sction explains the importance of sustainability.

1.3 Importance of sustainability

Though the importance of sustainability has been well highlighted in this chapter so far, in this section we will discuss the need for sustainability in more detail. One of the most important factors that urge the need for sustainability is the fast consumption of natural resources all around the world. An assumption is made that the natural resources, such as oil, will be largely consumed in the next 40 years whereas resources of natural gas and coal are supposed to be exhausted in 60 and 185 years respectively [11]. The percentages of remaining natural resources are represented with the help of the pie chart shown in figure 1.4.

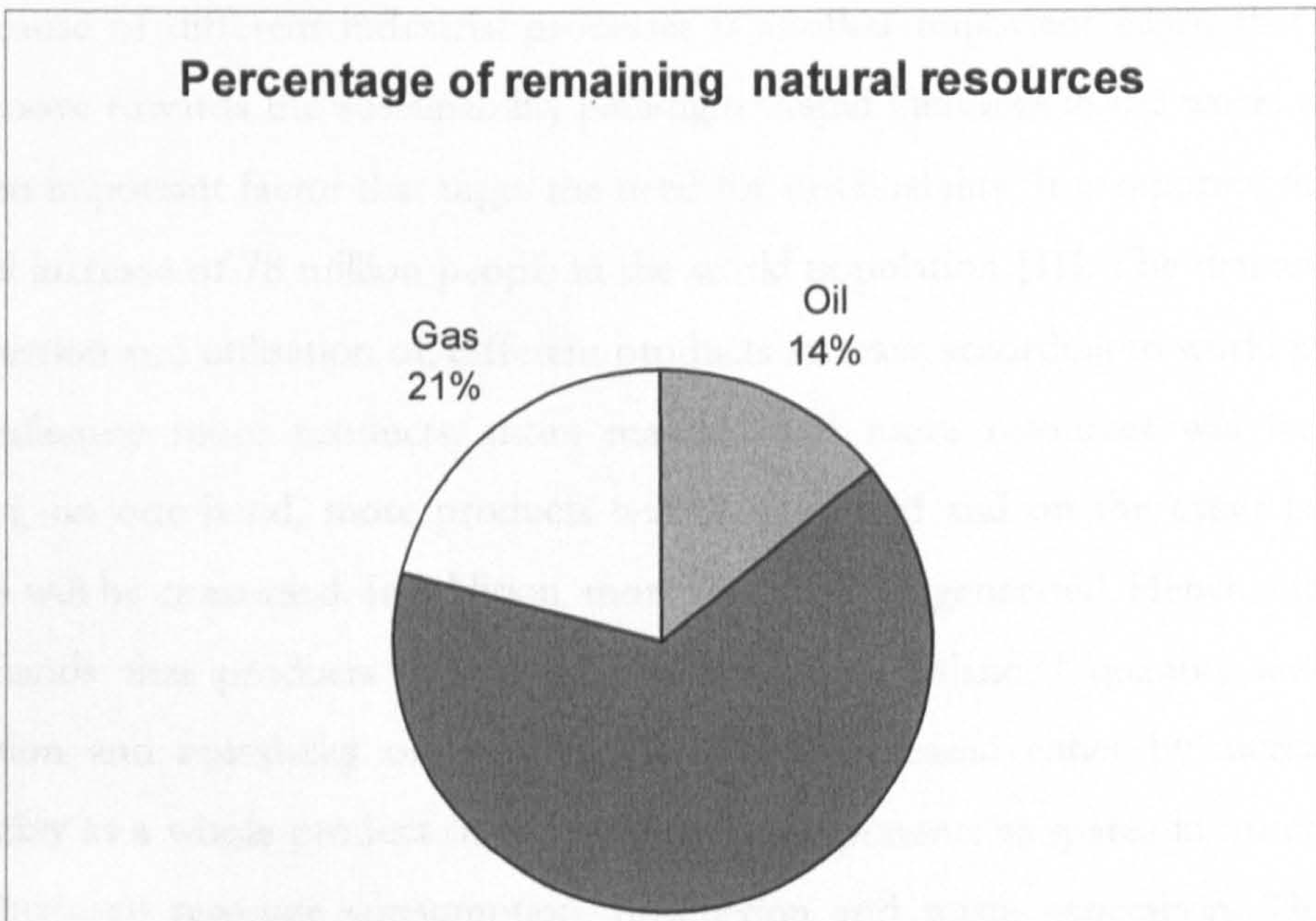


Fig.1.4. Percentage of remaining natural resources

The continuous supply of these natural resources is important because their role is fundamental in running plants that manufacture different kinds of products. If these natural resources are not available, no more products can be manufactured. The availability of these resources depends upon the capacity of the environment to take in different material streams and convert them into fossil fuels without being affected. Therefore, it also depends upon the quality of the material that is absorbed by the environment. The absorption of hazardous materials by the environment and as a result their hazardous emissions to the environment are badly affecting the natural cycle. Lack of spaces for landfill and accumulation of used products that are non-degradable in nature is increasing in the environment thus disturbing the overall ecosystem. This situation urges the need to move towards the sustainability paradigm in which products and their components can be reused or recycled in order to minimise the consumption of new material and to reduce the burden on the environment. The global warming problem that is due to the emission of hazardous gases because of different industrial processes is another important factor that urges the need to move towards the sustainability paradigm. Rapid increases in the world population are also an important factor that urges the need for sustainability. It is reported that there is an annual increase of 78 million people in the world population [11]. The demand for, and the production and utilisation of, different products increase according to world population. To manufacture more products, more material and more resources will be required. Therefore, on one hand, more products will be produced and on the other hand, more resources will be consumed. In addition, more waste will be generated. Hence, this situation also demands that products should be produced in a balanced quantity and that the recirculation and reusability of products should be increased either by increasing their functionality as a whole product or by using their components as spares in order to keep a balance between resource consumption, production and waste generation. The possible solutions for the treatment of products at the end of their useful lives are described later in this chapter. However, it is clear from the situation explained above that in the current scenario the need for sustainability is indispensable and in the same manner sustainable products as well. The next section explains the different phases of the product lifecycle.

1.4 Phases of the Product Lifecycle

The product lifecycle is segmented into three stages [12, 13]

1) BOL (Beginning-of-Life)
2) MOL (Middle-of-life)
3) EOL (End-of-life)

The BOL phase involves the development stages of the product. The data regarding this stage is comprehensive i.e. information related to design and production. For example, we have details like the manufacturing date and times as well as the process and design information like drawings and other manufacturing parameters. Comprehensive information regarding the product at this stage is available due to the employment of MIS, DBMS, and CAD software by the manufacturers. At BOL, the product is similar to a newborn baby whose details are to be entered into the council register.

The MOL phase includes the period after the delivery of the product to the customer. This involves the usage, service and maintenance of the product whereas the EOL phase can be seen as the time when the product is unable to perform its function due to failure or wearing out. Various researchers have defined EOL from their own point of view. Rose [14] defines it as the time when the product is no longer able to satisfy its initial user or purchaser. Teunter and Fortuin [15] define EOL as the period which begins when the product is no longer in production so that spares are no longer available and it ends when all the service contracts between the customer and company have expired. Many other definitions are also available in this regard. However, throughout this thesis, we will consider EOL in the very simplest manner as the time when product has lost its functionality due to failure or wearing out. A set of various situations like reusing the product after changing faulty components, reutilising some of the useful components as spares, recovering useful material from the product, or discarding the product to landfill can be seen as treatments for an EOL product. These are explained on the next page.

1.4.1 Options for Treatment of EOL Products

There are various options available for recovery from EOL products and components [16]. These options for product EOL management are shown in figure 1.5.

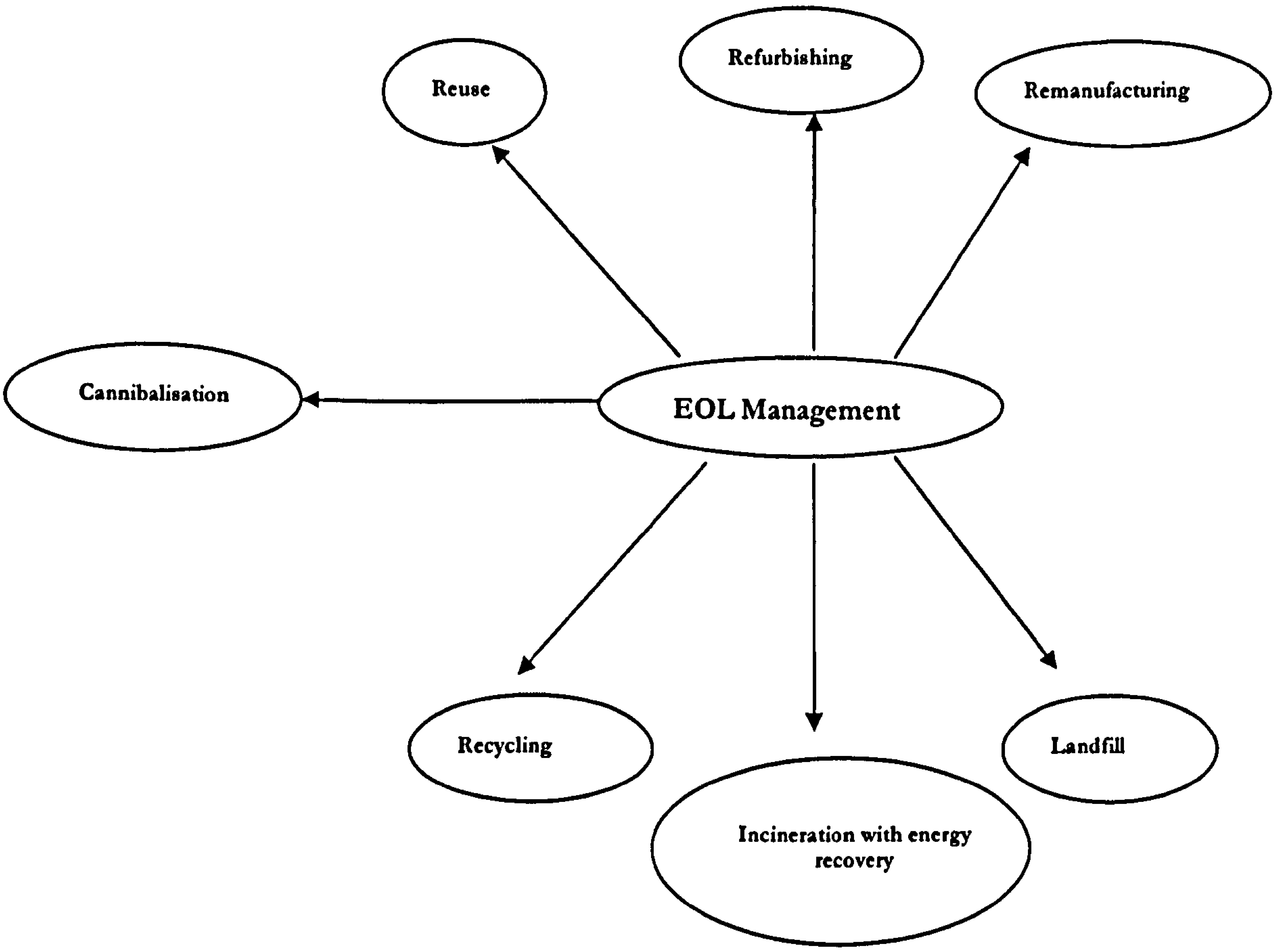


Fig.1.5. Various options for EOL product management

Repair and Reuse

Repair involves very limited disassembly of used products, fixing and replacing the worn out parts to return it to working order for reuse. However, this offers a product with a quality inferior to the new product.

Refurbishing

Refurbishing involves the disassembly of products to a certain functional level or module by inspecting and replacing the worn out or outdated modules with newer ones and making them ready for a second life. In refurbishing, it is also possible to replace the outdated modules with those with new technology. The quality of the refurbished product is limited to a particular or specified level.

Remanufacturing

Remanufacturing of the product involves the total disassembly of the product down to the component level, inspecting the parts and replacing the worn out or outdated components with newer ones or with new technology to meet the quality level similar to that for new products.

Cannibalisation

Cannibalisation involves the recovery of useful parts from the EOL product to reuse them as spares in repair, refurbishing or remanufacturing as a replacement for worn out components.

Recycling

Recycling involves the recovery of material from EOL product through some sort of separation process and, depending upon the quality of the recovered material, reusing it to manufacture the original or some other product.

Besides the five options mentioned above, the incineration of EOL products might also be possible to recover energy. For example, municipal solid waste can be burned to generate electricity rather than using coal, gas or some other fuel [17]. However, energy recovery from EOL products has other environmental hazards like the emission of SOx, NOx, traces of organic compounds, mercury, lead, etc. Finally, landfill should be considered as the least likely option for an EOL product if none of the other options are possible. It is supposed to be a very poor choice from the environmental perspective [18]. However, in the current scenario when environmental consciousness has increased a lot, legislative pressures are increasing constantly and landfill spaces are unavailable, landfill should no longer be considered as an EOL option. The next section describes different approaches for product EOL management.

1.4.2 Approaches for Product EOL Decision-making

Various researchers have proposed different approaches to find out an optimal EOL option for a product. Rose *et al.* proposed that the EOL strategy of a product depends on its characteristics[19]. In this regard a tool called ELDA (End-of-lifecycle Design Advisor) was developed, which employs CART (Classification And Regression Tree Analysis) to classify different EOL options for products according to their characteristics[20-22]. According to the proposed approach, product characteristics like wear-out life, design cycle, technology cycle, functional complexity, level of cleanliness, number of modules and access to product components etc. may influence the product EOL strategy at the design time. To demonstrate this, data was collected from various product designers for different types of products. The CART technique was then employed to classify products of different characteristics under different EOL strategies.

Bufardi *et al.* [23] proposed a method using a multiple criteria decision aid for the choice of the best product EOL option. The proposed method was based on economic, social and environmental factors; each having different indicators like transportation and collection, product cost, manpower to perform recovery operation, exposure to hazardous material, emission of oxides, etc., for decision-making. However, the shortcoming in the proposed approach is that it depends upon the choices of a single decision-maker not of a group as compared to ELDA, which uses feedback from various product designers.

Erdos *et al.* [24] used AND/OR graphs to model and evaluate the EOL options for a product. The proposed model was used to generate first the AND/OR product recovery graph using an algorithm, which is basically the disassembly of a product into its components. Another algorithm was then employed to generate the optimal disassembly plan/graph into sets of different components, called graph nodes, in order to maximise the revenues associated with product recovery. A third algorithm then judged the product recovery graph to determine the extent to which the recovery of a product is possible, so that the optimal disassembly plan remains unchanged. Attached to the disassembly plan are the two terminal nodes for the EOL option modelling. These nodes were attached with every node of the disassembly graph. At these nodes, the graph was terminated. However, this approach was limited to determine only two EOL solutions based on revenue maximisation for a product: these were landfill and reuse.

Based on profit optimisation, Krikke *et al.* [25] also proposed a strategy called the PRD (Product Recovery and Disposal) strategy. This strategy also involved the disassembly of a product into a disassembly tree followed by the application of a mathematical algorithm called the DP algorithm for net profit optimisation as an objective function. The objective function took into consideration technical criteria, commercial criteria and ecological criteria as constraints. Technical criteria included the technical possibility of recovery for reuse, the possibility of separating the materials from the product assembly, the recycling limit of materials, etc. The commercial feasibility criteria included the reusability in primary or secondary markets and the quality requirements for secondary products and materials whilst the ecological feasibility criteria included the obligations to remove hazardous material at the time of recycling or disassembling. A brief comparison of the approaches mentioned above is summarized in table 1.2 below.

	Factors considered for decision-making.	Technique used.	Proposed EOL solutions.
ELDA [20-22].	Various product characteristics like wearout life, design cycle, technology cycle, functional relationship between modules, etc.	Classification analysis and regression trees were used to classify products under different EOL choices.	Reuse, remanufacturing, recycling, incineration and landfill.
Bufardi et al. [23]	Economic, social and environmental factors like product cost, collection of EOL equipment, manpower required to disassemble a product, exposure to hazardous material, etc.	Multiple criteria decision aid was used to choose best EOL option for a product.	Remanufacturing, reuse, recycling, incineration with and without energy recovery and landfill.
Erdos et al. [24]	Optimal product disassembly was considered for profit maximisation.	AND/OR disassembly graphs were used to choose EOL option for a product based on maximum revenue.	Reuse and landfill.
Krikke et al. [25]	Technical, commercial, and ecological factors like recycling limit, reusability in primary or secondary markets, obligations for the removal of hazardous material for recycling, etc.	Profit maximisation algorithm to determine feasibility for a particular EOL option taking mentioned factors as constraints.	Reuse, recycling at different levels, disposal.

Table 1.2. Comparison of different approaches for EOL decision-making.

There are various barriers to the EOL management of products such as:

a) Products are widely spread among various customers geographically, so collecting the EOL products from various locations is very difficult.

b) Products are of different models and types belonging to different manufacturers and each product has a different EOL strategy.

Many other barriers are also present such as the improper flow of information between different phases of the product lifecycle. During the three phases of the product lifecycle, the information exchange gradually slows down and it seems to stop between MOL and

EOL. For various products, like household machines, consumer electronics and vehicles that are generating waste, it can be said that the information flow breaks down just after the delivery of the product to the customer [12]. Due to this incomplete information, it is sometimes difficult to choose the best EOL strategy for a product. For example, if some components or parts are changed or replaced with newer ones during the use phase of the product lifecycle, then the new parts may have a longer life than the standard life of the product. If the maintenance or service information, like maintenance logs and archives, associated with the product are not updated then this may lead to the use of a sub-optimal EOL strategy for a product. This highlights the importance of MOL in the product lifecycle. The EOL strategy for a product depends upon the available information or product data like material composition, value of assets, market demands, methods for recovery etc. [26]. The next section explains the importance of MOL in the product lifecycle.

1.5 Importance of MOL

As pointed out in the previous section, the MOL-associated information plays an important role in EOL decision-making and the unavailability of such information may lead to a sub-optimal EOL strategy. Also, from the lifecycle point of view, it is not feasible to use resources and energy in an inefficient manner and to concentrate only on EOL solutions for products without considering the environmental burden due to their inefficient use during their MOL phase. Consumers use long-life products inefficiently because they do not fail and keep on working [27]. During MOL, the product is not subjected to functional degradation only, but any degradation in its functionality increases the environmental load as well. For example, a car engine, which is not properly serviced or maintained, increases environmental pollution. On the other hand, a properly maintained car engine has less effect upon the environment. Product MOL activities like service and maintenance play an important role from the product lifecycle perspective, as they reduce the environmental effects produced by the product throughout its life. On the other hand, these activities increase the product life as well.

The basic aim of product lifecycle management is to maintain and maximise the product functionality for customer satisfaction and to minimise the environmental burden

[28]. In order to retain product functionality, MOL product management should be given preference over EOL management. Moreover, from an EOL perspective, reuse has preference over other EOL treatments like remanufacturing and recycling, which also means benefiting from the product functionality. If it is not possible to maintain product functionality efficiently, then EOL options like remanufacturing or cannibalisation should be considered [29].

So far, maintenance of a product has been taken in a negative sense, but as the product lifecycle management moves towards the sustainability paradigm, in which future manufacturers will play the role of service providers and customers will just utilise their services, the role of maintenance, especially predictive and proactive maintenance, will be increased. Unlike breakdown maintenance, which is carried out after the occurrence of a failure, predictive maintenance techniques involve fault prediction on the basis of the monitored working condition of the product. On the other hand, proactive maintenance aims to eliminate the possibilities of degradation in product performance by assisting the user to use the product in an efficient manner against different usage modes. Various techniques have been developed for timely fault prediction. Some predict faults on the basis of models that rely on the physics of the system, and some of them predict faults on the basis of process history [30]. However, history-based, predictive maintenance techniques are now a major consideration.

Advancements in information technology and use of electronics have added considerable intelligence, control and functionality to products [31]. These product features have enabled the possibility of integrating intelligent and remote diagnostic systems [32]. Therefore, in order to minimise the down time or to perform just-in-time maintenance, the integration of intelligent decision-making tools with conventional maintenance management approaches is indispensable [33]. History-based fault prediction techniques involving artificial intelligence can play an effective role from the predictive maintenance perspective. Different artificial intelligence techniques like expert systems, genetic algorithms, neural networks and fuzzy logic are being used as alternatives to human interpretation to predict machine faults in machine monitoring systems [34].

Various researchers have used these methods to predict machine performance; such as Lee [35] who proposed a neural-network-based model for measuring the degradation in machine performance. He used a cerebellum model articulation controller (CMAC) neural network as a learning tool for machine behaviour under normal or good modes of operation. A pattern discrimination model (PDM) was then used to calculate the performance measure or confidence value in order to compare the machine behaviour with trained dataset. Many other researchers have proposed approaches in this regard [36, 37]. However, most of these approaches require a large set of trained data associated with product behaviour under different conditions.

1.5.1 Characteristics of an ideal predictive maintenance system for MOL management

In general, an ideal diagnostic system for fault detection and prediction should have the following characteristics [30]:

a) It should be capable of detecting a fault and its symptoms rapidly.
b) The diagnostic system should be capable of identifying and distinguishing different types of faults.
c) The diagnostic system should be strong enough so that if the product fails, the performance of the diagnostic system remains unaffected.
d) The system should be reliable. It should be able to determine the probability of error in fault classification and detection.
e) The system should be mouldable, so that it can adapt to changes that are made in the product.
f) The diagnostic system should be capable of giving explanations regarding faults and their origination.
g) The system should have enough space to store the processing algorithms and processed data, as well as to use phase archives like maintenance and service logs.

The characteristics of an ideal diagnostic system are represented in figure 1.6. The next section explains the concept of intelligent product.

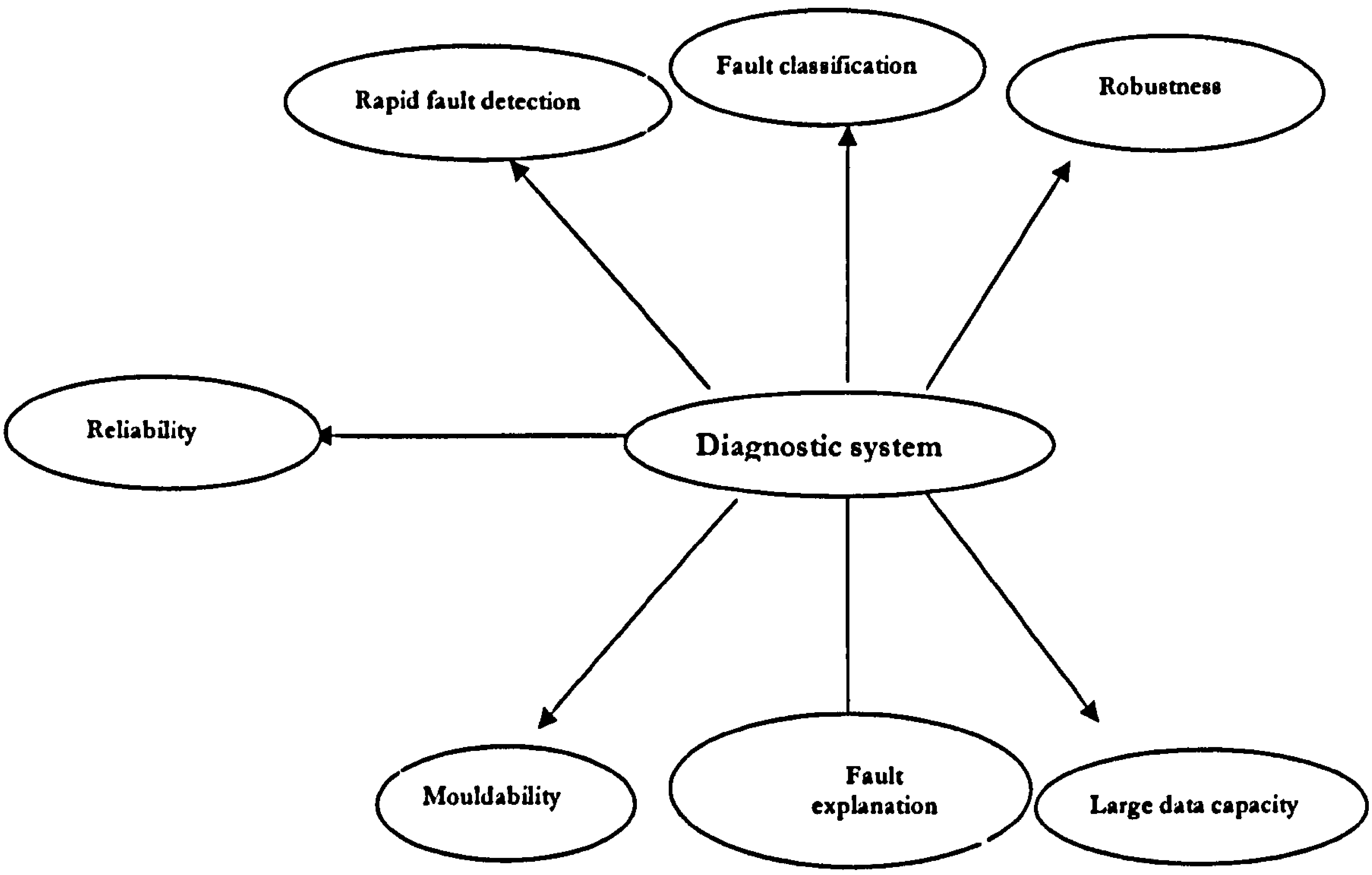


Fig.1.6. Characteristics of an ideal diagnostic system

1.6 Intelligent product

The absence of a proper structure for product recovery, high recovery costs and the unavailability of information regarding products are the factors that have made EOL product recovery difficult [38]. These constraints can be minimised by shifting the product management responsibility to the product itself. Due to the involvement of IT in every sector of life, the product lifecycle management and waste management systems are also dependent on IT tools. Efficient use of information technology integrated with product design can enable products to manage themselves in a semiautomatic manner at the end of their useful lives [39]. This means that the products themselves should contain information about the action to be taken at EOL. More advanced products in a dustbin may locate themselves and communicate with their recyclers through the Internet or some other communication technology. McFarlane *et al.* [40] define an intelligent product as follows:

"An intelligent product is a physical and information-based representation of a product which:

(1) possesses a unique identification;
(2) is capable of communicating effectively with its environment;
(3) can retain or store data about itself;
(4) deploys a language to display its features, production requirements etc.;
(5) Is capable of participating in, or making decisions relevant to, its own destiny".

However, product self-management is still an ideal concept and it is not limited to EOL product management since it falls into other categories like intelligent systems for energy management and maintenance. Self-maintenance involves, for example, a washing machine that can automatically adjust itself to the best parameters for its operation, if it judges any degradation in its performance. Research consortia like PROMISE (Product Embedded Information System for Service and End-of-life) are working to develop smart products by using embedded information devices, automatic identification techniques and internet technology to track the product lifecycle so that the manufacturers can get data about the product usage and modes of failure, the recyclers can get information regarding the EOL products, the maintenance experts will be able to perform timely maintenance and the designers will be able to develop better product designs [12].

PROMISE is a consortium of 22 partners, out of which 8 are the EU member states. Rest of the partners include some Swiss companies, product lifecycle management software pioneers, some advanced small and medium enterprises, and some internationally recognised research groups. PROMISE aims to develop new models for closed-lifecycle information flow between the three stages of product lifecycle. The developed models will provide a base for new software modules that are associated with decision making regarding preventive and proactive maintenance of products, product end-of-life, product design and development for reuse, product service and upgrade, etc. It is aimed that these software modules will be interlinked to each other through a web-based product lifecycle management system. This new product lifecycle management system will be responsible to make availability of product information via some local wireless connection and send it to distributed product lifecycle knowledge bases through internet connection. In this regard, PROMISE is considering smart tagging systems as one of the candidates to act as product-embedded information devices. Mobile reader devices are also under consideration to read product-embedded data, also the development of wireless internet communication software that will act as an agent to connect the mobile reader to the product lifecycle management software. Hence, the final aim is the development of a ubiquitous product lifecycle management system that consists of all these different software modules and knowledge bases that enable the concerned parties such as, product manufactures, maintenance persons, recyclers, etc., to track the information associated with a product throughout its whole lifecycle. In addition to this, other objectives of PROMISE is the standardisation of the tools and technologies that are used for the purpose of product lifecycle management. For example, standardisation of RFID technology, standardisation of product data management modules and systems, etc. Apart from these objectives, PROMISE also aims to establish new business models that can be used to make the proper use of new technologies for the purpose of product lifecycle management.

1.7 Proposed approach and scope of the research

Methods of automatic identification in combination with information technology can act as Embedded Information Devices (EID) to manage product-related information throughout a product's lifecycle. Moreover, advancements in micro-sensor technology have now made it possible to integrate various kinds of sensory devices on a single electronic chip in order to store sensory data as well [41, 42]. This can be considered as progress towards product self-management. According to the proposed approach in this thesis, embedded information devices can be classified into two types:

a) Passive EID
b) Active EID

1.7.1 Passive EID

Passive EID can be defined as an information device that stores or refers to the information associated with design, production and assembly activities that can be used at product EOL for selecting the most suitable EOL option for a product.

1.7.2 Active EID

Active EID has the characteristics of passive EID plus some additional features. It can be divided into two classes:

Smart EID

Smart EID has the capability to monitor sensory data plus it keeps a product update with repair and service records throughout the product lifecycle in order to increase the product's functionality.

Intelligent EID

Intelligent EID has the characteristics of smart EID plus the capability to predict the product's remaining life as well as advising the user concerning the different usage modes from the view of life optimisation of the product.

The proposed aims and objectives of this research are to review the existing research on these EIDs from the perspective of product lifecycle management. This involves investigation regarding state of the art technologies that can be used as embedded information devices as a solution to attain a sustainable approach toward product lifecycle management. As no such classification of embedded information devices has been proposed before, the proposed scope of research therefore involves the development of reference models and demonstrators for each class of embedded information device in order to investigate their potential for product lifecycle management. However, this section gives an overall view of the proposed scope of the research. The actual scope of a project for PhD research work can be identified only as a result of a comprehensive literature review such as that undertaken in chapter 2.

1.8 Structure of the thesis

The structure of the report, 'Utilisation of embedded information devices to support a sustainable approach to product lifecycle management' is described below:

Chapter 1 introduces the reader to the background and motivation for research. It explains the severity of the problems that are produced by waste generation all around the world. The reader is provided with the relevant information like facts and figures, the importance of sustainability, the phases of product lifecycle, etc. In this chapter the reader is introduced to the concept of product self-management that can be used as a solution to this problem. At the end of the chapter the reader is introduced to the broad approach and scope of project.

Chapter 2 presents a comprehensive literature review from Journal papers, papers from peer reviewed conferences, textbooks, etc. The review includes topics like product lifecycle data, information requirements for lifecycle management and the main technologies that are the possible candidates to be used as embedded information devices in order to attain a sustainable approach towards product lifecycle management.

As a result of this literature review, the actual scope of the project is defined at the end of this chapter.

Chapter 3 explains the experiments with passive EIDs. It describes experiments with RFID and i-button technologies.

Chapter 4 provides a description of the setup for a smart EID. It explains experimental work for smart EID.

Chapter 5 provides a description of the rig setup and gearbox case study for intelligent EID. It provides the reader with a general understanding of the gearbox environment. In addition to these, it explains the different modes of gear failure.

Chapter 6 provides a description of the tools and techniques that are employed in the life prediction algorithm of the intelligent EID. It provides a good understanding of the artificial neural networks and probability distributions that are used in common reliability practice. At the end of this chapter the life prediction technique is explained.

Chapter 7 explains the simulation for the choice of appropriate probability distribution that can be used for life prediction in the life prediction algorithm. Moreover, it explains the implementation of the life prediction algorithm. It also explains the bidirectional communication interface that is developed for the intelligent EID.

Chapter 8 presents an overall discussion.

Chapter 9 presents the overall conclusions and suggestions for future work.

Chapter 2

LITERATURE REVIEW

The literature was reviewed from various sources. These sources include the following:

- Journal papers
- Conference papers
- White papers published by the Auto-ID centre (MIT, USA and Cambridge, UK)
- Relevant Text books
- Websites

Most of the literature was reviewed from different scientific and engineering journals that have authenticity in the relevant field. A few white papers from the Auto-ID centre (MIT, USA and Cambridge, UK) repository were also reviewed in order to keep the reader updated with the recent research going on in the area. During the literature review, most of the conference papers cited were from peer-reviewed conferences. A few websites were also used during the literature review.

2.1 Classification of Product Lifecycle Data

Klausner and Grimm [43] say that product lifecycle data can be classified as static and dynamic.

2 .1.1 Static Data

Static data for a product is related to the product specification like manufacturing date, manufacturer information, material type, number of components, drawings, assembly instructions and instructions for preventive maintenance and service, etc. A more comprehensive static dataset may include disassembly instructions for proper EOL management. This data does not change and remains static throughout the lifecycle of the product. Therefore, static data can be stored on some sort of an external database and can be accessed by using a unique product identification code [43].

2.1.2 Dynamic Data

The dynamic data of a product contains information regarding the use phase of the product. It includes the information regarding how a product is used, what parts or components of the product have been repaired or replaced, how long the product has been used, etc. Briefly, we can say that it is the data associated with the changes in the product. As this data changes constantly, so it is dynamic. This dynamic data can be used at the time of product take back to get useful information regarding the product such as use patterns, length of usage, service and maintenance history. According to Simon *et al.* [44], this dynamic data can also be used to improve product design and reliability as well as for preventive and predictive maintenance in order to avoid any breakdown or failure. Dynamic data mainly consists of sensory data capture by some sort of an electronic device or data logger embedded in the product. These devices will be discussed later in this chapter.

Now we come to product information requirement, which is explained in the next section.

2.2 Product Information Requirement

Product information requirement can be broadly classified in terms of functionality, modularity and materiality. In addition to this information, other types of information like information associated with product identification, product location and distribution is also required.

2.2.1 Information associated with product materiality

Materiality information contains various details associated with a product like the number of materials present in a product, types of materials present, percentage composition of a material, etc. This information is mainly required for the purpose of material recovery. For example, while recovering material from an EOL product, information regarding material type helps in determining whether any hazardous material or materials are present in the product. Information like percentage composition and separation techniques can be useful to separate different materials from a mixed material during the recovery process. Moreover, information such as product weight and volume, as well as the weights and volumes of materials present in the product, help in determining the feasibility of recovery of a particular material by representing the amount of recovered material in terms of cost. In addition, it should contain information related to the processes that a product undergoes during its production phase. This may be helpful in judging the feasibility of using the recovered material for primary or secondary recycling.

Most of the data associated with materiality information is of a static nature. However, there is a dynamic aspect of materiality information as well, which is the measurement of material degradation. Ishii *et al.* [45] propose that sensors embedded in the product material can be used to provide input to some physics-based degradation model, which, with the help of sensory input and other information associated with material properties, will predict changes in the mechanical properties of the material. Thus, it will indicate the feasibility of using the material for a second time.

2.2.2 Information associated with product modularity

Information associated with modularity contains disassembly information regarding the product, i.e. into how many modules or components a product can be disassembled. It also contains information regarding the methods and tools that are required to disassemble a product. Product disassembly information plays an important role in product lifecycle. Even for material recovery, products require disassembly up to a particular level. Besides disassembly information, information related to modularity also contains information regarding accessibility and demountability. In addition to these, it contains information regarding the physical structure or shape of the product and the shape of the product module or subassembly, which plays an important role in product identification at the time of product disassembly as it makes the physical identification of the product and/or its modules easier. The manufacturers already manage this type of information in the form of CAD drawings. Information such as the product BOM (Bill Of Materials) gives an idea of the number of modules or components that are present in the product. The accessibility information helps in judging how difficult it is to access a particular module inside a product, what level of disassembly is possible and what is the estimated time to disassemble a product into its respective modules. Information regarding demountability gives us an idea of how easy it is to detach a module from a product, what type of fasteners are used, etc.

2.2.3 Information associated with product functionality

Information associated with functionality is the information related to product reliability, wear and tear, and patterns of use that affect the product functionality. It also contains service and maintenance information as well as records of critical events that occur during the lifecycle of the product because all these things are directly or indirectly associated with product functionality. Product reliability information gives us an idea regarding the expected or designed life of the product or its components. Reliability data is useful to calculate the product's remaining life. The designed life of a bearing in terms of running hours is an example of reliability data. The usage mode information may be used to assess the product's functional status, whether it has been used lightly or heavily, so that the total operating hours of the product can be determined, which can be helpful in determining the feasibility of further use or reuse of a product. Information attributes like time stamps of starts and stops can be used to determine the length of usage and thus the usage modes.

Sensory data can be considered as an important data attribute associated with product functionality. Sensory data like, temperature, pressure, current, voltage, humidity and vibration can be used to identify the product's functional status or the cause of product failure. It can also be used to predict the degradation in performance of a product for the purpose of predictive maintenance in order to avoid any failure and to increase the product use phase in an efficient manner. For example, a sudden temperature rise in a motor winding may cause the motor to stop or malfunction. Current overshoot or a rise and drop in the voltage above a critical, or threshold, limit may cause an electronic or electrical product to stop functioning. Abnormal vibration may generate excessive stresses or forces, resulting in damage to, or the malfunctioning of, a machine component, such as a crack in a bearing of a motor, or a misalignment of the rotating components of a machine. These attributes are presented in table 2.1

2.2.4 Information associated with general product identification

Information associated with general product identification like manufacturer ID, product type or model number, product serial number, manufacturing date, manufacturing time, etc. Availability of this information aids in general product identification. Information like production date and time helps us to know how old a product is. Moreover, other attributes of product identification information like manufacturer ID and product type or model number can be used to access product-related information from, for example, the Internet, product catalogues and maintenance manuals.

2.2.5 Product location and distribution information

Location and distribution information gives an idea of the quantity of a particular type of product that is present at a particular geographical location. In addition, it is useful to locate a product across its supply chain. Location and distribution information is useful in making estimates for EOL collection of a product from a particular geographical location. For example, a washing machine manufacturer can determine in which country most of the models of his washing machine are used and in what quantity. According to Parklid *et al.* [38] this type of information will ultimately be helpful at the time of EOL waste collection, so that a manufacturer can manage his logistics for EOL collection according to the geographical concentration of a product. Moreover, this information also aids in the development of better marketing strategies for a product.

2.2.6 Other information associated with product

Other types of information that are associated with a product are legislative information and information regarding costs and market demands. This type of information may include legislation associated with the reuse of a particular product or legislation on the recovery of a particular material, costs associated with product disassembly and material recovery, demands for refurbished products or disassembled components, the market for recycled materials as spares, etc.

As mentioned before, the best lifecycle practice is to retain product functionality; therefore, from the three basic types of product-related information, functionality information should be given preference over modularity and materiality information. Some attributes of product information are presented in table 2.1. For more details, the reader is referred to Mueller [46]. The priority of product-related information is shown in figure 2.1.

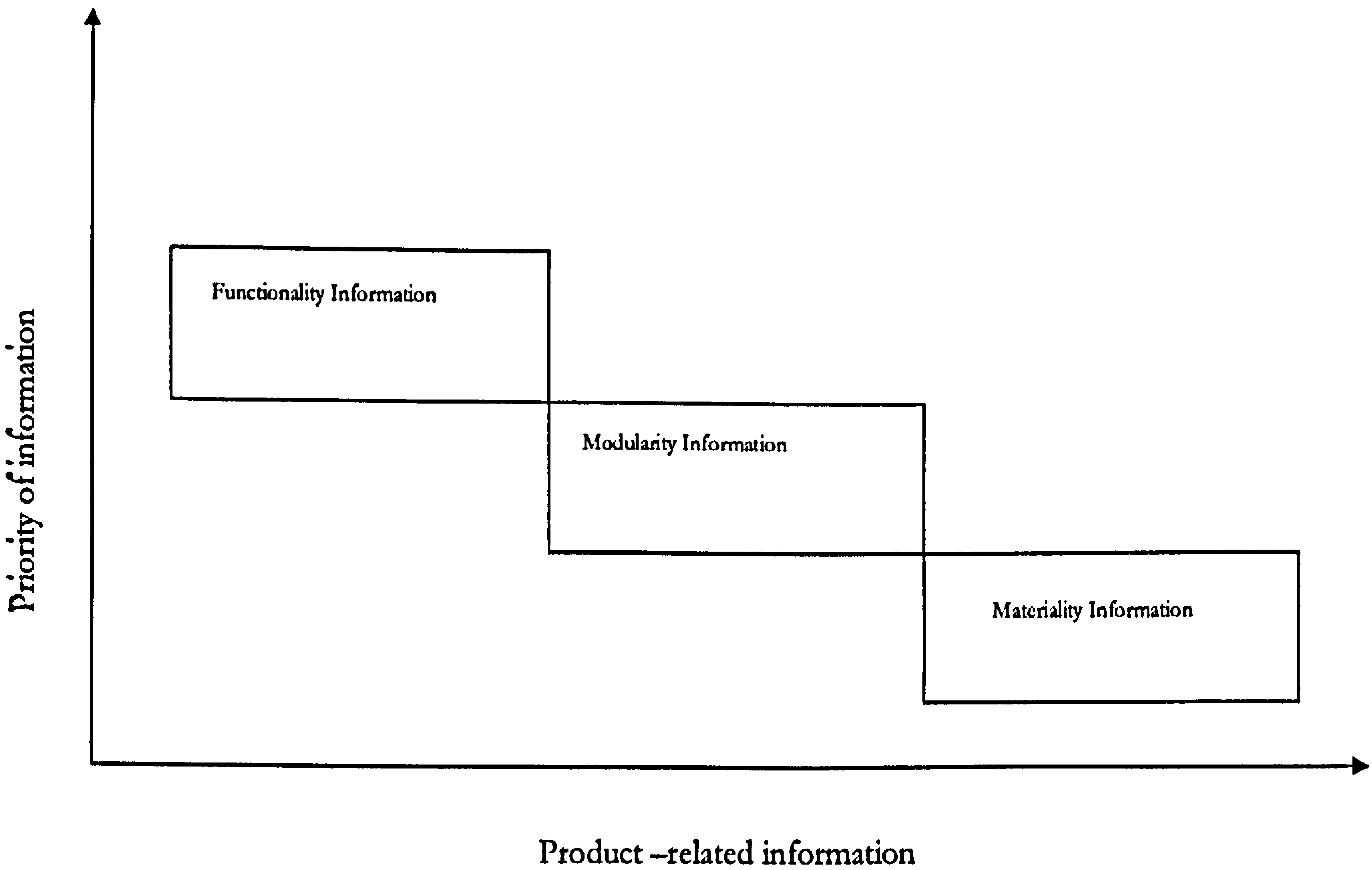


Fig.2.1. Priority of product-related information

Information	Some Possible Attributes		Purpose	Nature
Product General identification	Manufacturer ID Product type or Model no. Product serial no. Manufacturing date Manufacturing time		To identify a product, to access product-related information from databases, product catalogues, manuals and websites, etc.	Static
Functionality associated information	Reliability Information	MTTF MTBF	To predict product life, acquiring information regarding degradation in product performance to perform predictive and proactive maintenance. To maintain product functionality for proper MOL management of product.	Dynamic
	Sensory information	Current Voltage Temperature Pressure Humidity Vibration Operation time stamps		
	Maintenance logs	Maintenance date Maintenance type Type of fault Identified fault no. Number of faults Faulty part no. Replaced part no. Noted running hours		
	Other Important Information	Power Maintenance manual reference Lubricant grade / no.		Static

Modularity information	Total no. of modules Total no. of parts Module or part no. Type of fasteners used Optimal disassembly sequence Disassembly instructions Part drawing reference Tools required for disassembly Total disassembly time	To obtain information regarding product disassembly requirements. To manage resources for optimum and efficient disassembly operation.	Static
Materiality Information	Product weight Product volume % Composition No of materials used Weight of materials Material identification no. Nature of material Hazardous materials Processing Techniques	To obtain necessary information regarding product material at the time of recovery. To determine the feasibility as well as to plan the process or method for material recovery.	Static
	Rate of material degradation due to oxidation, contamination etc.		Dynamic
Location Information	Installed location/ Owner's house no. City code/ Name Country code/ Name	To manage the logistics for product recovery. To improve marketing strategies. To locate a product in a supply chain.	Dynamic
Other Information	Legislation associated with the use/ reuse of different materials, recycling laws, product reuse etc. Cost associated with material recovery, disassembly cost etc. Market demands for recycled material, used products, components and modules etc.	To get information regarding laws for EOL management in different countries. To determine the feasibility of a particular EOL treatment.	Change with the passage of time

Table 2.1. Some attributes of product-related information

2.3 Product lifecycle management technologies

According to Saar and Thomas [47], two types of automatic identification or tag technologies: optical tag technology and RFID tag technology, are being considered for product lifecycle management. Some other technologies like electronic data logs are also possible candidates. Barcodes are frequently used all around the world. As compared to barcodes, the usage of RFID technology is less common but it is expected to increase in the near future whereas the use of electronic data logs is in its infancy. Overall, the usage of all these technologies for lifecycle management is still new (see figure 2.2 for classification). These technologies are explained in the coming subsections.

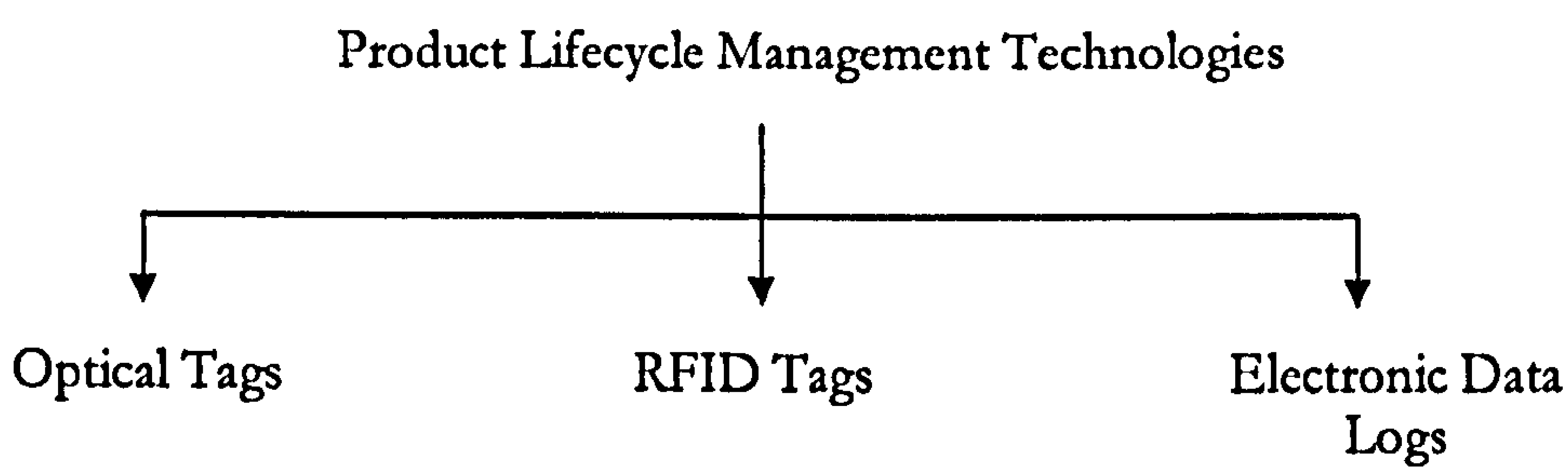


Fig.2.2. Technologies for product lifecycle management

2.3.1 Optical Tags

Optical tags include simple barcodes also called one-dimensional or linear barcodes, and two-dimensional (2D) codes.

Linear Barcodes

The use of barcodes has been a common practice for about 20 years. Internationally the famous EAN (European Article Number) and its US subset, the UPC (Universal Product Code), are frequently used on almost every grocery item. Barcodes are composed of bars and gaps arranged in a particular pattern embedding information in them. An optical device called a scanner, which may be either contact based or contact-less, reads the barcodes. These bars and gaps reflect and modulate the light from the scanner, which is then converted into a binary code from which a further process retrieves the information.

Osman and Furness [48] mention that the data storage capacity of linear barcodes ranges from 8 to 30 characters. A typical barcode system is shown in figure 2.3.

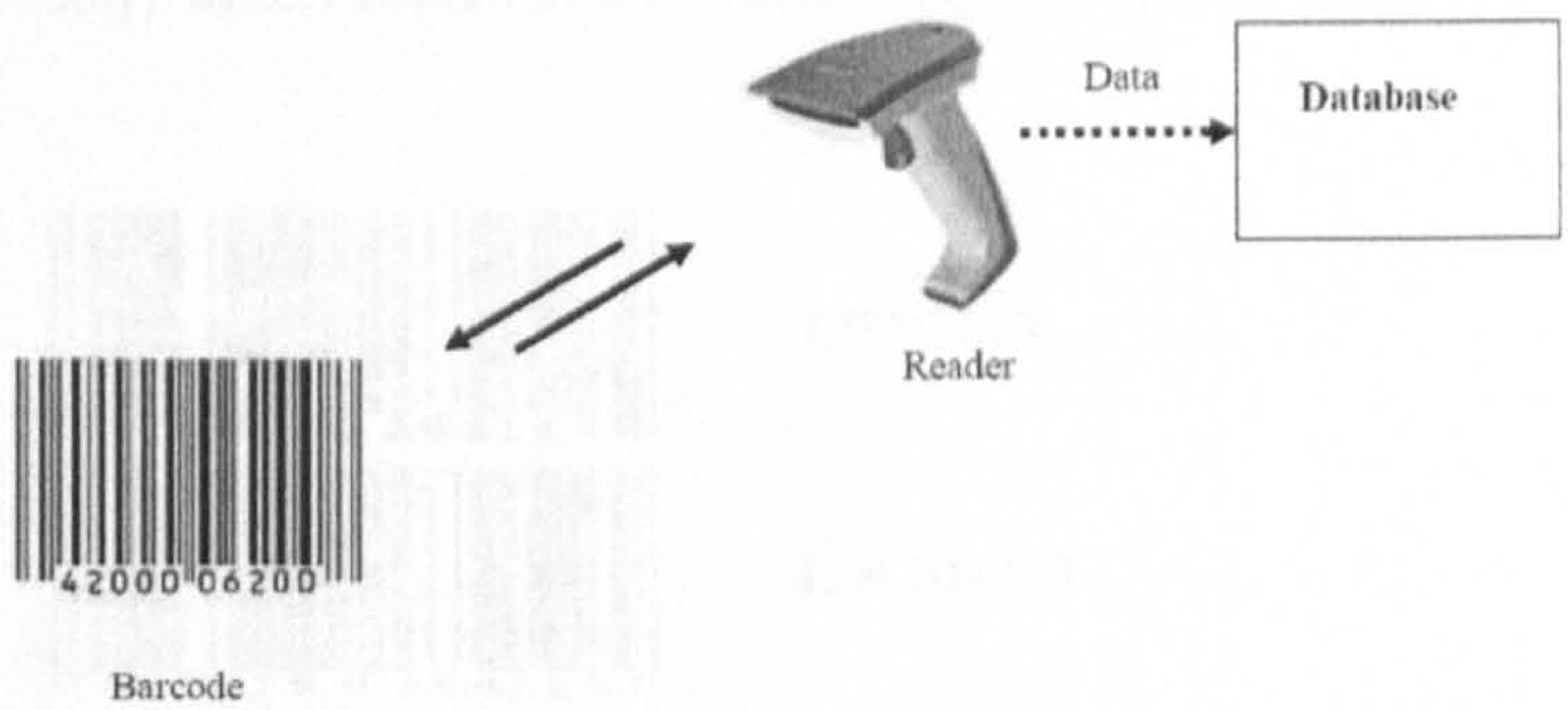


Fig.2.3. A barcode system

Symbology is the way or method of encoding the bars and spaces as per rules defined for every barcode type. The symbology of a barcode consists of various things like self-checking methods, character set and length or density. The character set of a barcode symbology consists of the data characters that a symbology can encode. A symbology is said to be self-checking if a character is not misinterpreted into some other character of the data set because of a single misprint. A check character in a barcode has a particular place and by this character, the scanner detects whether the data is decoded correctly or not. Start and stop codes in a barcode symbol are used to tell the scanner where the barcode symbol starts and where it ends. Start and stop codes consist of specific arrangements of bars and spaces placed at the start and end of the barcode symbol. The minimum width of the thinner bar of a barcode is called the X-dimension or module, whereas the others are called scaled dimensions. The ratio between the widths of wide and narrow elements is called the wide to narrow ratio, and it varies up to a standard value, normally between 2 and 3. The blank areas before and after the barcode are called quiet zones. They are necessary while reading the barcode. A barcode symbology may be continuous or discrete. In continuous symbology, there are no inter-character gaps. It means that every character in continuous symbology starts with a bar and ends with a space. Whereas, in discrete symbology the two consequently encoded characters are separated by an inter-character gap containing no data.

The number of characters that a barcode can hold in a single inch is called the barcode density. Some symbologies in linear barcode systems can use only numeric characters; some can use numeric plus upper case letters, whereas some have the capability of encoding the full ASCII set or other symbols. Linear barcode systems contain a machine-readable identification number or key, which serves as a reference in a computer database.

UPC-A

EAN-13

Fig.2.4. UPC-A and EAN-13 barcodes

UPC and EAN

The UPC is a very popular version of barcodes, widely used in consumer goods. UPC code is available in three flavours. UPC-A which has the capability of encoding 12 digits, UPC-E, which has the capability of encoding 6 digits, and UPC-D, which is not in frequent use but is available to encode variable length messages. The UPC-A barcode consists of 12 digits, the first digit indicates the type of product represented by the barcode, and then the next five digits represent the manufacturer. The next five digits to the manufacturer's identification contain the product information, while the last one is the check digit. The UPC-A is divided into two halves each of 6 digits. There are two right and two left guard bars enclosing the two halves, whereas two central guard bars separate the two halves. These guard bars in the code serve as start and stop patterns. The data is encoded in the form of two bars and two spaces within seven modules. Version E is the compact version of UPC-A, which is used for small items. It has the capability to encode a product code up to six digits. EAN (European Article Number) is supposed to be the superset of UPC code. Every scanner, which has the capability of reading EAN code can easily read UPC code **[49]**. There are two versions of EAN code, EAN-13 and EAN-8. EAN-13 is capable of encoding 13 digits whereas EAN-8 can encode 8 digits only. EAN 13 is similar to UPC-A but it also contains an additional digit, which is used to represent two flag characters in combination with the 12th digit of the code. These flag characters are used to represent the country code. The EAN-8 consists of a country code represented by two flag digits, five digits for data and one check digit. Figure 2.4 shows UPC-A and EAN-13 barcodes.

Interleaved 2-of-5 barcode

An interleaved 2-of-5 barcode consists of only numeric data. It is so-named because one digit is coded into a bar and the next one into the space. So the bar and spaces are interleaved together. Each data character of 2-of-5 barcode consists of five bars or spaces, two of which are wide and the remaining three are narrow, hence its name. In 2-of-5 interleaved code two data characters are paired together, to form a character pair called the symbol character. If 4 and 1 are paired together to form a symbol character representing the number 41 then the most significant digit, which is 4, is represented by five bars and the less significant digit 1 is represented by five spaces. The bars representing the 4 and spaces representing the 1 are arranged in an alternate pattern to represent the symbol character 41 i.e. the first bar of the most significant digit (4) then the first space of the less significant digit (1). Next to this is the second bar of the most significant digit and then the second space of the less significant digit and so on. According to Lindau and Lumsden [50], interleaved 2-of-5 code is mainly used for product identification in distribution and warehouses involving activities like packaging and picking. Figure 2.5 shows an interleaved 2-of-5 barcode encoding the number 12345670.

12345670

Fig.2.5. Interleave 2-of-5 barcode

Code 39

Code 39 is another frequently used barcode. It has bars and spaces of different thicknesses arranged in an alternate pattern. Code 39 is supposed to be the first barcode containing the alphanumeric character set. The data-encodable character set of code 39 contains digits from 0-9, and upper case alphabetic characters plus 7 additional characters. This code is called code 39 because of its data character, which is represented by nine elements (five bars and four spaces), out of which three are wide. Code 39 is a discrete code composed of a quiet zone and a start symbol character preceded by symbol characters encoding data and then a stop character following a quiet zone. The start and stop characters in Code 39 are represented by the * symbol. Code 39 with X dimension 0.010 inch and 3:1 wide to narrow ratio has a barcode density of 6.25 CPI (characters per inch)[51]. This code is used in the defence and health sectors in the USA. A Code 39 barcode is shown in figure 2.6.

TEST8052

Fig.2.6 Code 39

Codabar

Codabar is another barcode, which is used in blood banks, libraries and parcel applications [52]. Codabar barcode contains a quiet zone; a start symbol character that is preceded by data characters then a stop symbol character and a quiet zone. Codabar contains a 16 character set: the numeric 0-9 and -$:/.+ characters. With these Codabar also contains four characters A, B, C and D that are used as start and stop characters. Each character in Codabar consists of four bars and three spaces between them. With X dimension 0.010 inch and 3:1 wide to narrow ratio, Codabar has a barcode density of 8.33 CPI [51]. A Codabar barcode is shown in figure 2.7.

Code 128

Code 128 (see figure 2.8) is a high-density code. It is used in various applications where large amounts of data need to be encoded in a limited space. Code 128 consists of alternating bars and spaces of four different thicknesses. Each character of code 128 consists of 11 modules. It has three character sets A, B and C. Code 128 consists of a quiet zone then a start code which tells what character set is used and which is preceded by data, a check character, a stop character and then a quiet zone again. Code 128 has the capability of encoding the ASCII 128-character set. It is mostly used to encode shipping information or identifying an object by placing a serial number on the object. According to Osman and Furness [48], a less than 5cm code 128 is enough to store the type, manufacturer information and a unique serial number. The data types that can be encoded by different 1D symbologies are summarised in table 2.2.

A40156B

Fig.2.7. Codabar

HI345678

Fig.2.8. Code 128

Symbology	Data Type	Application
UPC and EAN	Numeric	Consumer goods
Interleave 2-of-5	Numeric	Distribution and Warehouses
Code 39	Alphanumeric plus some additional characters	Health and defence sectors
Codabar	Numeric plus some additional characters	Blood banks, libraries, air parcel services
Code 128	ASCII 128 character set	Shipping or to store serial number information

Table. 2.2. 1D barcodes data type

2D Codes

1D codes normally contain a unique number, which serves as a reference key in the computer database carrying the detailed information of a product. In the harsh industrial environments where it is not possible to access a computer database, 2D codes serve as portable data files as they carry a large amount of information as compared to conventional 1D code. Hence, 2D codes eliminate the requirement for an external database system.

In the case of an assembly cell where a product moves from one station to another station, it is sometimes difficult to access the centralised database to get the product information, for example assembly instructions. By the use of 2D codes, it is possible for the product to carry its own assembly information in the form of a portable data file. The same can be done in the case of product lifecycle management where it is difficult to get product-related information from a database. A product itself can carry information using 2D codes. Moreover, due to their large size, conventional barcodes cannot be placed or printed on small items like electronic components; also, it is difficult to place them on mechanical components, which are subjected to a harsh environment. On the other hand, 2D codes are scaleable; easy to read even when they are very small and can be marked directly on components giving them an advantage over conventional barcodes. Another advantage is that, as 2D codes contain large amounts of data therefore, they have the capability to detect and correct errors occurring during the data capture process. Various 2D codes employ different error detection and correction algorithms to recover or reconstruct the code in case of damage or defective code. There are about 20 types of 2D codes available, most of them are proprietary, however, some are available for use in the public domain. 2D codes can be classified into three groups, stacked or multi-row symbologies, matrix and dot codes and composite symbologies. See figure 2.9 for the classification of 2D codes.

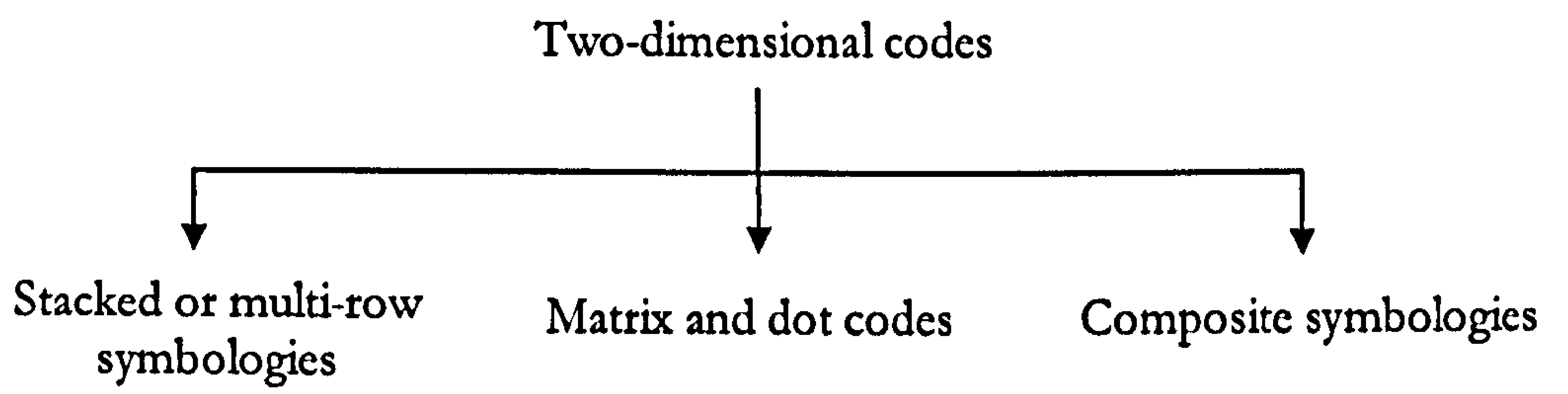


Fig.2.9. Classification of 2D codes

Stacked or multi-row symbologies

Stacked or multi-row codes are actually the two dimensional barcodes. These consist of various barcode-type structures stacked or arranged in rows and columns. Laser scanners having raster scanning capabilities can read these codes. PDF-417 (see figure 2.10) is a famous two-dimensional barcode introduced in 1993. PDF stands for portable data file. It has the capability to encode more than 2,700 data characters. The PDF-417 barcode includes the 255 character ACSII set [53]. The PDF-417 barcode consists of bars and spaces arrange in rows and columns. There is a start and a stop symbol present at the left and right of the barcode respectively. Two row indicators, holding the information about the numbers of rows and columns as well as about the error correction level are also present after start, and before the stop pattern. The symbology of PDF-417 encodes data in the form of code words between these two row indicators. Every code word consists of four pairs of bars and spaces of unique widths arrange in an alternate pattern. The symbol length descriptor, which is the first code word, contains the total number of data code words in the barcode. It can be printed using ink-jet, thermal transfer and laser printers.

Fig.2.10. PDF barcode

The symbology used by PDF-417 is in the public domain, so that it can be utilised for various applications without any propriety restriction. Like other two-dimensional symbologies, it also has error detection and correction mechanisms. There are different levels of error correction in PDF-417. A PDF-417 code with 0 level does not allow error correction, whereas at level 8, the code can be successfully recovered even if it is 50% damaged [54, 55]. As PDF-417 is able to encode in binary and ASCII format, therefore, it can store biometrics as well. Various techniques have been developed to embed biometrics like picture and fingerprints with other information in PDF-417 barcode [56]. Hence, these barcodes are used to hold personal information in various documents like ID cards, driving licences and passports in order to protect the data from being tempered with. In the industrial sector, PDF-417 is widely used by many companies. Rolls Royce has used PDF-417 to carry complex assembly information with equipment at remote locations. These barcodes are used in the automobile sector to carry out assembly information between various stations inside the plant. Moreover, information associated with drawings can also be encoded into these barcodes [53]. Another version of PDF-417, called Micro PDF-417, is also available and is used in applications where PDF-417 cannot be used due to limitations of space.

Besides PDF-417, other multi-row stacked symbologies are also available in the market. Code 49 (see figure 2.11) is a multi row barcode. It has the capability of encoding the 128 ASCII character set. There are 18 bars and 17 spaces in each row of code 49. A row number identifier is present in each row and identifies every row, whereas the last row has information regarding the total number of rows present in the code. There are two to eight rows in a code 49 symbol. There is a row separator placed between every two rows. Each row of code 49 contains four words and each word consists of any two characters from the character set represented by four bars and four spaces. Each row of code 49 is started by quiet zone following the encoded data, which is ended by a stop symbol with another quiet zone. Code 16K has a more or less similar architecture to that of code 49 but the data in code 16K can be encoded up to 16 rows making 16K denser than code 49[49].

Fig. 2.11 Code 49

Matrix codes

Matrix codes consist of a two dimensional array of light and dark elements. The data encoded in the matrix code depends upon these elements. Similarly, dot codes (see figure 2.12) encode data based on the absence or presence of dots in the two dimensional array. These types of codes are a good choice for direct part marking. Data matrix code (see figure 2.13) looks like a checkerboard of black and white squares and has a greater capacity to store data. A barcode containing 8 to 22 characters occupies 1inch whereas data matrix code containing 500 characters of information requires only 0.05inch [57]. The main advantage of data matrix code is its scalability i.e. the code can be scaled to large or small size irrespective of the quantity of encoded information. However, the minimum size of code is dependent on the printer resolution as well as the quantity of information held by the code and the type of dataset being used. Like other 2D systems, data matrix code also has an error correcting and checking (ECC) capability in case of damage or missing code. Data matrix code can be directly printed onto the product and can be read at any angle. However, data matrix codes need a two-dimensional CCD camera to be read, which is expensive as compared to the linear barcode systems which require cheaper laser scanners for reading purposes. It can store data up to 2,335 text characters [48]. Data matrix codes are widely recognised in the electronics industry for small-part marking where it is difficult to implement the linear barcode systems due to limitations of space. Nokia is using data matrix code for part identification and to carry assembly information during the production process. Data matrix codes are also employed in the automobile industry to carry production information and correct part identification during the assembly process. For this purpose, codes are directly marked onto the components. Rolls Royce uses a proprietary code called dot matrix code (DMT). The DMT code is used to mark aerospace items with a unique code for part identification. There are three methods for direct part-marking i.e. laser marking, inkjet marking and pin marking [58]. Laser marking is expensive and is used to make the permanent marks on the object. According to Dumont *et al.* [59], laser marking has proved useful for marking a 2D data matrix over glass in the pharmaceutical industry. Inkjet marking is cheaper than laser marking and is used where the production rate is high. Pin marking employs a carbide tip for marking and is a good choice to mark dot codes as compared to matrix codes. Maxi Code and QR (Quick Response) code are some other matrix codes used in highly rapid sorting applications. Maxi and QR codes are shown in figures 2.14 and 2.15 respectively.

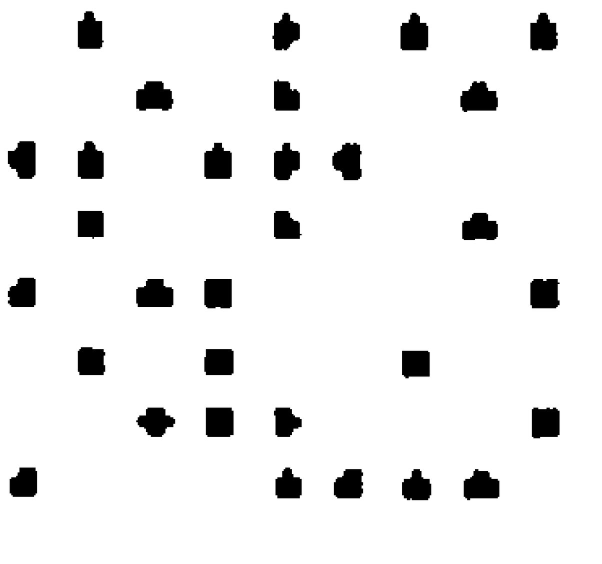


Fig.2.12.Dot code

Fig.2.13. Data matrix

Fig.2.14. Maxi code

Fig.2.15. QRcode

Composite codes

Composite symbologies have the characteristics of both linear barcodes and 2D codes. Normally, a composite symbology consists of a linear component and a multi-row stacked barcode component or 2D barcode called Composite Component (CC). So depending upon the requirement, if additional data is required to be encoded it can be encoded in the 2D part of the symbology. RSS-14 (Reduce Space Symbology) was mainly designed for small items and contains a 14 digit linear component capable of numbering items as UPC or EAN but it takes less space than EAN-13 or UPC-A. In addition to this, it has a linkage flag, which is the first character that indicates the presence or absence of a two-dimensional component for encoding data. The stacked version of the RSS-14 symbology is split vertically into two halves, which are separated by a separator having no data. The stack version also contains a linkage flag. RSS stacked symbology has a capacity of 74 characters. The composite components associated with these barcodes have different capacities. The CC-A which can be linked with RSS-14, has the capacity to encode 53 characters whereas CC-A with the stacked version of RSS-14 can encode 338 characters while 2,361 characters can be encoded with the CC-C composite component [60]. Figure 2.16 shows a composite barcode. Data capacities of some 2D codes are mentioned in table 2.3.

Fig.2.16. A composite barcode

2D Code	Numeric	Text Characters	Bytes of Data
PDF-417	2710	1850	1108
Micro PDF-417	366	250	150
Data Matrix	3116	2335	1556
QR Code	7366	4464	3069
Maxi Code	138	93	-

Table 2.3. Data capacities of some 2D codes [48]

Merits and demerits of barcode technology

Barcodes provide the cheapest way of applying low-cost labelling to products. However, this type of labelling cannot be used for all types of products, because barcode technology is not very resistant to dust, dirt and damp. Therefore, this technology is not suitable for products that are exposed to a harsh environment. On the other hand, one major advantage of barcode technology is its standardisation. Standards for barcode technology are well developed and maintained all around the world. The barcode technology is highly customisable and is being practised well in various sectors. Therefore, we can say that barcode technology has gained a high degree of familiarity as compared to other technologies. Beside all these good points, one major drawback associated with this technology is that it requires line of sight, which makes this technology very labour intensive. Both 1D and 2D barcodes require line of sight for proper data acquisition. Moreover, with 1D barcodes very little information like serial number, item code, manufacturer number etc. can be encoded, which can refer to detailed data stored in some external database. Therefore, if someone needs to encode different types of information on an item using 1D barcode, then they may need to use multiple 1D barcodes. That is why, on most of the packaging cartons, information is encoded with the help of two or three 1D barcodes. However, 2D barcodes have eliminated the need for multiple 1D barcodes and external databases as they have greater data capacity but with both types of barcode, one major problem is that their physical size increases with the increase in the amount of data. However, with improved printing technology, it is possible to print barcodes with good resolution but considerations must be made while tagging small-sized objects with barcodes. One other constraint associated with barcode technology is that, once written on the barcode, the information cannot be changed or amended. Therefore, dynamic information storage with this technology is not possible. This type of labelling is a much suitable tagging solution for low-cost, simple products having shorter lives and which are exposed to less harsh environments. The merits and demerits of barcode technology are summarised in table 2.4.

Merits	Demerits
Low cost labelling technology Globally recognised and well defined standards Most commonly used technology Easy to tag on different products Easy to customise according to requirements Availability in different varieties More data capacity with 2D codes No need of database with 2D codes Error checking capability Data recovery capability with 2D codes in case of damage	Requires line of sight therefore labour intensive Shorter lives, less resistant to the environment Less security, can be easily decoded Lower data capacity with 1D codes Dependency on external database with 1D codes

Table 2.4. Merits and demerits of barcodes

One way to use barcodes for the purpose of product lifecycle management is to use them for BOL management of products. As mentioned in the literature review that various companies are using 2D barcodes to encode assembly instructions for part assembly that are assembled at various assembling stations inside or outside the plant. Therefore, barcodes can be used for this purpose at the early stage of product life. However, barcodes require line of sight that makes this technology labour intensive but barcodes provide a cheap solution as compared to the other existing technologies. The other way to use barcodes for the purpose of product lifecycle management is the use of this technology to store EOL information. For example, 1D barcodes can be used to store some materiality information like recycling information of some product or 1D barcodes can be used to encode the web address where recycling information regarding a product can be available. Similarly, 2D barcodes can be used to store more detailed information such as disassembly information or packaging information of a product that can be used at its EOL phase. For the purpose of product lifecycle management, 2D barcodes can be printed directly onto the products.

2.3.2 RFID Tags

Unlike barcode technology, RFID (Radio Frequency Identification) tags employ radio technology that does not require line of sight access; moreover, data contained by RFID tags (see figure 2.17) can be changed by writing data to them. As RFID technology does not requires a line of sight, products can be identified in the form of lots or batches through this technology. Use of RFID technology is not very new. Jones *et al.* [61] report that RFID technology was first used in World War II for military applications but for commercial applications, it has been in use since the 1980's[62].

The RFID System

An RFID system consists of three components:

1) Tags or transponders that serve as electronic data carriers bearing an ID code and are attached to different objects.

2) A reader or interrogator that corresponds with tags through electromagnetic waves at radio frequency.

3) A host computer to process and distribute the data over a network.

A tag consists of an integrated circuit (normally a resonating circuit), an antenna and memory. The tag and reader communicate with each other through electromagnetic waves. Radio frequency tags can be broadly classified into two types: active tags that require a power source and passive tags that do not. In active systems, a tag's own battery drives the tags or transponders. As active tags have their own power, it is easy to increase the read range in active systems but they have short lives, which are totally dependent upon the battery. Cold weather is the main reason for the battery life reducing rapidly. However, active RFID systems can perform more complicated tasks as they have the capability to integrate various kinds of sensors and even the microcontroller with them. These types of systems are used for various applications like temperature and humidity logging and environmental monitoring [63]. Passive systems do not have their own power source; instead they derive their power from the electromagnetic field generated by the reader. As compared to active RFID systems, the passive RFID systems are cheap and can be produced at low cost, which nowadays makes them a major focus. Passive systems have a shorter range as compared to active systems. For passive systems, the reader energises the tag by inducing a constantly changing electromagnetic field inside the tag when it comes within the interrogation field of a reader. When the field of the reader affects the tag, a DC voltage is produced in the tag's antenna and the tag begins to oscillate in response to the reader.

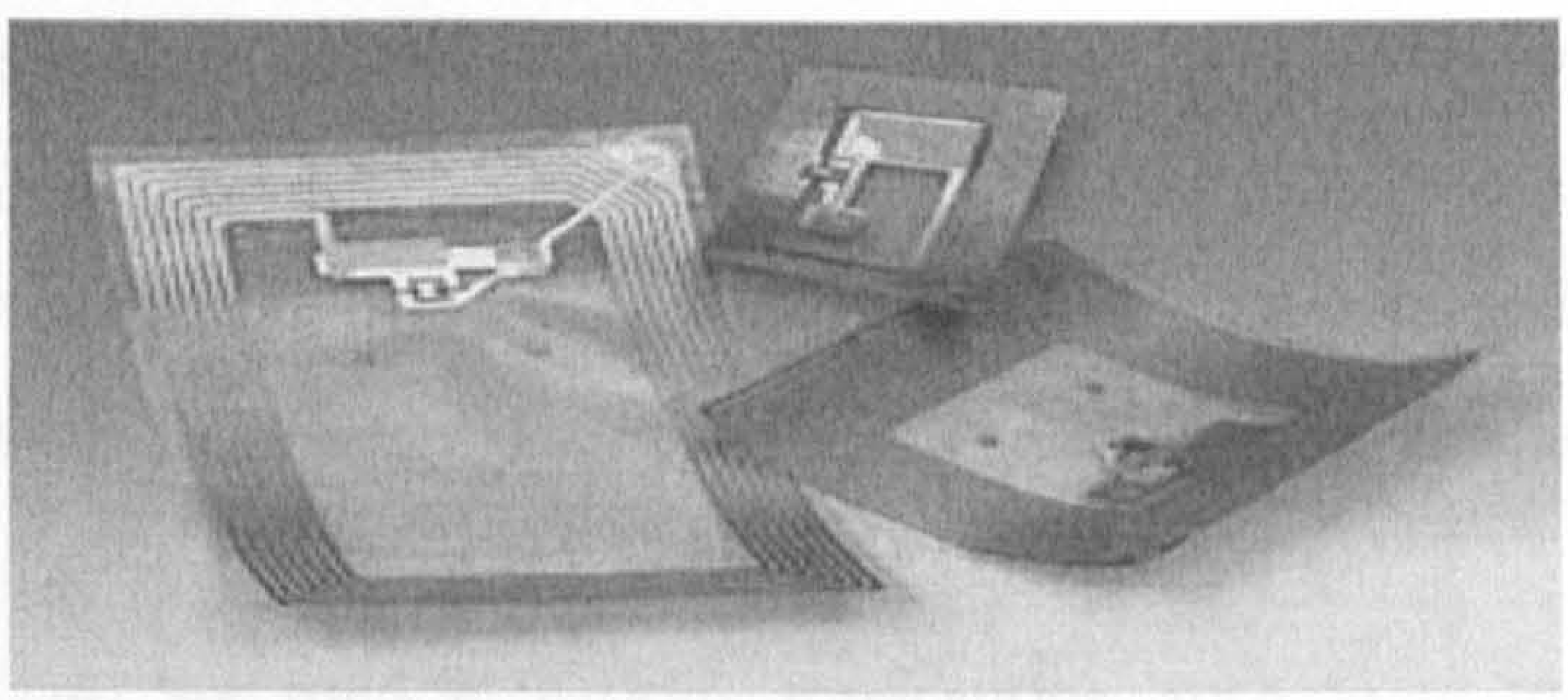


Fig.2.17 RFID Tags

The reader produces a constantly changing electromagnetic field from its antenna, which is normally a wire in the form of a circular loop. The magnetic field produced is perpendicular to the plane of the antenna's loop. If B is the strength of the magnetic field and I is the current in the antenna's loop having radius **'a'** with **N** number of turns, then B can calculated as follows **[64]**:

$$B = \frac{\mu_0 INa^2}{2(a^2 + x^2)^{3/2}}$$

Where μ_0 is the permeability of free space and x is the distance perpendicular from the centre of the loop.

The signal sent by the reader to the tag is called the carrier signal, some portion of which is reflected by the tag to send back the data to the reader. When the tag receives the signal it resonates in response to the carrier signal of the reader, the tag IC decodes, modulates and reflects back a portion of the signal, sending a stream of data to the reader known as backscatter modulation. The reader then decodes this modulated signal to retrieve the information from the tag. Normally, a reader system consists of an oscillator circuit, a power amplifier and a tuning circuit for impedance matching between the reader's antenna coil and the power amplifier. It also contains filters to eliminate the noise from the backscatter signal sent to it by the tag. After filtration, the backscatter signal from the tag is fed into the microcontroller for data processing that is further connected to the host computer via some standard communication protocol, usually RS-232. Then it is easy for the host computer to store information in a database or to send it over some global network like the Internet. The memory capacity of RFID tags ranges from 64 to 32,678 bytes. Active tags are read/written from a distance of approximately 5 to 100 feet whereas passive tags can be read or written from less than six feet and in various cases this is limited to up to 2 feet [65].

Currently, RFID tags are used in various applications, such as in material handling to identify different types of materials. RFID tags can be attached to the container or objects for more efficient warehouse management and these tags may be used for the identification of various types of tools in a workshop. All the information regarding the tool and its usage is programmed into the RFID tag, which is attached to the tool. RFID tags are widely used for toll and fee collection. Automobiles bearing an RFID tag containing information regarding the user or driver's account are passed against an RFID reader, which is mounted at some point on the highway and the fee or toll is automatically deducted from the person's account. RFID technology is also used to read industrial electric, gas and water meters with the help of a portable reader. RFID tags are also used for maintenance purposes. Tags containing information regarding equipment are placed on the equipment so its maintenance information or use history can be retrieved or updated easily on site, thus reducing the amount of paperwork [66]. Based on RFID, a smart toolbox is proposed by Romer *et al.* [67]. This application is found to be useful in aircraft maintenance planning systems [68]. Goodrum *et al.* [69] also reports their use in an application to manage small tools on construction sites.

The manufacturing sector is also exploiting the benefits of RFID technology. Car manufacturers like Ford, BMW and Vauxhall are using RFID tags. Ford is using an RFID based system called Escort Memory Systems (EMS) for tracking auto and truck frames during different production stages at body, paint and assembly shops. This is different from Ford's previous system, which employed paper identification sheets circulating with the product at different stations in the manufacturing plant. Similarly, BMW and Vauxhall are using RFID tags to manage product specifications according to the customer's order **[70]**. Moreover, RFID technology is frequently used in animal identification systems. Tags bearing a unique ID are available in various varieties like collar tags, glass tags that are injected inside an animal's body and ear tags placed in an animal's ear. A calf with RFID ear tags is shown in figure 2.18

Fig.218. An RFID tag in the ear of calf

The reader generates an electromagnetic field and when the animal bearing RFID tag comes into its field the tag responds and the animal is identified. Both active and passive types of transponders are used for this purpose **[71]**. The dairy industry is using this technology to identify cows and allow or restrict their access to particular feeding stations for feed control to ensure that no cow eats more than the allowed quantity of food **[72]**. Besides the broad classification into active and passive tags, RFID tags can also be classified as inductive and capacitive tags, SAW tags, and memoryless tags.

Inductive and Capacitive tags

Passive tags are mostly inductive in nature i.e. the coupling relation between the reader and tag antenna is inductive in nature and operates on the 13.56 MHz frequency. In the case of inductive RFID systems, the reader antenna coil and tag antenna coil can be seen as the primary and secondary coils of a transformer. The reader's coil serves as the primary because it induces a voltage in the tag antenna coil, same as a transformer. Therefore, the voltage $V_{induced}$ in the tag's antenna coil can be calculated as the rate of change (with respect to time t) of the magnetic flux ϕ times the number of turns N_T in the tag antenna's coil **[64]**.

$$V_{induced} = -N_T \frac{d\phi}{dt}$$

The magnetic flux ϕ is defined as the total number of magnetic lines of force passing through the surface area of the tag's antenna coil. Capacitive tags normally have a printed antenna made of conductive ink. The coupling between tag and reader antenna is capacitive in nature. These conductive ink antennas can be easily printed onto a sheet of paper by employing some standard printing techniques **[73]**. Screen-printing and inkjet printing are the possible methods for printing RFID antennas on paper to reduce the cost of an RFID tag. However, rotary letterpress and flexographic printing are also being tested for printing RFID tag antennas **[74]**. These printed antennas are then connected to the IC by using some ACA (Anisotropically Conductive Adhesive).

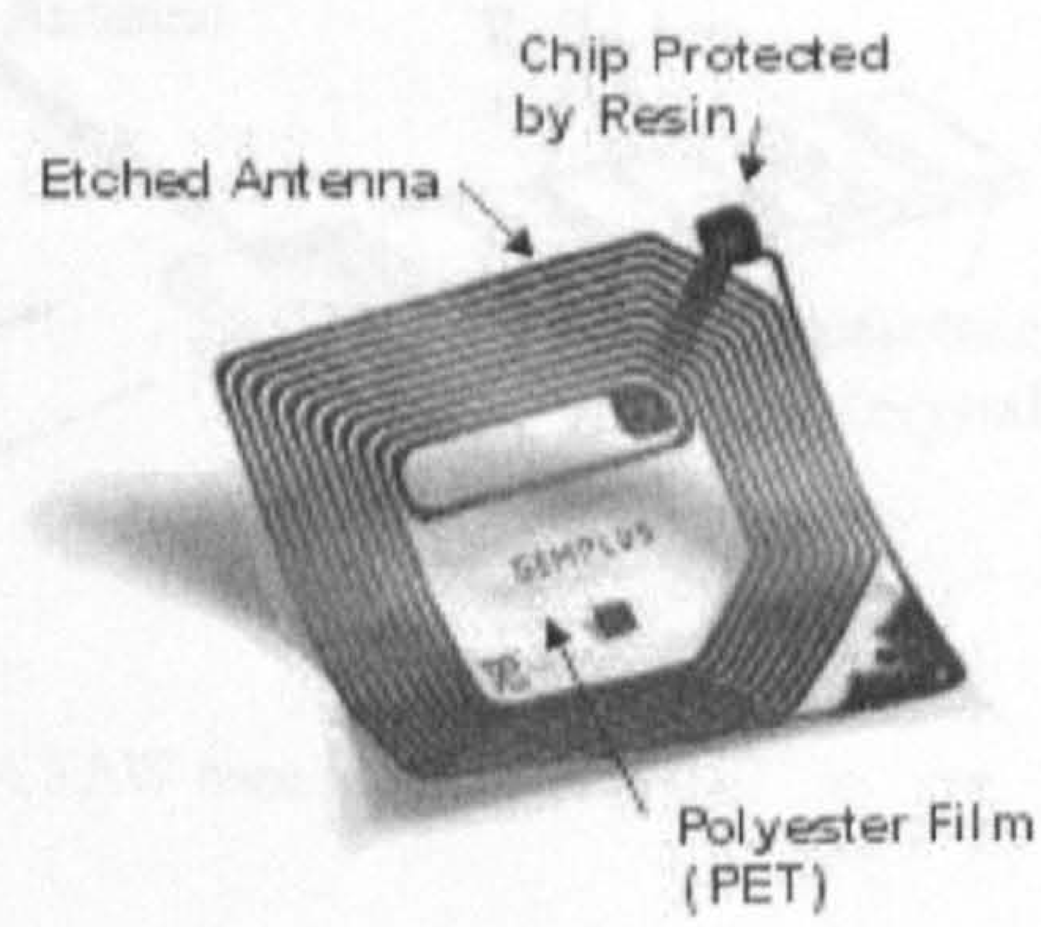


Fig.2.19 An RFID tag with PET substrate

ACA materials contain electrically conductive particles with some adhesive thus eliminating the requirement for conventional solder alloy, which is not possible for paper substrates. The Motorola BiStatix tag is a capacitive tag that consists of a radio frequency chip attached to a carbon ink antenna printed on paper using ACA **[75]**. These smart tags or paper tags are more environmental friendly and a step towards the development of low cost RFID solutions. Anisotropic adhesives mainly contain adhesive fillers like silver or nickel with a non-conductive polymer binder. ACAs are available both in the form of pastes and films. Instead of paper, Polyethylene terphthalate (PET) films can also be used as a substrate as it is highly resistive to tear, moisture and offers good flexibility [76]. However, the Motorola BiStatix tags use a paper substrate, hence they can be placed easily over corners, curved surfaces, and odd shapes. These tags operate at a frequency of 125 kHz.

SAW (Surface Acoustic Waves) Tags

Surface acoustic waves are actually sound waves that travel along the surface of an elastic material. The substrate used for SAW devices is a piezoelectric material. Generally, piezoelectric materials are very sensitive to force or pressure and generate a charge or voltage in response to it, which is called the direct piezoelectric effect. Conversely, if a high charge or voltage is applied to them, they show change in their stress or strain properties. This is called the converse piezoelectric effect [77].

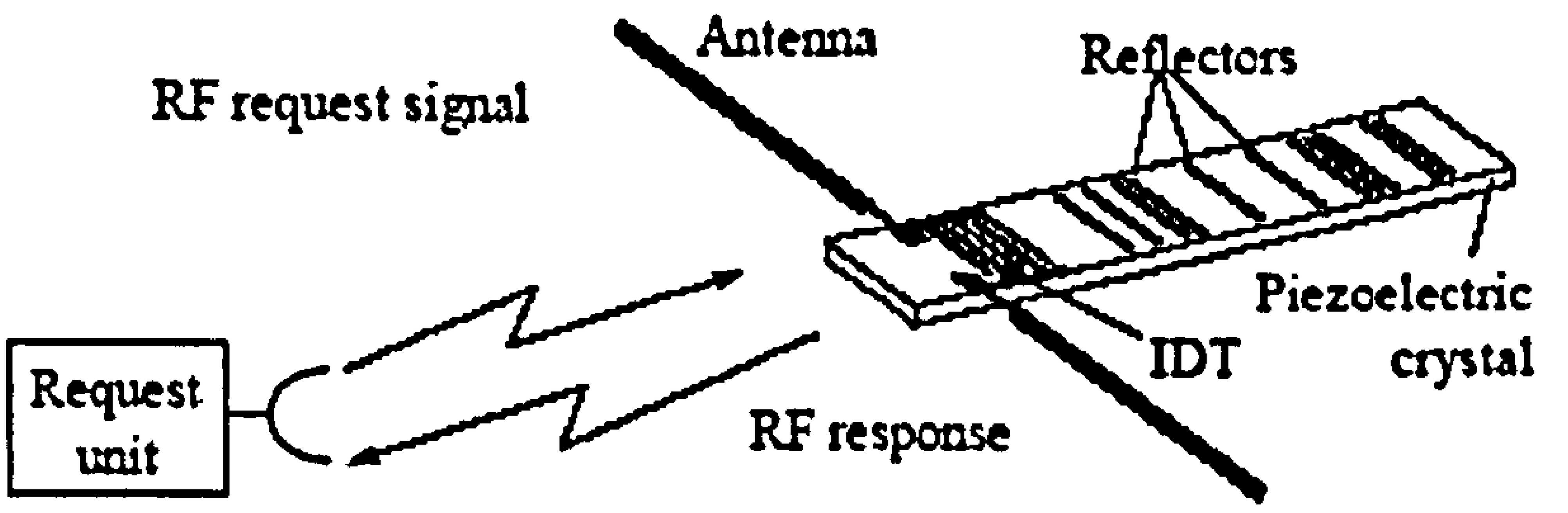


Fig.2.20 A SAW based system [73]

The SAW tag (see figure 2.20) is a passive tag that receives a signal from the reader through its antenna connected to an IDT (Inter Digital Transducer) which converts it into a SAW on a piezoelectric substrate, normally quartz, Lithium Tantalate ($LiTaO_3$) or Lithium Niobate ($LiNbO_3$). Reflectors that are metallic strips and facing the IDT, then reflect a portion of the surface waves. The reflectors reflect the SAW to the IDT, which then converts the SAW back into an electric pulse. These electric signals are then sent back to the station through the antenna. The position of the reflectors actually defines the ID code of the SAW tag, which is placed in a unique order in every tag. At different positions over the SAW tag, a reflector is either absent or present, which can be encoded as 0 or 1. The standard number of reflector positions on a SAW tag is 32. So 2^{32} tags each bearing a unique ID can be identified. Due to the sensitivity of the piezoelectric materials, SAW devices can be used as sensors. The measuring principle of a SAW device is based on the rule that measurement causes a delay or change in the time interval between the responses of two pulses. Therefore, various physical quantities like temperature, pressure, stress or strain can be directly measured by using these devices. Coating these devices with some chemical- or gas-sensitive layer can make them a bio or chemical sensor [78]. Actually, the velocity of surface acoustic waves is affected if the piezoelectric material is subjected to some sort of physical force, such as pressure or stress, thus causing a delay in response to the pulse. SAW sensors are used for measuring various physical quantities like temperature, pressure, torque and current. Their use in different applications is reported by Reindl *et al.* [79]. In Europe, the allowed operational frequencies for these types of devices include the frequency ranges of 433.07 MHz – 434.77 MHz and 2.4 – 2.483 GHz.

Memoryless tags

Memoryless tags are simple inductive systems that contain a tuned circuit. These tags do not possess any unique ID so they do not require memory. These tags are used for EAS (Electronic Article Surveillance). When passed against some RF generating source that energises the inductive circuit of the tag, the tag responds at a frequency which is half of the generated frequency, thus activating the alarm. These tags are used by clothing stores as an anti-theft application [80].

EPC (Electronic Product Code) and RFID

The Auto ID centre at MIT (Massachusetts Institute of Technology) is nowadays working on a system for the identification of products globally by using RFID. This system will use an RFID and EPC (Electronic Product Code) which will be assigned to every object (see figure 2.21).

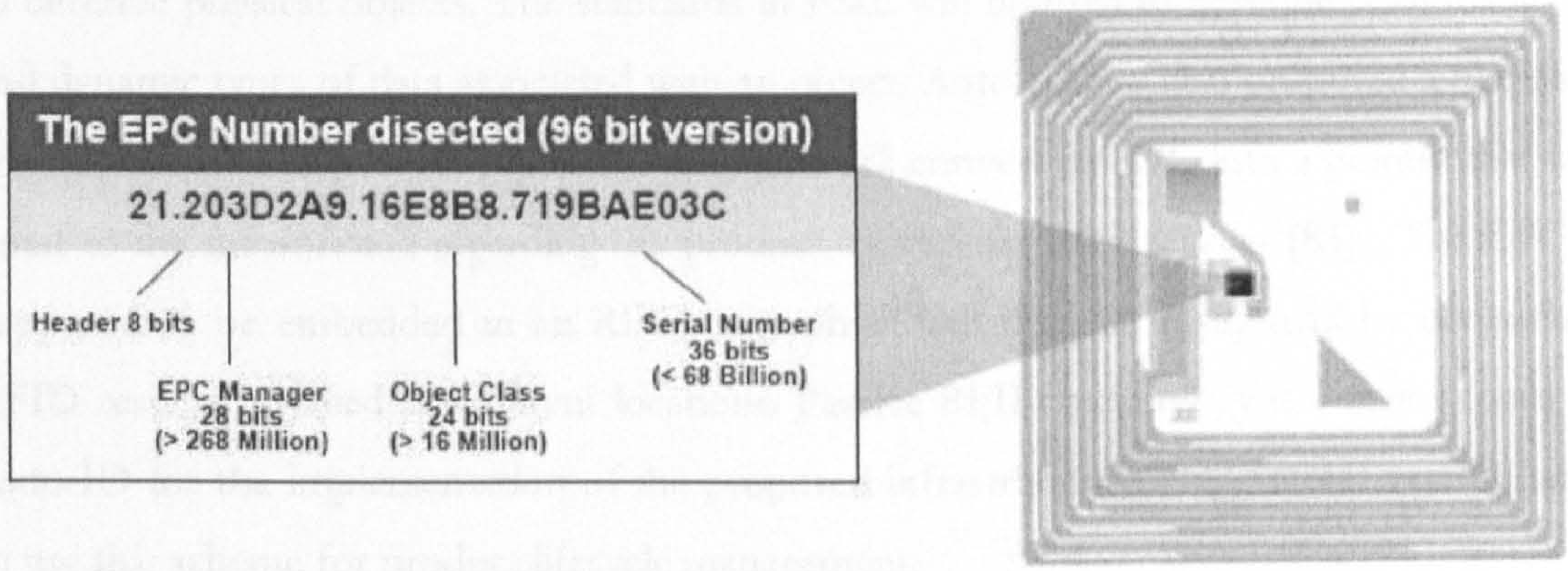


Fig.2.21 EPC and RFID

The EPC is supposed to identify all physical objects by a unique identity, which cannot be duplicated. The basic version of EPC is a 96-bit code. The first 8 bits will serve as the code header, which is used to define the number, type and length of the data partitions. The remaining bits will contribute to the data partitions of the code. The EPC-96 type 1 code consists of an 8 bit code header and will contain 28 bits to define the product EPC manager who will be responsible for managing the object class and the unique product serial number, normally the product manufacturer, 24 bits for the object class, which will be any grouping, batch or lot identification scheme developed by the manufacturer, whereas 36 bits are kept for a unique product serial number borne by the product **[81]**. The EPC will have the capability to encode assemblies, aggregates or collections of objects. A compact version of EPC is also available as a 64-bit code called the compact electronic product code. In EPC-64 type 1 code there is a 2-bit header, 21 bits are reserved for the EPC manager, 17 bits are used to define the object class whereas 24 bits are reserved to assign the product a unique serial number. The EPC-64 type 2 code consists of a 2 bit header, 15 bits for the EPC manager, 13 bits are reserved for the object class and 34 bits will be used to assign a unique serial number to a product **[82]**. According to the Auto-ID centre scheme, each EPC associated with a product will refer to some networked information, which will be stored on some information server called PML (Physical Markup Language) information servers. PML is a language based on XML (Extensible Markup Language) that will be used to describe physical objects. The standards in PML will be used to describe both the static and dynamic types of data associated with an object. Auto-ID has also proposed a mapping service called ONS (Object Name Service) that will convert an EPC into a pointer that will point to the information regarding the product on various PML servers [83]. The EPC is supposed to be embedded in an RFID tag, which will then be easily read by networked RFID readers installed at different locations. Passive RFID technology is a major focus of Auto-ID for the implementation of the proposed infrastructure. The Auto-ID centre aims to use this scheme for product lifecycle management.

Shortcomings of the Auto-ID centre scheme

The Auto-ID centre has proposed EPC as a universal coding scheme. However, it should be kept in mind that standardisation of the EPC is a major challenge that will be faced by the Auto-ID centre in future. Another issue associated with the Auto-ID scheme is that this scheme needs some authority or organisation that will be responsible for managing and assigning the EPC code to different products. Another issue is the management of such a huge amount of data, which will be maintained at the item level i.e. for every physical object to which an EPC code will be assigned. Moreover, due to cost constraints, the RFID tag will just bear an EPC, which will serve as a pointer to some information server. These factors limit the functionality of an RFID tag in a similar way to those affecting a linear barcode, which refers to the product-related information stored in some external database. In the next section a new approach, called the product centric approach, is explained.

The Product Centric Approach

In comparison to the challenges of global standardisation that are faced by the Auto-ID centre, another approach is proposed by Helsinki University of Technology to manage the products at an item level like EPC. This approach called the product centric approach [84]. It involves information-sharing between interested parties using a peer-to-peer network. The product centric approach is based on a dialogue system. In this system, the object is identified by two pieces of information. One will be the identification part, which contains a numeric identity, string, etc., and a Uniform Resource Identifier (URI), which is actually an agent associated with the tagged object. The agent is basically a service denoted by URI, and the functions of an agent include such things as product information requests and maintenance information requests. The proposed ID will be like an email address ID@URI. RFID technology is selected as the basic technology for this system [85], however, barcodes can also be used. For RFID tags, the tag identification number can be used as the ID part, which will be stored in the tag, whereas the URI part, which might be the name of the company responsible for holding the data for a particular RFID tag, can be stored in the program. Similarly for the barcodes, the ID and the URI parts can be coded into two separate barcodes or into a single barcode using a separator. As in the proposed dialogue system, all the partners will be connected in a peer-to-peer fashion, therefore, there will be no need for global data management since each partner will be responsible for managing their own data.

RFID technology benefits, issues and considerations

The major plus point of RFID technology as compared to barcode technology is that data can be written/appended several times on an RFID tag. Karkkainen *et al.* [86] and Karkkainen [87] reported that data can be written 300,000 times over RFID tags. Moreover, unlike barcode technology, RFID technology has a greater capacity for data storage. As RFID technology uses electromagnetic waves for data transmission, it can therefore be said that this technology does not require line of sight as compared to barcodes. Limitations with RFID technology include the short read ranges (passive tags), greater cost, legislation, tag de-tuning, multiple standards and incompatibility of products. Some of the important considerations associated with the use of RFID technology are discussed below:

Legislation

One of the major issues associated with RFID technology is the legislation associated with its use. Different governments in different regions of the world allow different frequencies for RFID operation. The permitted frequency bands for operations are not the same all around the world. However, there are some bands of frequencies that are common in America, Europe and Japan. For example, the frequency range of 125-134 kHz and 13.56 MHz is allowable in the countries of Europe, Japan and North America for RFID operation. Other countries in the world have allocated different bands for operation, for example, Australia has allocated the 918-926 MHz band for RFID operation [88]. Therefore, there is a need for a band that can be commonly used all around the world, such as the 2.45 GHz band, which is unlicensed in many parts of the world and could be used for RFID operation [88].

Multiple standards

As compared to the established and well defined standards of barcode technology, RFID technology is in the process of standardisation. Standardisation is one of the serious issues related to RFID technology. Due to lack of standardisation, different RFID products from different manufacturers are incompatible with each other, thus posing a major constraint to the adoption of this technology. Various organisations are working simultaneously on standards for RFID technology.

At international level, the ISO (International Organisation for Standardisation), the IEC (International Electro-technical Commission) and the ITU (International Telecommunication Union) are working. Many other institutes are also working at regional level, like ANSI (American National Standard Institute), BSI (British Standards Institute), and ETSI (European Telecommunication Standards Institute), EAN (European Article Number) and UCC (Uniform Code Council). ISO is working with IEC on standardisation of commands to operate RFID-based devices, physical characteristics, transmission protocols and radio frequency power levels. However, most of the standards belong to smart identification cards or contactless integrated circuit cards and devices employing radio frequency identification that operates at 13.56 MHz frequency. ISO and IEC have also worked out some standards that are specific to RFID tags, such as ISO/IEC 15961, which is associated with the syntax and functional commands of RFID for item management. Other ISO/IEC standards in this series deal with information exchange and a numbering scheme for unique identification [88]. On the other hand, the Auto-ID centre has proposed its own EPC numbering scheme and other protocols for data transmission. These multiple standards have created a 'what to choose and where to go' situation. For example, different types of readers available in the market have different command sets for reading or writing data on tags, or communication with tags. Most of the readers that are available in the market are compatible with tags that are provided by the same manufacturer. However, some readers have the ISO standard command set in addition to their own command set. For example, Texas Instruments RFID readers have the capability to work with the ISO command set in addition to their own customised command set. ANSI has developed its own set of standards to aid application development for RFID devices [89]. Other issues of standardisation like a tag's physical structure, formats for data storage, operating frequency, protocols for data transmission, etc., are the constraints that may be considered as barriers to the adoption of this technology.

Briefly, we can say that standardisation of RFID technology is an important issue, which must be taken into account. However, standardisation of RFID technology is in progress and it is hoped that with the passage of time, clear standards for this technology will be developed.

Collision Issues

One of the benefits of RFID technology is its anti-collision feature. Whenever two or more tags come in the vicinity of an RFID reader, they try to respond simultaneously. The response received by the reader is a mixture of two or more signals; therefore, the signal cannot be decoded truly. This is called 'collision of tags'. To avoid this situation, different vendors have provided different anti-collision algorithms, either in the tag or in the reader. The purpose of these algorithms is to singulate a tag from a group of tags in order to read the tag accurately. This anti-collision feature enables RFID technology to identify and read a number of tags per second. Various methods are employed for this purpose like identifying a tag on the basis of proximity i.e. the nearest tag first; some approaches involve serialisation of tags i.e. on the basis of unique identification number and many other solutions [90] are available in this regard. Also, the collision occurs when the interrogation zones of two or more readers intersect, so they are not able to communicate with the tags present in their interrogation zone. This situation is called reader collision. Different solutions are also available in this regard [91].

However, the issue again lies in standardisation because, due to the lack of standardisation, different RFID products have different anti-collision algorithms and protocols, which are not compatible with the products from other manufacturers. Therefore, two readers from different manufacturers working nearby may create interference in each other's interrogation field.

Tag de-tuning

The material properties of the tagged objects affect the performance of RFID tags. The operating frequency of RFID tags is disturbed if they are placed over or near particular types of object, especially metallic objects or objects containing liquids, because metals, liquids and some materials absorb electromagnetic waves. The inductance of a tag decreases due to loss in electromagnetic waves thus disturbing the resonant frequency of the tag. Therefore, inductive tags need special tuning by adjusting their capacitance or inductance to maintain their performance when placed over metallic objects. However, the performance of capacitive tags is reported to be satisfactory over metallic objects [73], but capacitive tags operate at 125 kHz frequency, which is less common as compared to the 13.56 MHz that is being used by inductive RFID tags. Therefore, the author performed a simple experiment in order to check the de-tuning of inductive RFID tags by placing them over different objects of different materials. This is described in Chapter 3.

Sensitivity to orientation

Though RFID technology is supposed to be a non line of sight technology, it is slightly sensitive to orientation as well. Orientation of a tag affects the signal attenuation. However, RFID tags are read at any possible orientation if they are close to the reader. The merits and demerits of RFID technology are summarised in table 2.5.

Merits	Demerits
1) Non-line of site technology as compared to barcodes, which require line of site for proper data transmission.	1) Somewhat sensitive to orientation; antennae need to be positioned in order to attenuate and reflect the RF signal at maximum level.
2) Capability to withstand a harsh working environment, which is not possible in the case of barcodes which are sensitive to dust, dirt and damp.	2) Interference from metals and liquids. Specialised tags are required to be placed over metallic objects or vessels containing liquids.
3) Tags can be read and written several times (300,000 times), data can be appended as compared to barcodes which are WORM (Write Once Read Many times).	3) Legislation on use. Operate at different radio frequencies therefore requires a licence for operation in different countries of the world.
4) Have anti-collision feature due to which several tags can be identified per second.	4) Incompatibility in RFID products from different suppliers due to lack of standardisation. Standardisation is still in progress.
5) Longer read ranges with Active RFID system up to 5-100 feet.	5) Shorter read ranges of passive RFID systems, limited up to 2 feet.
6) Large memory capacity 64 to 32,678 bytes.	6) Costly, cost increases as memory increases.
7) More automatic due to non line of sight and anti-collision features. Has ability to read/scan objects in the form of groups and lots. Therefore, less labour intensive as compared to barcodes.	
8) Sensors, even microcontrollers, can be incorporated with active tags. Passive SAW tags can also be used as sensors.	

Table 2.5 Merits and demerits of RFID

From the perspective of product lifecycle management RFID technology can be used to store product-related information during its BOL phase; for example, in a manufacturing cell, where product has to pass through different stages or work stations. As data on RFID tags can be erased and written several times, therefore, this advantage of RFID technology can be used to keep the product status up-to-date throughout its manufacturing process. However, use of high memory tags for this purpose may add an additional cost to the manufacturing process, therefore, ID-only RFID tags can be used to link the product to some centralised database against the unique ID of the tag to record the production activities associated with a particular product. Moreover, non line of sight property proves RFID technology as a potential candidate in a manufacturing environment where products are dispatched in the form of a lot, as the whole lot can be identified at once rather than passing each tagged object in front of the reader. High memory tags can be used to store some attributes that are associated with product identity, such as, manufacturer ID, product type/model no., product serial no., etc., then it can be used to trace the product identity at its EOL. A compromise on costly tags can be made for a high value industrial equipment with high salvage values such as, a machine tool; high density memory tags can be used to store necessary product information that are mentioned in table 2.1.

2.3.3 Electronic Data Logs

As mentioned earlier, there are two types of product lifecycle data: static and dynamic. Electronic data logs and other systems are proposed to manage mainly the dynamic part. However, very few attempts have been made up to the present to capture the dynamic part of the product lifecycle data. Those that have are explained below:

Green Port

Scheit and Zong [92] proposed the concept of a green port to capture the lifecycle data in order to get information for the reuse of electronic items. According to them, electronics products should consist of a modular structure rather than a traditional design. Because they have a modular product structure, individual functional modules of products can have a greater possibility for reuse. According to the proposed approach, each module should be provided with a memory unit, called the identification (ID) unit, in order to store the static and dynamic data. The lifecycle data from the product can be retrieved using a port, which they named the green port. All ID units installed in individual modules of products will be connected to each other through a common bus called the green bus. The green bus will be further connected to the green port for the purpose of data retrieval from the product.

The authors of the paper proposed that there are different levels for the implementation of ID units. At the initial level, necessary product information and material information can be stored. At the medium level of implementation, other concerned parties, like service personnel and recyclers, will have the provision to input data into the ID unit, while at the highest level of implementation, lifecycle data will be collected in an autonomous mode via sensory devices.

EDL

Klausner and Grimm [43] proposed a system called ISPR (Information System for Product Recovery). The ISPR consists of an electronic device called EDL (Electronic Data Log) embedded in the product to record the dynamic data related to the product. This EDL was mainly developed for use in electric motors in order to retrieve dynamic data to judge whether the motor could be reused in other products [93]. The proposed EDL contained a circuit board with a microcontroller and EEPROM. EDL also had temperature and current sensors. An LED was employed to transmit data from the ISPR to an electronic reader. A DC power supply was used to power the EDL. The EDL was supposed to be embedded inside the housing of the product. It had the capability to count the motor's starts and stops. It was able to store the time for each and every individual operation cycle, thus it could calculate the total running hours of the motor. The EDL could also store and process the sensory data regarding motor current and temperature for every single use cycle, thus it was able to calculate the peak and average values of the data. EDL had three bytes in its memory to keep a unique product identity for product identification. It had the capacity to log data for about 2,300 hours of operation. The logged data was then transferred through an LED read by an electronic reader containing photo diodes and an electronic circuit to amplify the signal received from the LED. The electronic reader could be connected to a PC via an RS-

232 communication port in order to make data available for the visualisation and interpretation software. The interpretation software utilises an algorithm that predicts whether the motor is suitable for reuse or not. Though EDL was designed to get dynamic information for the purpose of product reuse, one of its shortcomings was its limited capability to store the sensory data. Other MOL information like maintenance, repair, and service information, which are essential to determine the feasibility for product reuse, could not be stored in that EDL.

LCDA

Unlike EDL, which was just able to record sensory data, the LCDA (Lifecycle Data Acquisition) system proposed by Simon *et al.* [44] was able to store the other MOL activities like maintenance, service and repair updates. The proposed LCDA consists of sensors for data acquisition, a clock and a microprocessor to manipulate the sensory data plus a non-volatile memory and a communication system to retrieve data from the LCDA. The LCDA was supposed to perform different functions like counting the starts and stops of a machine; controlling various functions, such as controlling an actuator; recording the date and time stamps for the start of each individual cycle along with the duration of operation for each machine cycle, thus giving the total running hours for the machine. The embedded software in the microcontroller took 8KB of memory. The software was responsible for performing basic control operations. The LCDA was provided with a socket for data communication to a host computer. The host computer then employed software for online monitoring during operation. Based on the LCDA concept, various prototypes have been developed and tested on washing machines. For a case study of an LCDA device, named White Box, applied to washing machines, the reader is referred to Moore *et al.* [94]. The authors also proposed that static data such as the IDs of components present in a product, the components' designed life etc. should be stored in the LCDA during the production phase of the product. Although the LCDA was able to carry out online operation monitoring of a product and was able to detect the abnormalities in operation, it was not able to predict the remaining lifetime of the product.

Watchdog Agent

All the systems explained above are not so intelligent as to be able to predict when the product is going to fail or the causes of failure or degradation in performance of the product like a concept of watchdog agent proposed by Djurdjanovic *et al.* [95]. The basic objective of a watchdog agent is the efficient MOL management through predictive and proactive maintenance. The main functions of a watchdog agent are to assess and predict the machine performance degradation by using data from multiple sensors, prediction of faults and finding the reason for, or cause of, the fault. These features are not only useful from a maintenance point of view but also useful to predict the product's remaining life. Various tools can be employed in such a type of agent, such as fuzzy logic, neural networks and signature analysis, to predict and assess the performance of a machine. The functional elements of a watchdog agent are a sensory system, signal processing, condition monitoring, performance assessment, prognostics, decision-making and representation.

The watchdog agent has been implemented in various applications. However, its areas of implementation are limited to large products or industrial equipment like elevator doors and material handling devices, which are not a basic consideration from the perspective of waste management. The implemented version of watchdog agent uses a logistic regression model in combination with a feature extractor to measure the degradation in performance of the elevator door. Recommendations from maintenance experts, time for opening and closing of door, and the maximum speed of elevator door are used as features to measure different parameters for logistic regression and to measure the performance of elevator in terms of a confidence value. A PC-based software is developed to assist the user for the purpose of performance visualisation. For a good or normal behaviour of the elevator door, the software shows a high confidence value but any degradation in the performance of elevator door, such as if a person is leaned against the elevator door then it shows a low confidence value because of the damp created by the person. Apart from the logistic regression technique other versions of watchdog agent employ CMAC (Cerebellum Model Articulation Controller) neural networks to calculate confidence value. This technique is explained in detail in chapter 6 under section 6.6.9 that is associated with the techniques for life prediction.

Another version of watchdog agent is applied to machine tools. This version of watchdog agent employs some time-frequency based technique for performance assessment. It uses a Labview based application to capture and record the sensory data from different machine tools across the shop floor. Data from various machine tools is then searched with the help of a web-enabled tool against different searching attributes like plant, machine, sensor, date and time. The data is then collected and downloaded for detailed performance analysis. Plots of signatures of principal components that are logged over a period are then displayed for visualisation. The signature plots are then compared with the signatures under normal operation, therefore, any deviation from normal behaviour indicates performance degradation. The watchdog agent is claimed to be a tool to asses and predict the performance of a machine or process, however, attempts are being made to use this tool for the purpose of collaborative product lifecycle management and to judge the remaining lifetime of machine components for the purpose of reuse. Efforts are being made to aid the plug and play approach for watchdog agent, so that it can operate without the assistance of an expert person. Participation of watchdog agent in the area of product lifecycle management also aims to achieve the objectives of PROMISE. The target is the integration of watchdog agent for the purpose of closed-looped design and lifecycle management. Implementation of a watchdog in white goods may prolong their length of usage in an efficient manner. However, the cost of implementation is the major constraint in this regard. Moreover, the major shortcoming in the watchdog agent is its dependence on external PC-based software for decision-making, forecasting and performance measurement, which is similar to the previous approaches that are explained above. The logic for decision-making should be embedded inside the prognostic and diagnostic agent to ease its implementation for different product types. Another challenge that needs to be addressed is the deployment of user-friendly language in order to make products more intelligent, so that they interact easily with users rather than displaying complex interpretations or visualisation graphs. Also, the challenge lies in making such systems capable of assisting or guiding the users in different usage modes for efficient lifecycle management.

ELIMA

ELIMA (Environmental Lifecycle Information Management and Acquisition) is a project funded by the European Commission with the objective of managing product lifecycle data in order to promote a sustainable society [96]. In this regard, developed prototypes called Identification and Data Units were implemented in different products to collect the sensory data during the use phase. The ELIMA prototype consists of a microcontroller with 8KB of memory, which utilises a 125kHz RF link for data transmission. The IDU uses seven different sensors to record dynamic data from the product. The recorded data is then transferred through the RF to the local computer, which sends the data to the Intelligent Management System (IMS), which is basically ELIMA's lifecycle management software, via the Internet. The IMS is supposed to be the backbone of ELIMA and it consists of a database and tools to perform the decision-making tasks which are necessary for lifecycle management. A brief comparison of all the approaches discussed above is presented on the next page in table 2.6 .

	Objective	Information type	System	Life Prediction
Green Port [92]	To promote reuse of individual modules of electronic products with modular design.	Static and all types of dynamic information at different levels of implementation.	Devices and sensors embedded in different modules for data acquisition at different levels of implementation. Data can be retrieved and fed to some external decision-making agent.	Unable to predict product life.
EDL [43]	To determine the feasibility for reuse of electric motors.	Only sensory data could be stored.	Embedded system having a limited number of sensors aimed at low cost implementation. An LED was used to transmit to some external software to make the decision for reuse.	Unable to predict product life.
LCDA [44]	To manage a product's lifecycle, especially the use phase. Applied to white goods.	Use-phase dynamic data like sensory and maintenance or service archives. Also proposed the storage of relevant static data like ID of components.	Embedded system with sensors to perform online monitoring of operation. Data was transmitted to external PC through a communication network for online monitoring.	Unable to predict product life
Watch dog [95]	To manage products efficiently during their MOL phase by assessing degradation of their performance. Applied to large products e.g. industrial equipment.	Maintenance-related dynamic data necessary for predictive and proactive maintenance.	Embedded system fully equipped with different sensors. Data is sent to intelligent prognostic and diagnostic software on an external PC, which measures gradual degradation in the machine performance.	Able to predict product life through different types of models by assessing product performance.
ELIMA [96]	To manage product lifecycle data in order to promote a sustainable society. Applied to consumer goods.	All types of data associated with the product lifecycle.	Embedded system equipped with sensors. Uses RF link to transmit data to local PC, which then sends data to the decision-support system via the Internet.	Able to predict product life by using statistical models.

Table.2. 6. Comparison of different approaches for datalogs

2.4 The i-button: a new technology

One simple technology developed by Dallas Semiconductors is the i-button, which is simply a semiconductor chip enclosed in a tiny, stainless steel can (see figures 2.22 and 2.23). Each i-button can has two contacts, the lid and the base. The lid is the data contact, which is the top of the can whereas the base, the bottom of the can, is the ground contact.

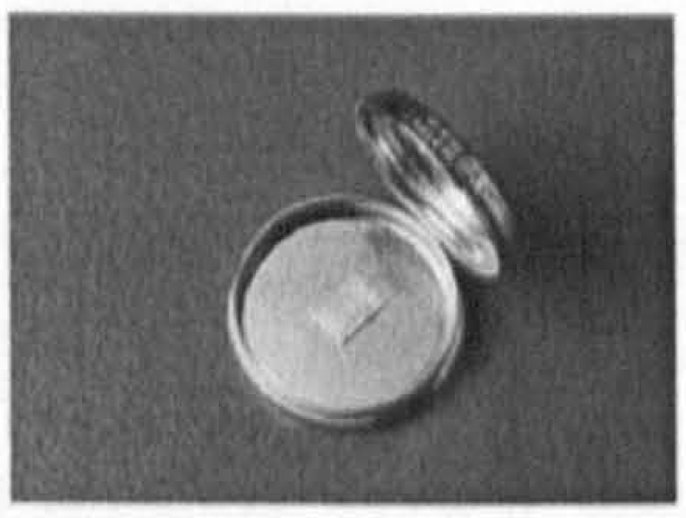


Fig.2.22. An i-button from inside

Each i-button is provided with a unique factory-etched number in its silicon chip. The unique identity inside the i-button can be accessed using a probe or a blue dot receptor (see figure 2.25) that uses the 1-wire protocol, also developed by Dallas Semiconductors.

Fig.2.23. An i-button from outside

The 1-wire protocol uses a single wire that is employed for both device signalling and power. The probe or blue dot receptor is connected to a PC via a serial or parallel port and the ID inside the i-button can be read by simply making a physical contact between the i-button and the probe or blue dot receptor. These buttons are available in various varieties. The ID-only i-buttons consist of a 64 bit ROM that contains a factory-etched unique ID.

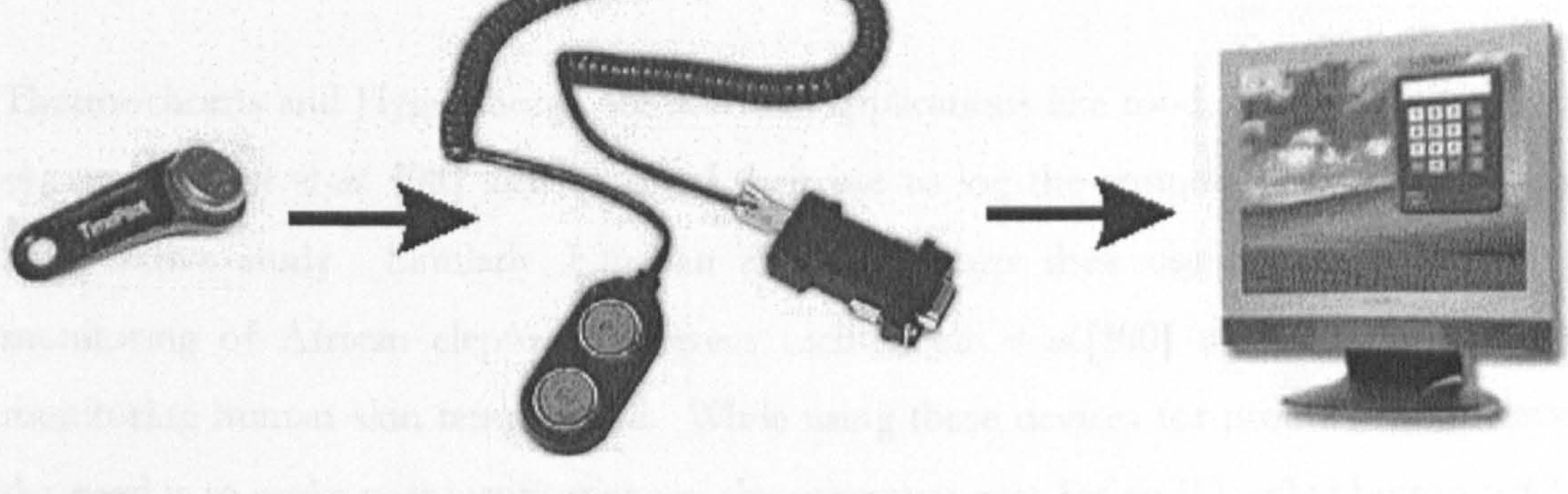


Fig.2.24. An i-button data acquisition system

Other flavours of i-button include memory devices that have a read/write capability and capacities which range from 1 Kbit to 64 Kbits. EEPROM i-buttons also have a read/write capability with limited write cycles but their capacity ranges from 256 bits to 32 KB. These devices are also available in the form of data loggers. Thermochorn and Hygrochorn belong to the family of i-buttons that are used for temperature and humidity logging. These devices can be easily attached to the surface of the object whose temperature or humidity data is to be logged. Standard versions of these devices can take 2,048 readings with a time interval of 1 to 255 minutes whereas advanced versions are capable of takinge 8,192 readings for interval ranges from 1 second to 273 hours **[97]**. However, as these devices need physical contact for data transmission, this makes this technology rather more labour intensive.

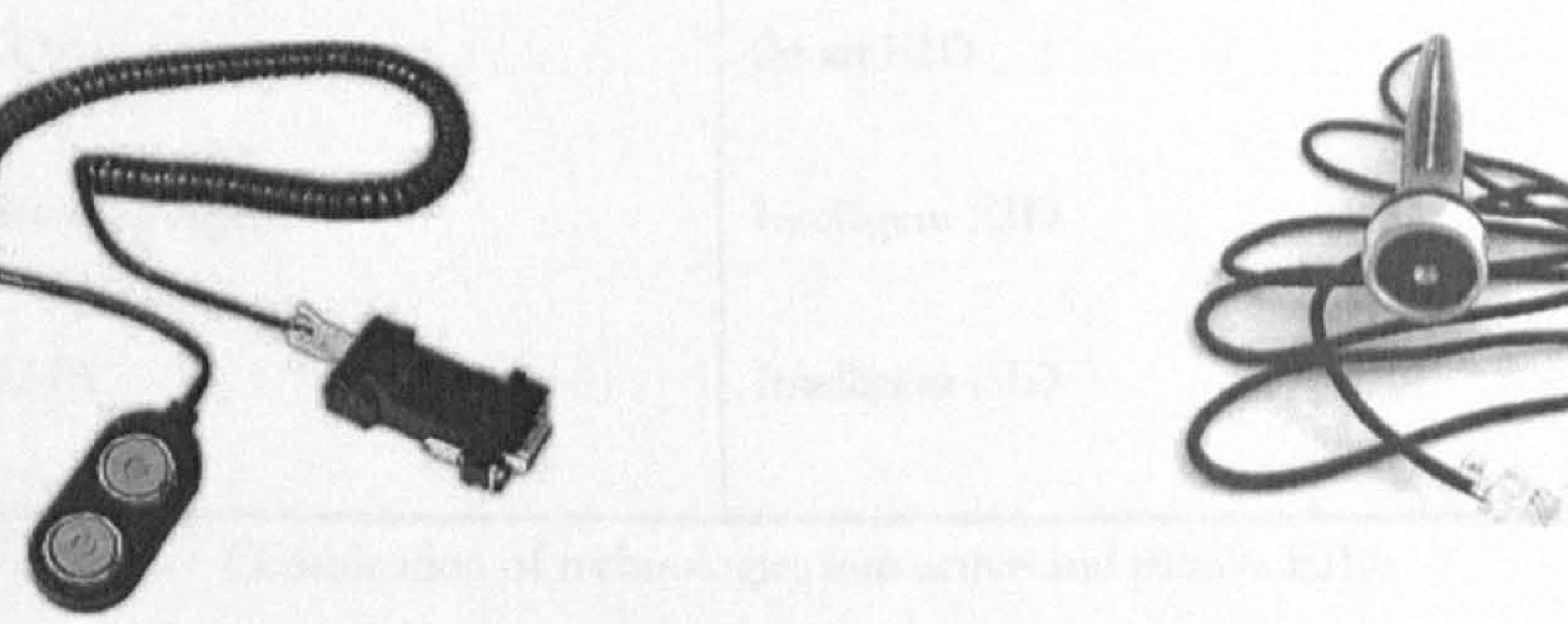


Fig.2.25. Blue dot receptor and probe for acquiring data from an i-button

Thermochorns and Hygrochorns are useful in applications like food, chemicals and HVAC systems. Taylor *et al.* [98] also reported their use to log the temperature of reptiles for a comparative study. Similarly, Kinahan *et al.*[99]reports their use for daily temperature monitoring of African elephants whereas Lichtenbelt *et al.*[100] mentions their use for monitoring human skin temperature. While using these devices for product identification, the need is to make cost justifications as the minimum cost for an ID-only i-button is $2.23 whereas in 2001 the RFID tag's reported cost was around 50 cents [101].

2.5 Classification of technologies into Active and Passive EIDs

All the technologies that are discussed above can be classified in terms of EIDs as follows:

No.	Technology	Class
1	1D Barcodes	Passive EID
2	2D Barcodes	Passive EID
3	Passive RFID Tags	Passive EID
4	Passive i-buttons	Passive EID
5	Green Port	Smart EID
6	EDL	Smart EID
7	LCDA	Smart EID
8	Watchdog Agent	Intelligent EID
9	ELIMA	Intelligent EID

Table.2.7 Classification of technologies into active and passive EIDs

2.6 Examples of lifecycle management with Auto-ID technologies

Lifecycle management of products can be geared up with the existing technologies in the market. The commonly available barcode technology can gear up the lifecycle management to a considerable extent rather than waiting until standardisation for a unique product identification code like EPC arrives. Simple barcodes can refer to details of a particular product and its sub-components in a database to help recyclers to identify the markets where these parts can be used as spares [102]. A demonstration system has been developed to link the recycling information of a product available on the web using a simple barcode, which is already present on the product. The proposed system was designed to link the recycling information of mobile phones by using the standard barcodes already present on them. The barcode present on the mobile phone contains the international mobile equipment identity (IMEI) which is unique for all GSM mobile phones. The software developed for this purpose contains the IMEI number of the mobile phones and the web addresses, which have disassembly information regarding a particular model of mobile phone. Thus, by typing or scanning the number from the barcode the software opens the website containing the disassembly information for that mobile phone.

Hitachi has worked out a system for the lifecycle management of used PCs by using RFID technology [103]. This system employs an RFID tag that is attached to the PC during the manufacturing stage. The tag contains all the relevant information regarding the PC. The additional information is maintained by the centralised database system. All this information is obtained at the disposal plant while dissassembling the PCs to segregate useful, waste, and hazardous components. A collection management number is assigned to every PC by writing it over the RFID tag when the user brings the used PC to the retailer, which is responsible to register the collection of used PCs. The used PC is identified through this collection number from the retail centre to the disposal plant and its status is updated throughout against this ID.

RFID tags are being used in trashcans for garbage collection in Europe, the USA and Canada [39, 104]. Households pay as they throw. The trucks for garbage collections are provided with weighing equipment. The payers are identified through their trash cans on which an RFID tag is placed. The truck is also provided with a reader to read the garbage cans' RFID tags. The information about the waste generated is downloaded against each owner's ID and households are billed according to the weight of garbage they produce. In Germany, the percentage of garbage collections using such a system is reported to be 20% [39].

2.7 Summary of chapters 1 and 2

Briefly, we can conclude:

- In the future, legislative pressures, customers and market demands will force manufacturers to take back their products at the end of their useful lives. Hence, product lifecycle management will become a serious issue. Therefore, to ensure their future survival, manufacturers will have to make a compromise with additional costs for product take back and lifecycle management systems.

- A major constraint to successful product recovery is the improper flow of information from the MOL phase to the EOL phase, which has been given very little importance in the research so far. To overcome this problem, there is an essential need for embedded information devices that carry product-related information throughout the lifecycle of a product, especially during the MOL phase.

- Normally in the literature, barcodes and RFID tags are proposed in order to refer to product-related information in some external database. Most of the proposed approaches (especially that of the Auto-ID centre) focus on storing product-related data, particularly the use-phase data, at item level in some external database.

- In addition to Barcodes and RFID tags, electronic data logs are also proposed to store or monitor sensory data of products throughout their lifecycles.

- A new technology, called i-button technology, shows promise as passive information devices for product lifecycle management.

- For long life products with high functional complexity, the requirement for a fully integrated mechatronic system or an intelligent embedded information device (EID) is indispensable in order to prolong their use phase in an efficient manner through predictive and proactive maintenance.
- All the approaches proposed in this regard are not intelligent in the sense that they can exactly predict the product EOL. They still lack the ablity to have a useful dialogue with their user or the external environment for knowledge-sharing and information exchange.
- For the full integration of intelligent EID into future products, it is necessary that the intelligent logic should be totally inside the chip or inside the system. All of the approaches that are discussed in this report lack this feature and are found to be dependent on some external agent or system for decision-making.
- Briefly, a single technology cannot be proposed as a solution to apply on every product. There is an urgent need of proper classification to apply different technologies on different products on the basis of various factors like product complexity, data requirements or the environment to which the product is exposed.

2.8 The scope of research

The literature review indicates that the actual scope of this research lies in the area of intelligent EID, an area which is very broad. However, for a PhD project, the main objectives of research are identified as follows:

- To research an intelligent EID system and technique in order to predict the remaining life of a product in terms of hours depending upon the product usage mode. This will add intelligence to a product in the sense that it will be able to communicate with its user by providing him the information in numbers that when the product is going to fail.

- To investigate a communication interface in order to make the product intelligent enough to communicate with its external environment in terms of knowledge exchange. This knowledge exchange will be bidirectional i.e. from the product to its external environment and from the external environment to the product itself. By doing so, the product and its user or the concerned parties will be able to engage in a dialogue in terms of knowledge and lifecycle information-sharing. This feature will make the product really intelligent in the sense of behaving like an intelligent agent which percepts from its environment, acts according to the gained knowledge, and then, in response, gives back some information to the external environment for lifecycle management and further product improvement .
- To make the intelligent EID independent of an external processing system for the process of life prediction. In other words, to embed intelligent logic for life prediction totally inside the chip or system. This will ensure the full integration of intelligent EID in future products. All previous approaches that are discussed in the literature review lack this feature and are found to be dependent on some external agent or system. The aim is to develop a system that has on-chip, life-prediction capability.
- In addition to the objectives that are defined above, the potential of passive and smart EIDs for product lifecycle management will be investigated and demonstrated.

Chapter 3

EXPERIMENTS WITH PASSIVE EIDS

In order to determine and demonstrate the capability of passive EIDs, experiments were performed to investigate RFID tag detuning and their data storage capability. The potential of i-buttons to support product lifecycle management was also investigated. These experiments and their findings are described in this chapter.

3.1 Experiments with RFID

Experiments on RFID tag detuning and information storage were performed. These experiments are described below:

3.1.1 Experiments on de-tuning

Experiments were performed by the author using a Texas Instrument RFID evaluation kit (RI-K10-001A). This kit includes a Texas Instruments RFID 6350 reader board. The board is enclosed in a plastic housing with an antenna. The kit can be connected to the host computer via a serial communication port. A 9-pin, D type, male-female connector is used to connect the reader module to the PC. The reader is powered by a 9V DC power supply. The Texas Instruments 6350 reader operates at the 13.56 MHz frequency. The reader has a very limited range in inches. Sample Texas Instruments inductive RFID tags (RI-I03-110A and RI-I1-110A) provided with the kit were used for experimentation. These tags have a rectangular shaped, etched aluminium antenna with a PET substrate. Their data storage capacity is just 32 Bytes and they can retain data for more than 10 years. Figure 3.1 shows the Texas Instrument reader that was used in the experiment.

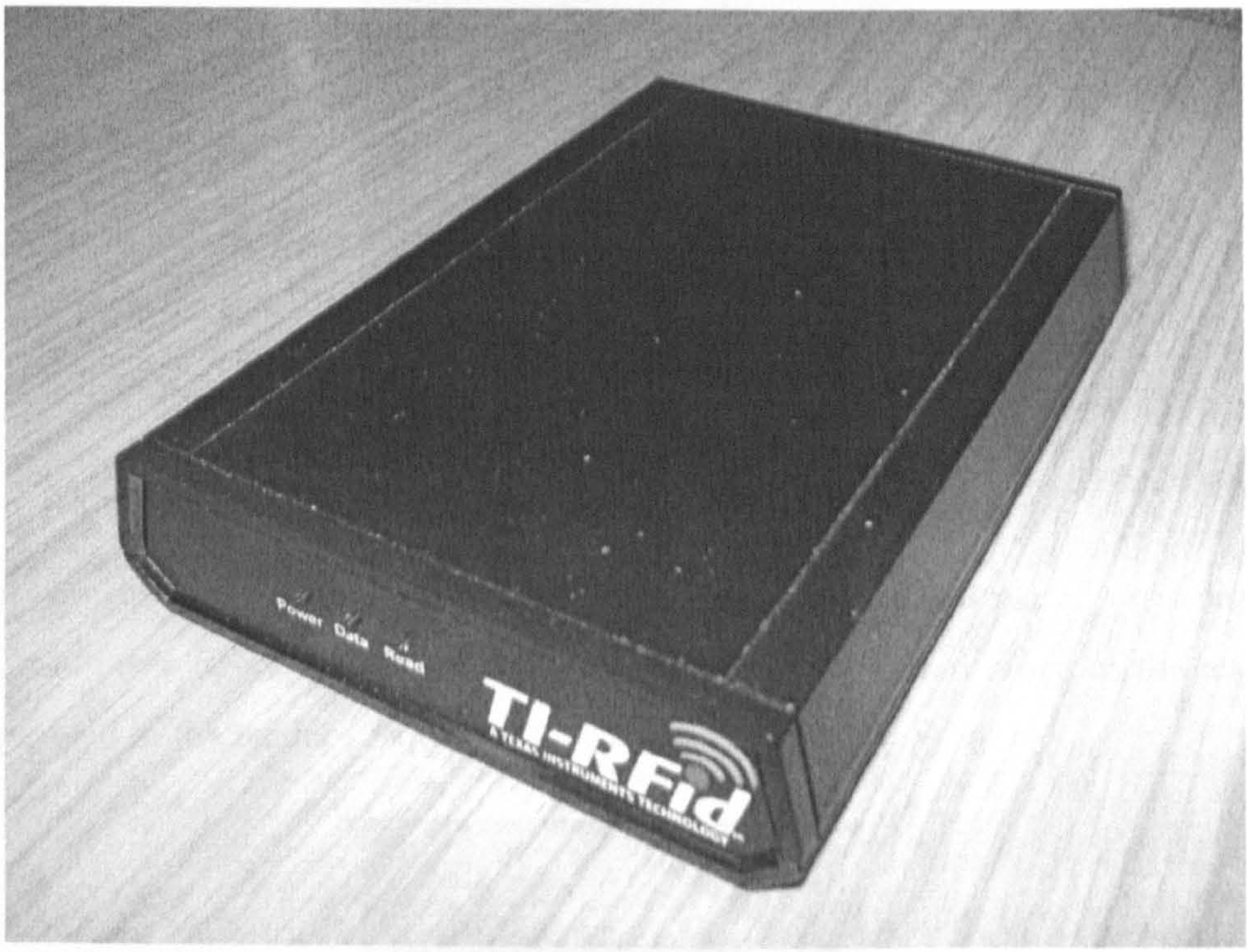


Fig.3.1 RFID reader used in the experiment

An experiment was performed with the help of utility software provided with the kit for experimentation purposes. The software has the capability to send different commands to the reader in order to detect, read, write and lock data onto the tags. A Texas Instrument RFID tag was placed over an induction motor (see figure 3.2), having a metallic casing. When the tag was brought into the field of the RFID reader, the tag did not respond.

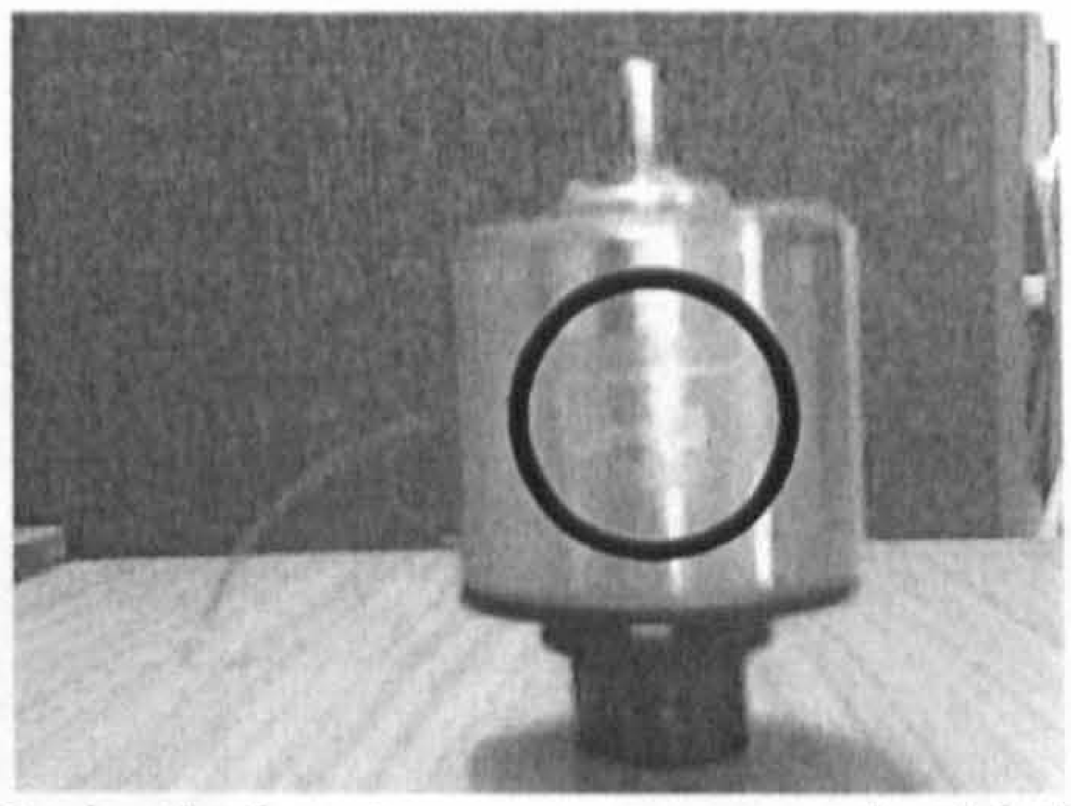


Fig.3.2. An induction motor tagged with RFID

The tag was then tried with a plastic object. This time the tag was placed on a disposable plastic bottle (see figure 3.3). When the bottle was brought within range of the reader the tag responded to the reader's request.

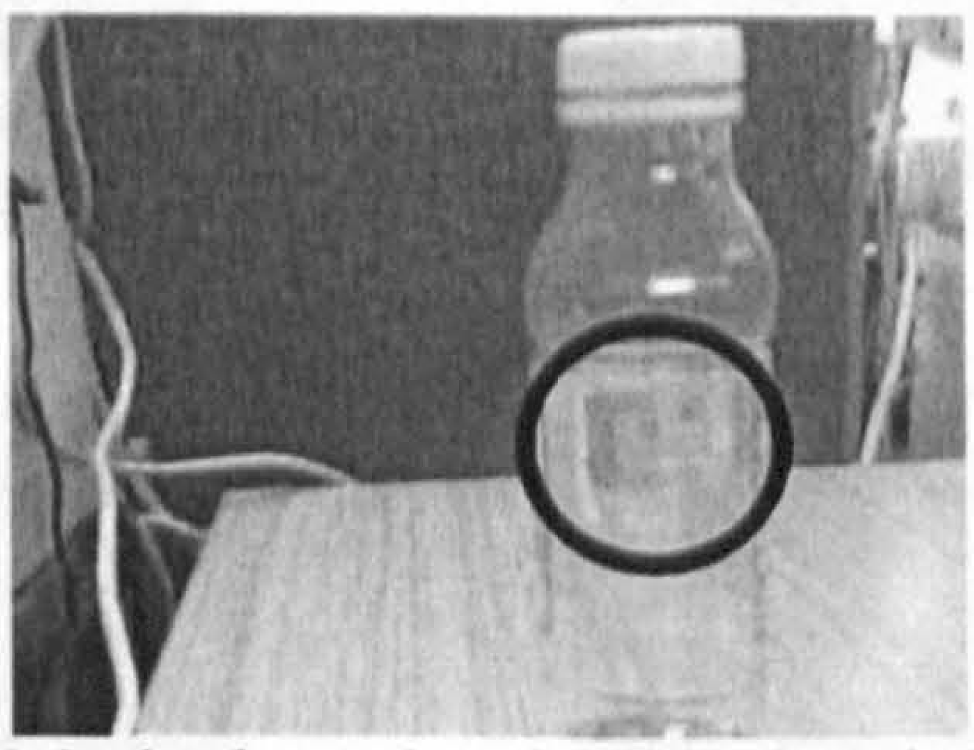


Fig.3.3. A plastic bottle tagged with RFID

To determine the suitability of RFID tags for carton-type packaging, the tag was then applied to a cardboard carton.When the carton was brought into the reader's field, the tag started to respond. The idea was then adopted to tag a metallic object with the RFID tag with an insulator between the tag and the metallic surface. The tag was then placed over a paper and then attached to the metallic object. The tag did not respond when brought into the field of the reader. The same tagging experiment was performed with a ceramic material by placing the tag over a ceramic mug, this time the tag was detected when brought into the vicinity of the reader.

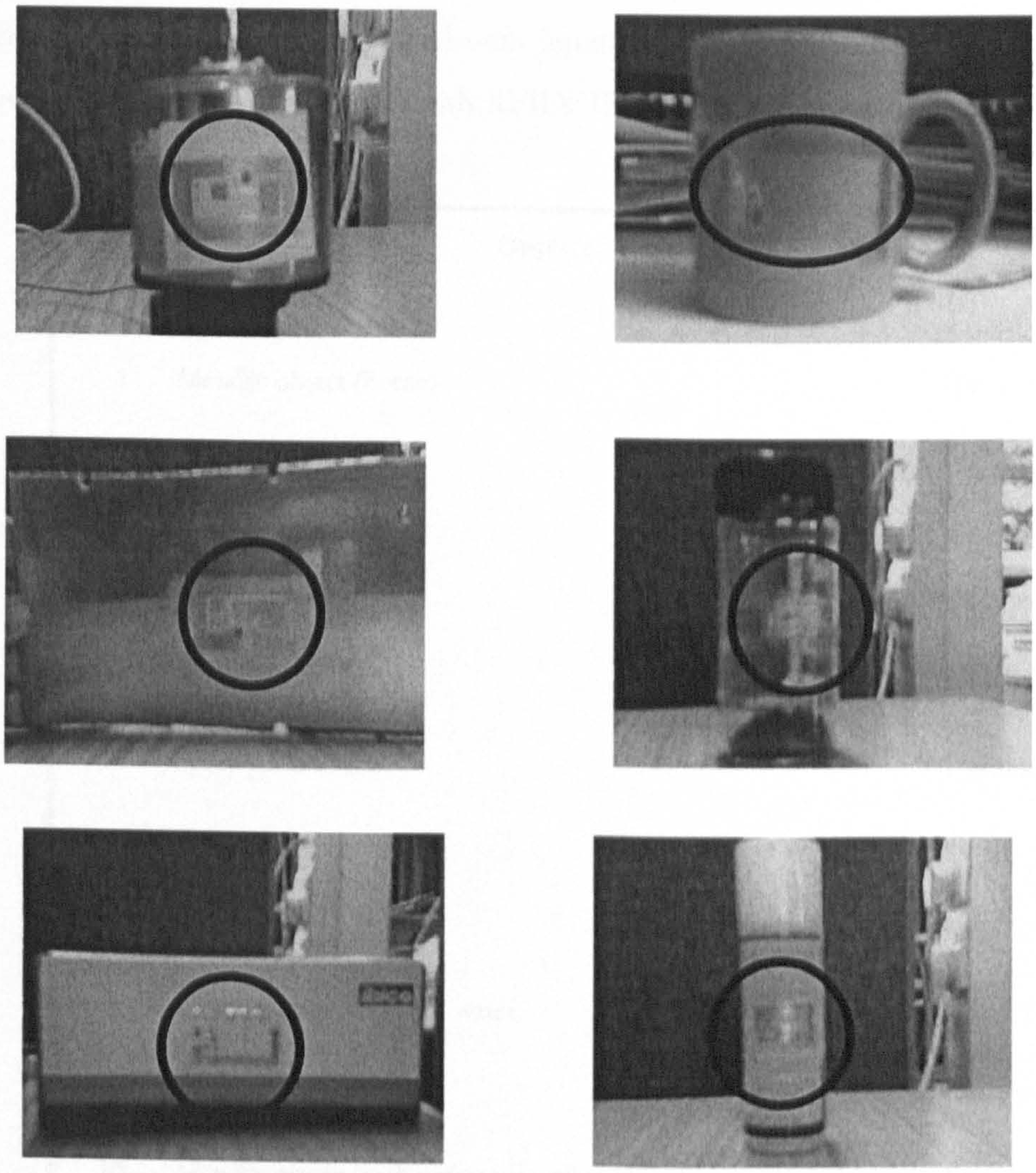


Fig.3.4. Different objects tagged with RFID

De-tuning in the taggs was observed when taggs were placed over other metallic objects like an Aluminium plate and a spray bottle. However, taggs did not de-tune when placed over objects like a glass jar, a bottle filled with liquid (water) and a piece of wood. Figure 3.4 shows the different objects tagged with RFID. The results are summarised in table 3.1.

No.	OBJECT	Results
1	Metallic object (Ferric)	De-tune
2	Plastic objects	OK
3	Cardboard Packaging	OK
4	Paper	OK
5	Spray paint bottle	De-tune
6	Glass jar	OK
7	Ceramic mug	OK
8	Plastic bottle filled with water	OK
9	Aluminium Plate	De-tune
10	Metallic object (with paper as insulator between tag and object)	De-tune
11	Wood	OK

Table 3.1. Effect of different materials on RFID tags

From the results mentioned in the above table, it is clear that RFID tags do not work well when tagged used on metallic objects. So, considerations must be made while placing RFID tags over these objects. There are specialised tags available that can be used with metallic objects [105]. Actually, the presence of metal results in the absorption of an RF signal. If the metal absorbs radio energy, then it de-tunes the RFID tag because, by doing so, it reduces the energising energy required by the passive RFID tag in order to respond to the reader. However, if the metal reflects RF waves accurately then it can act as an antenna for an RF signal. Therefore, these specialised tags use a dielectric layer that turns the metal surface of the tagged object into the tag's antenna because the dielectric layer acts as a capacitance tuned to that frequency. So, the metal surface becomes a part of the antenna thus increasing the tag's efficiency to receive and reflect the signal from the reader. Liquids, especially water, also absorb RF waves, therefore they can also affect the performance of RFID tags. However, with Texas Instrument tags, the author did not observe any malfunctioning in the performance of the RFID tags when tagged to objects containing water. The tags even showed satisfactory performance with non-metallic objects in the presence of metals. However, the author could not observe the degradation in their performance due to very short range of the reader.

In a case where metallic objects require direct RFID tagging, then due to the possibility of de-tuning, proper choice of a specialised tag must be considered. Though RFID technology is independent of line of sight but tags get the best attenuation when they are placed parallel to the reader's antenna. Therefore, considerations must be given to placing the tag in such a position that the tag's antenna can get maximum attenuation and is therefore able to reflect the signal at maximum level (see figure 3.5). For example, placing the tag at the bottom of an object can make it little difficult for the tag to be detected.

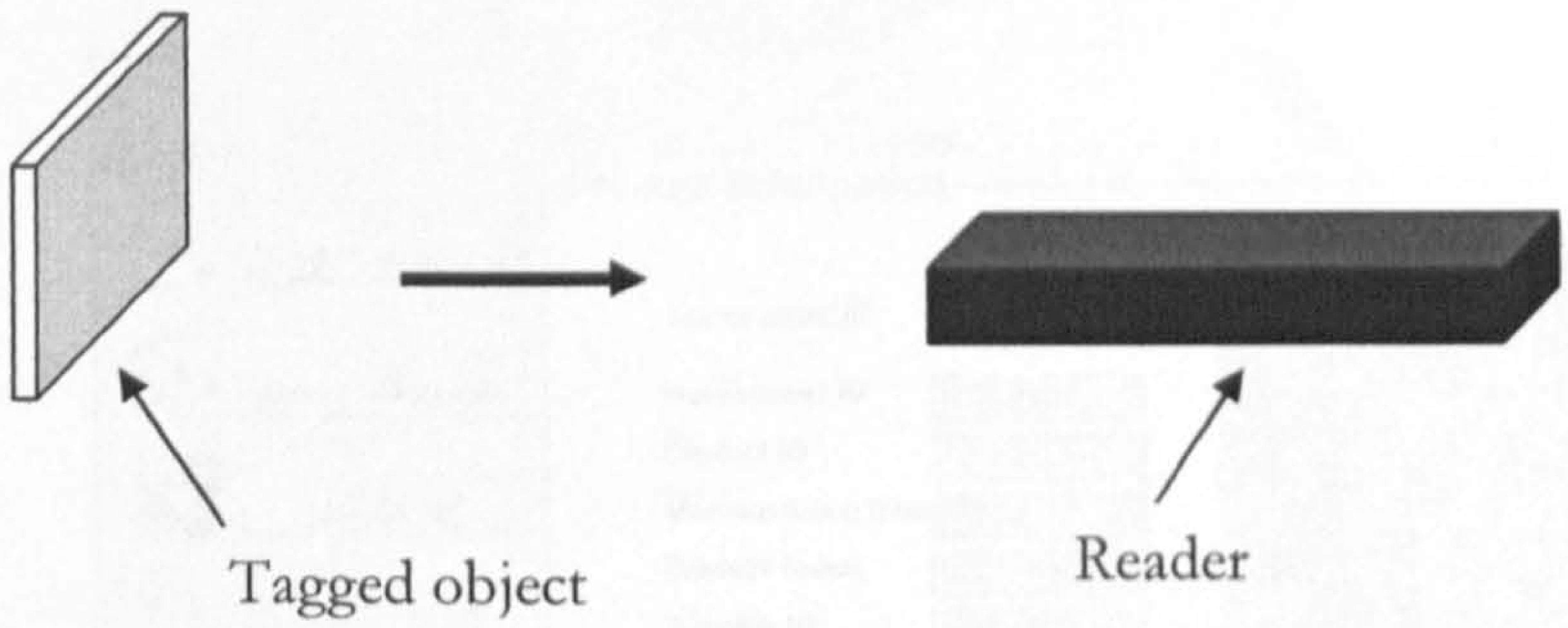


Fig.3.5. Best tag position with respect to reader

3.1.2 Information Storage

For information encoding, experiments were also performed with RFID technology. The same equipment that is described above was used. As explained before, the data storage capacity of RFID tags used in the experiment was limited to 32 Bytes only, therefore, the experiment was performed within these limited conditions. The memory of the RFID tags used was divided into 8 blocks, each with a capacity of 4 Bytes. The data is stored on the tags in hexadecimal format. Each block of data can contain an eight-digit number.

The storage of necessary product-related information in this limited data capacity was attempted. In this regard, software called 'RFID demonstrator' was developed in the Microsoft Visual Basic environment using the specific command set provided by Texas Instruments for the 6350, 13.56MHz reader. Although the 6350 reader is compatible with ISO commands and protocols, the author's familiarity with the available Texas Instrument command set lead to it being preferred. The software consists of two interfaces, the read interface (see figure 3.6) to read information from the tag and the write interface (see figure 3.7) to write and update information onto the tag.

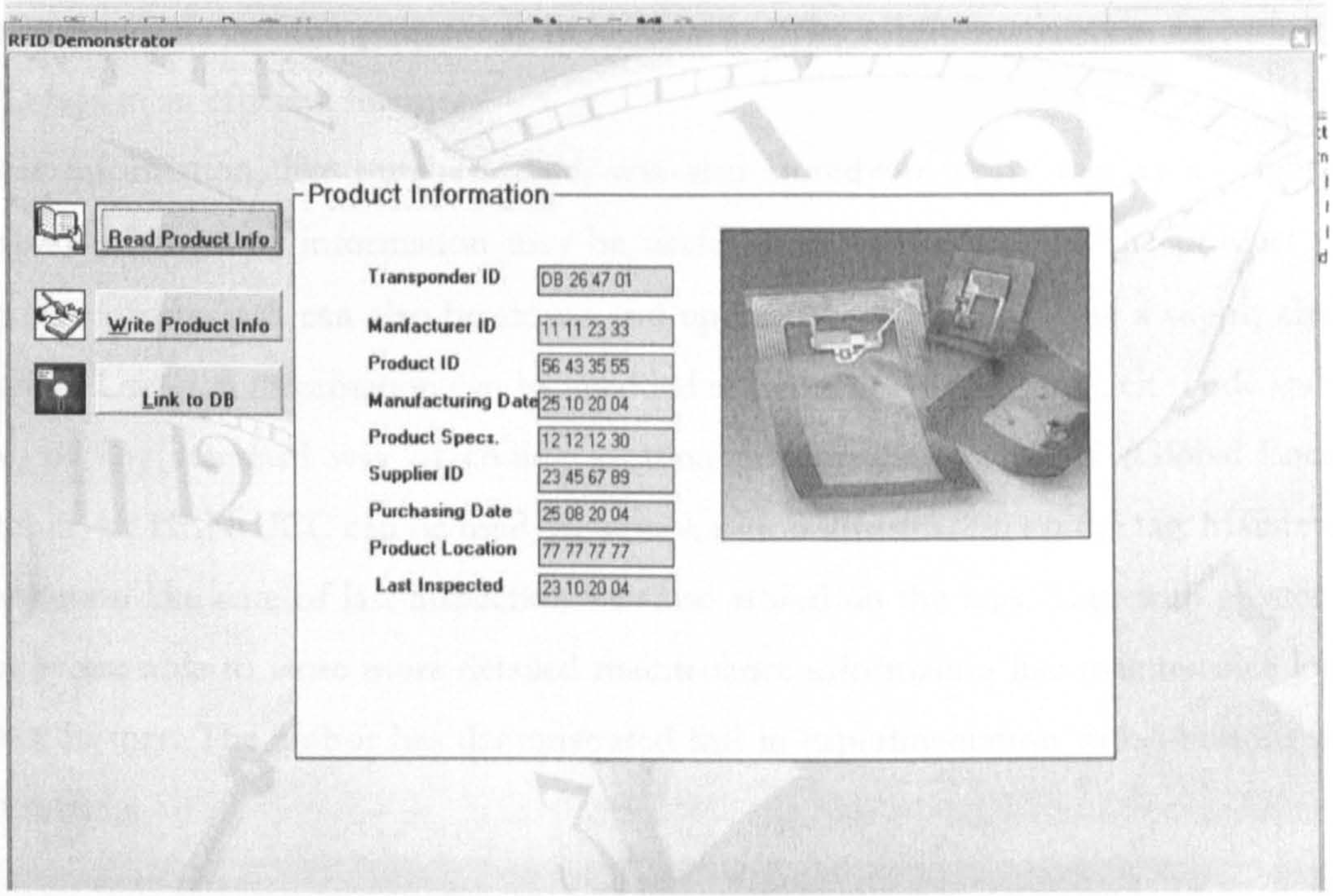


Fig.3.6. Snapshot of the read interface of RFID demonstrator software

Data can be written block-wise on the tag. Data cannot be written simultaneously on all data blocks. Therefore, the user has to select a particular field in the write mode to update or change the information. Different types of information were then stored in RFID tags, such as manufacturer ID, product ID or serial number and manufacturing date. Each field was assigned a single data block. It is also possible to store the product and manufacturer information in RFID tags in the UPC and EAN style. However, the purpose of this experiment was just to explore and demonstrate the capability of RFID technology to store information.

Attempts were also made to store product specifications like length, width, height and weight. To do this, a single block was used to store this product data. As mentioned before, data can be stored in a single, eight-digit block of which two digits were used to define each of the four attributes i.e., length, width, height and weight. Therefore, if an eight-digit number is stored as 12131404 then its length, width, height and weight can be decoded as 12, 13, 14, and 4 respectively. Explaining this does not mean that this coding scheme is being proposed, but the purpose is to demonstrate how information can be written on RFID tags in an efficient manner.

Other information, like purchase date, was also stored on RFID tags as an eight-digit number; this type of information may be useful to get an idea about the product's age. Location information can also be stored and updated as required in case a supply chain is involved. Location information can be encoded in terms of country code, city code and area code, or any standard way of coding location information e.g. GLN (Global Location Number) by EAN-UCC can be used, to write location information on the tag. Maintenance information like date of last inspection was also stored on the tags. Tags with greater data capacity are able to store more detailed maintenance information like maintenance logs or service history. The author has demonstrated this in experimentation with i-buttons in the next section.

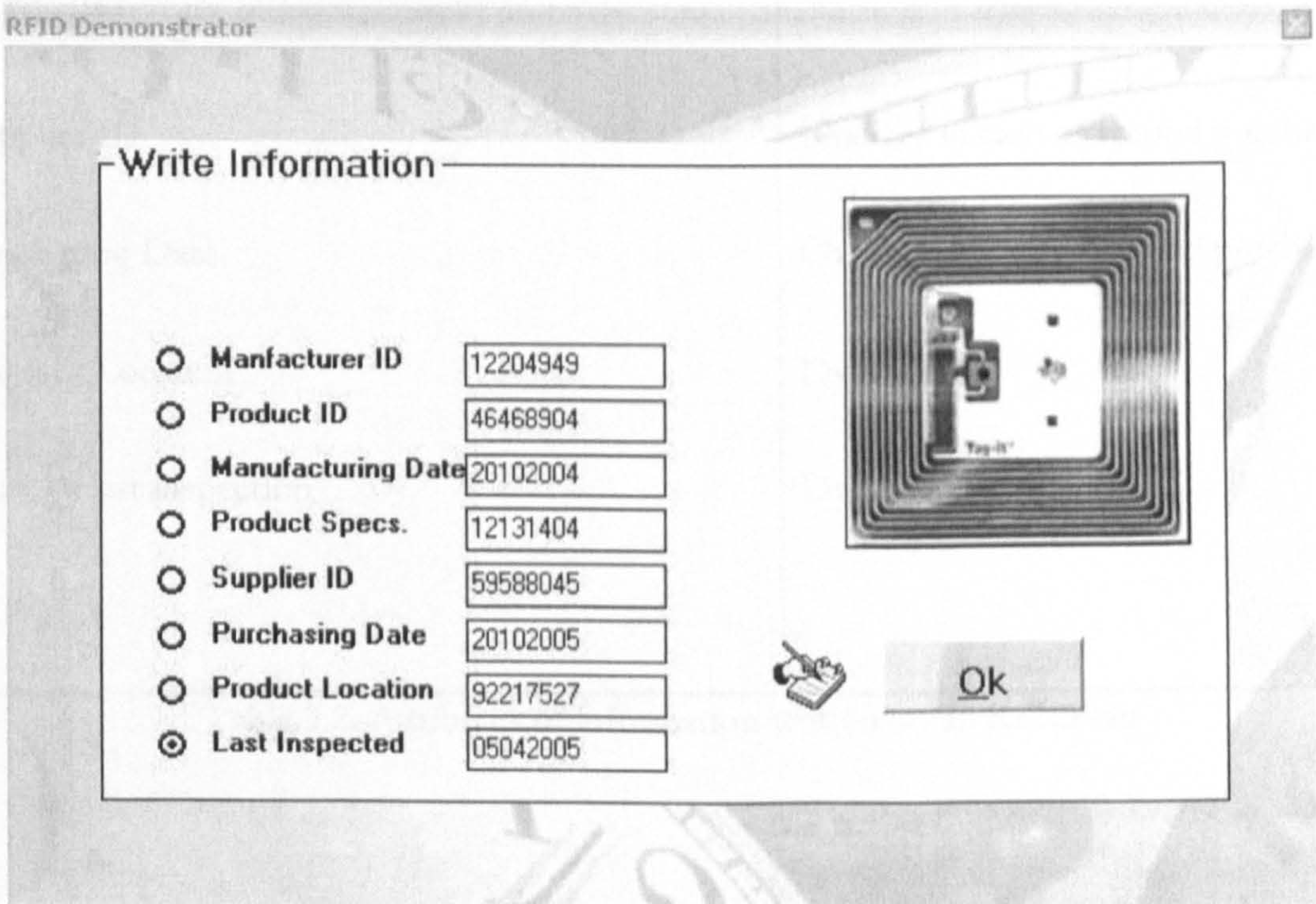


Fig.3.7. Snapshot of the write interface of RFID demonstrator software

RFID tags having this information can be easily linked to a standard database that contains other information like materiality and modularity information. However, the manufacturer should manage this information against the product type or model number on the web in the form of e-manuals or catalogues. Overall, RFID technology is suitable for carrying the necessary product-related information for the products that are exposed to less metallic environments. Table 3.2 shows the attributes of the information stored in an RFID tag.

Attributes of stored information	Nature
Manufacturer ID	Static
Product ID	Static
Manufacturing date	Static
Product specifications like length, width, height and weight	Static
Supplier ID	Changes in case of second purchase
Purchasing Date	Changes in case of second purchase
Product Location	Dynamic
Date of last inspection	Dynamic

Table.3.2. Attributes of information written on an RFID tag

3.2 Experiments with i-buttons

The author also performed experiments on information storage with i-buttons. As explained before, i-buttons are available in various varieties. Due to its large data capacity, a Dallas Instruments DS1996 memory i-button was used to store product-related information in this experiment.

The DS1996 is a read/write non-volatile memory that has a data capacity of 65,536 bits. Moreover, it has a 64-bit memory to store a factory etched unique ID or registration number that cannot be changed, and a 256-bit scratchpad memory, which verifies the data before copying into the memory. The read/write memory of the DS1996 is divided into 256 memory pages, with a memory of 256 bits or 32 Bytes each. The DS1996 has a communication speed of 142 kbits/sec. It can retain data for more than 10 years.

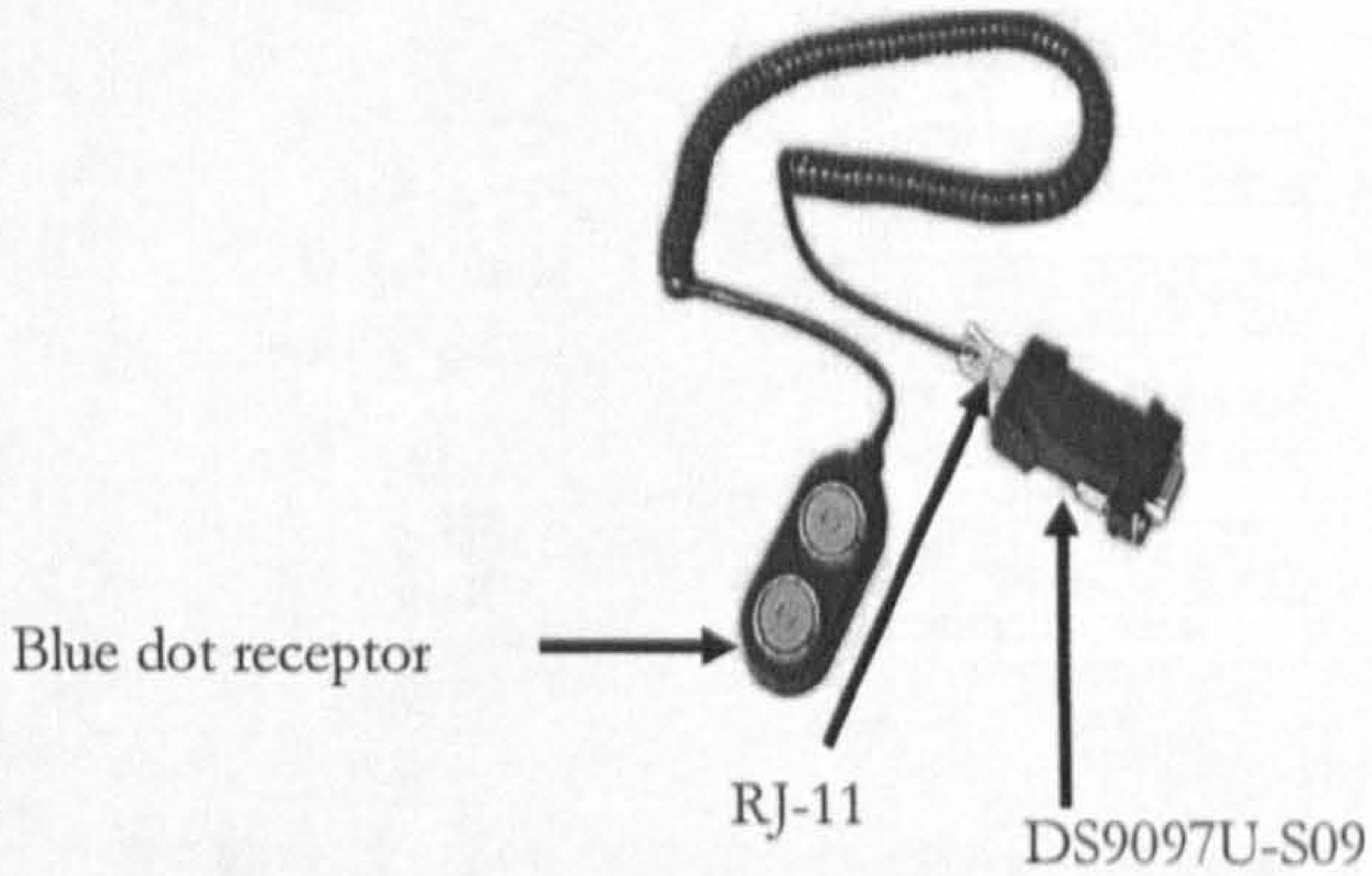


Fig.3.8. DS9097U-S09 1 wire adapter and blue dot receptor used in the experiment

To link the i-button with a PC, a DS1402D blue dot receptor was used. The receptor can be easily connected to any serial or parallel 1-wire adapter. However, in this experiment a DS9097U-S09 one wire adapter was used which can be connected to the PC through a 9-pin serial interface. The blue dot receptor can be connected to the DS9097U-S09 through an RJ-11 connector (see figure 3.8). There are two blue dots on the receptor and the i-button needs to make physical contact with either of them in order to read/write data.

3.2.1 Information storage

In order to judge and demonstrate the information storage capability of i-buttons, an information encoding software called 'i-button demonstrator' was developed in the Microsoft Visual Basic programming environment using the one-wire API (Application

Programming Interface) provided by Dallas Instruments to aid the development of i-button-based applications. The software has the capability to read and write product-related

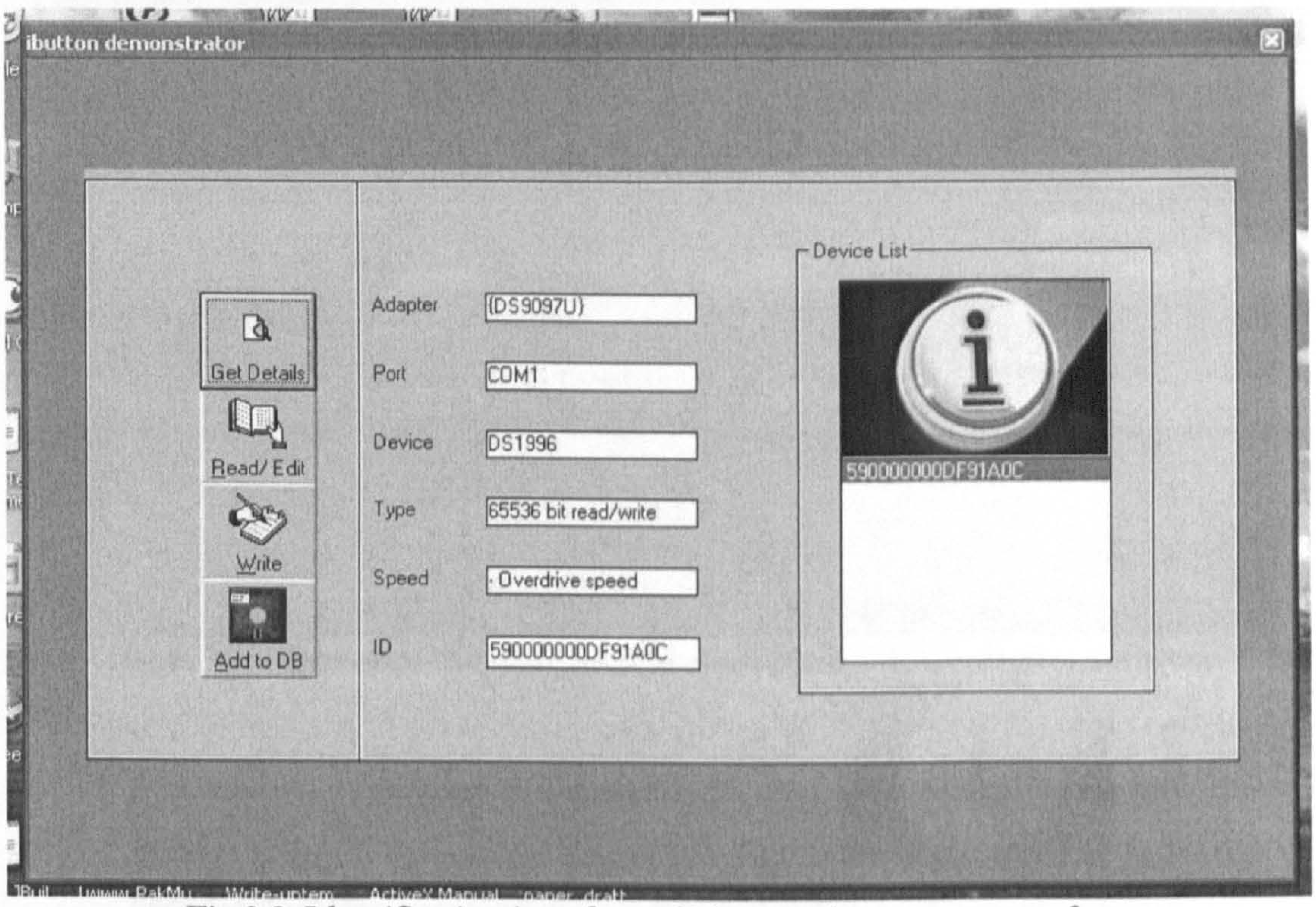


Fig.3.9. Identification interface of i-button demonstrator software

data on read/write memory i-buttons using the DS9097U-S09. The software has three basic interfaces: the identification interface (see figure 3.9), the write interface (see figure 3.10) and the read/edit interface (see figure 3.11). The identification interface is used to identify the type and unique factory-etched identity of the i-button device. It also identifies the type of one-wire adapter that is used to read the i-button as well as the connected port.

The second interface, the write interface, is developed to write different types of information onto the i-button, whereas the third interface, the read/edit interface, is developed to read, edit and update information on the i-button. Product information, like maintenance information during the use phase of a product, can be updated through this interface.

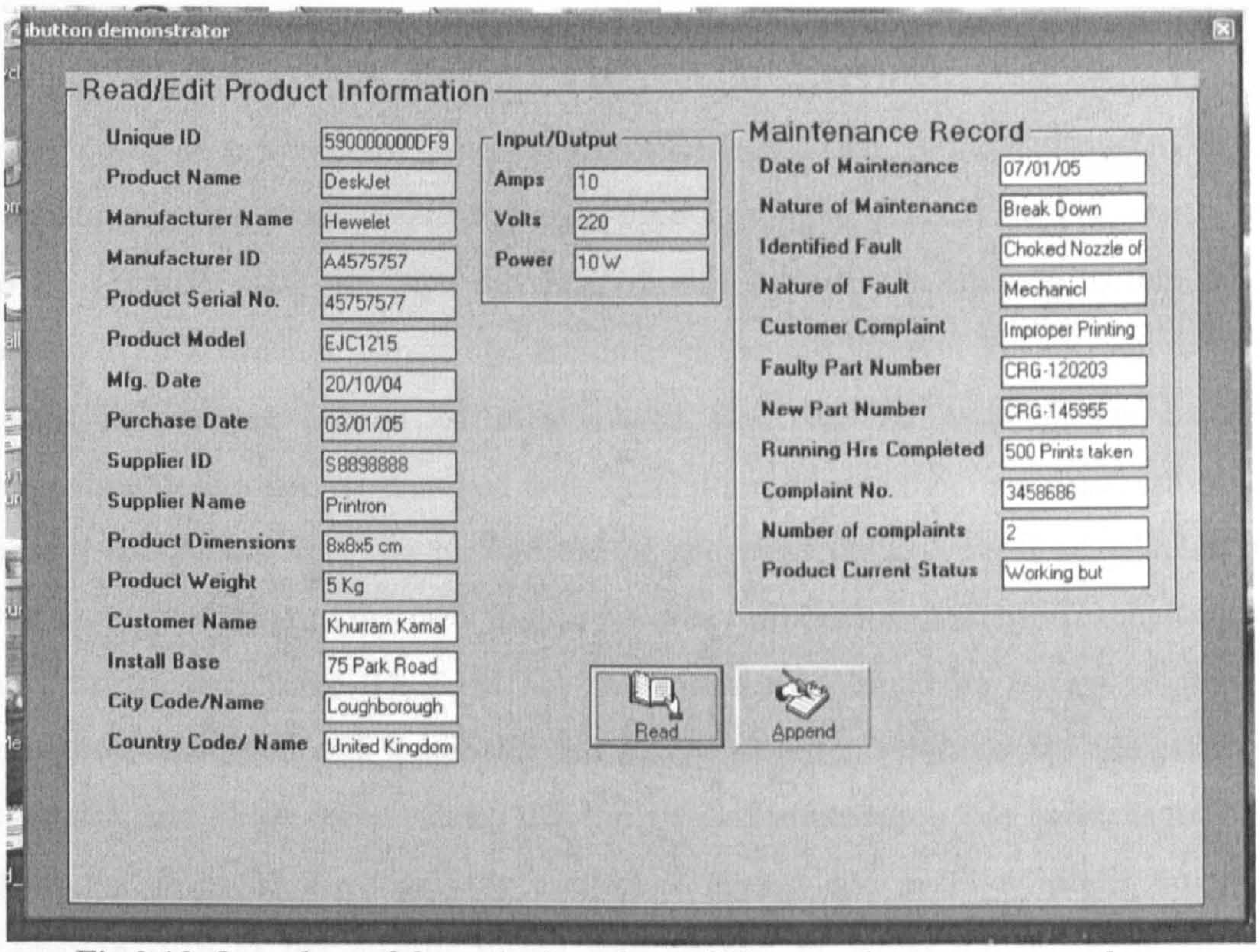


Fig.3.10. Snapshot of the write interface of i-button demonstrator software

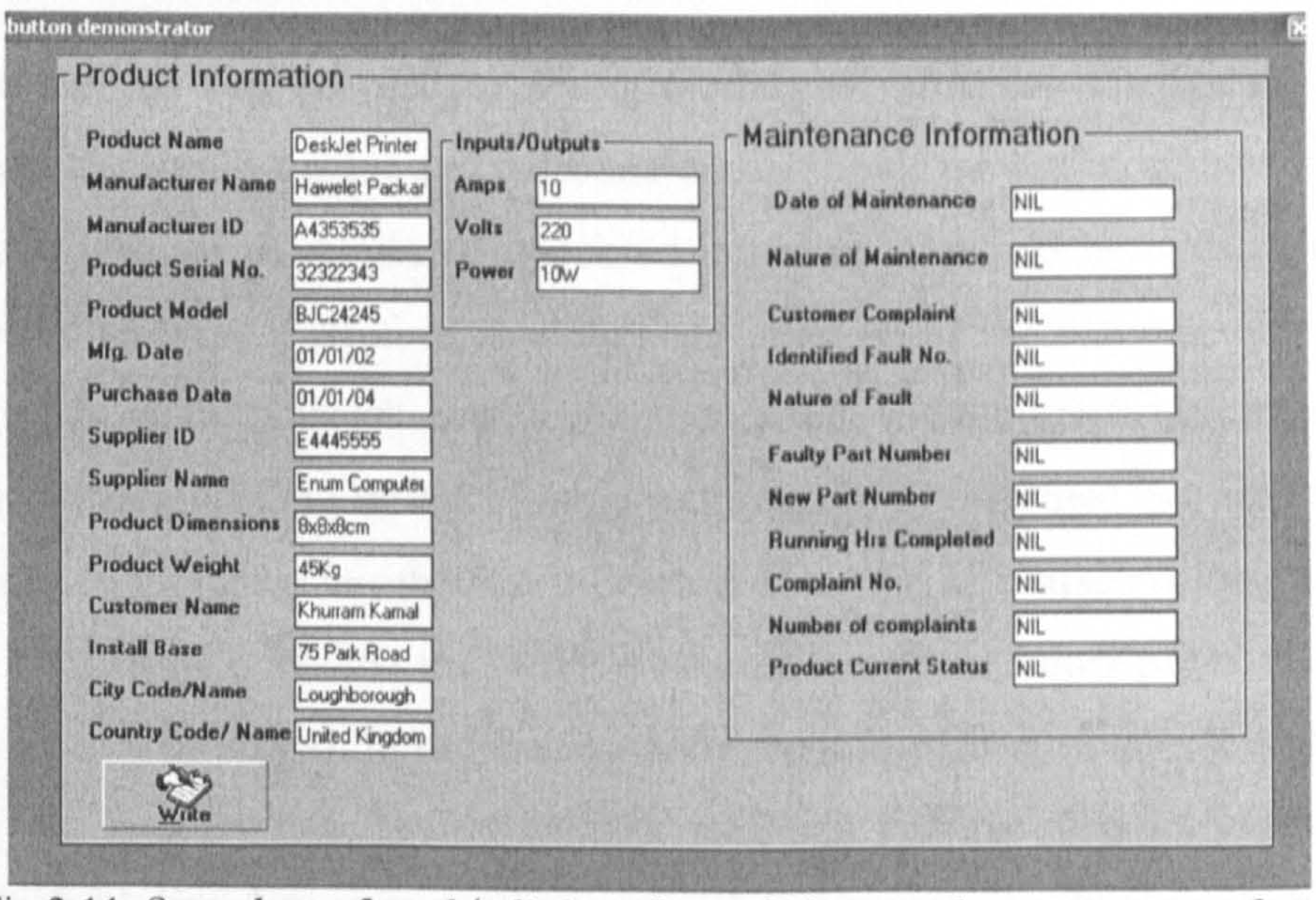


Fig.3.11. Snapshot of read/edit interface of i-button demonstrator software

Various types of information for product identification like product name, model no., manufacturer name, product serial number, product weight, dimensions, etc., were written onto the i-button using the write interface of this software. In addition to this, product information of a dynamic nature like customer name and location information as well as dynamic information related to maintenance like date of maintenance, nature of maintenance, description of identified fault, description of customer complaint, information regarding faulty parts etc., can be updated or appended through the read/edit Interface. However, the author is of the view that all necessary product-related information of a static nature, like manufacturer ID, serial no. and model no, should be factory-programmed. Information associated with materiality can also be stored in i-buttons like names or codes of materials and %age composition. But this type of information can be managed on the web in the form of e-manuals or catalogues against the product model no. Access information such as the manufacturer's web address to access e-manuals or catalogues should be provided on these devices.

The same method can be used to access modularity information regarding a product. Information like supplier name and customer details should be written at the time of selling the product, whereas maintenance-associated information should be updated throughout the product's lifecycle. Therefore, the read/edit interface of the software only allows the updating of those fields which need to be ammended, while other fields are kept locked. Each memory page of the DS1996 i-button was assigned to each field. So, each field can be 32 Bytes or 256 bits long. In other words, each field can be 32 characters long, as an ASCII character consists of 8 bits. As the DS1996 i-button has 256 memory pages, therefore, 256 fields of data can be stored. In order to optimise the information storage, it is also possible to assign one memory page to two fields or to assign multiple memory pages to a more descriptive field. For demonstration purposes, the software uses 29 memory pages of the DS1996 i-button, thus leaving 227 memory pages blank to store more information in the future.

From the above experiment, it has been shown that i-button devices have the potential to store and carry necessary product-related information. This information is stored in hexadecimal format and can be converted easily into readable form. ID-only i-buttons that have just a unique factory-programmed ID can be a good solution for a CMMS (Computerised Maintenance Management System) to tag and link equipment-related information to a centralised plant database. Though i-buttons need detection through physical contact, which makes the use of this technology rather labour intensive, compromises can be made on the basis of their large memory capacity that enables their use as a portable data carrier for product lifecycle management. Table 3.3 shows the attributes of information stored in an i-button.

Attributes of stored information	**Nature**
Unique ID	Static
Product Name	Static
Manufacturer Name	Static
Manufacturer ID	Static
Product Serial No.	Static
Product Model No.	Static
Manufacturing date	Static
Purchase Date	Changes in case of second purchase
Supplier ID	Changes in case of second purchase
Supplier Name	Changes in case of second purchase
Product Dimensions	Static
Product Weight	Static
Customer Name	Changes in case of second purchase
Installed Location, City, Country	Changes in case of second purchase or supply chain
Input/Outputs like Operating voltage, Ampere rating, Power	Static
Date of last maintenance	Dynamic
Description of maintenance nature	Dynamic
Description of identified fault	Dynamic
Description of fault nature	Dynamic
Description of customer complaint	Dynamic
Complaint No.	Dynamic
Faulty Part No.	Dynamic
Total No. of complaints	Dynamic
Running Hours completed	Dynamic
Description of current status of product	Dynamic

Table. 3.3. Attributes of information stored in an i-button

3.3 Summary of chapter 3

- In the light of the reported experiments, it has been shown that RFID, i-button and barcode technologies have great potential to be used as passive EIDs in order to support a sustainable approach to product lifecycle management..
- Moreover, RFID and i-button technologies have the potential to store not only the static but, to some extent, the dynamic data such as small maintenance logs.
- The author in the performed experiments has successfully demonstrated that use-phase data can be stored into a product with the help of these automatic identification technologies. The author performed experiments with RFID technology as well as with a new technology, called i-button technology. In the past, no-one has demonstrated the usage of i-button technology for storing the product use-phase data like maintenance logs. The author has demonstrated and presented it in the literature for the very first time.
- In the light of experiments, due to their robustness and large data capacity, i-buttons proved more advantageous than RFID tags for use in harsh environments. Unlike i-buttons, which are contact-based devices, RFID tags do not require line of sight but their performance is affected sometimes in the presence of metals, therefore, specialised tags are required to tag metallic objects. This makes the choice of an RFID tag somewhat application-specific. Therefore, in addition to RFID tags, i-button technology is proposed as a new solution to store product identification and use-phase information.
- Barcodes can be used to encode product-related information for low-cost and simple products that are not exposed to harsh environments. However, as data once written on barcodes cannot be changed, therefore, barcodes cannot be used to store product use-phase information. They can be used only to store information like product ID, manufacturer name, recycling or packaging information for very simple products. Barcodes may also be use to encode the website address to refer someone to a source of useful information.

Chapter 4

EXPERIMENTS WITH SMART EID

The previous chapter explains the experiments with passive EIDs. This chapter explains experiments to demonstrate the concept of smart EID. In the start, it explains the subject that is chosen for the implementation of smart EID concept. Later, it explains the implementation of smart EID system by describing its hardware. Understanding of this hardware is also necessary from the perspective of intelligent EID. In the end, it presents the data logged by the smart EID system.

4.1 Subject for the implementation of smart EID

The subject chosen for the implementation of smart EID is a domestic refrigerator. The reason behind choosing this subject for implementation of smart EID is that as mentioned in chapter 1 that household items contribute about 43% of the total waste generated, therefore, a domestic refrigerator can be a good choice for the implementation of smart EID. Moreover, compressor that is the most important component of a domestic refrigerator is designed for a service life of 10 to 20 years **[106]**. Therefore, from the perspective of reuse scenario, a refrigerator's compressor should be given considerable importance. RMS (Root Mean Square) is one of the most important vibration based metrics that are of great importance for measuring the health of a refrigerator compressor as RMS of compressor vibration increases with wear and tear and the accelerated age **[106]** . It is defined as the square root of average of the square values. The smart EID concept is implemented to calculate the RMS of refrigerator compressor vibration and to log the MOL data. This data can be used by some expert to judge the condition of compressor to come to a decision for reuse scenario at EOL stage of the refrigerator. However, this smart EID does not have a capability to predict the life of equipment. This topic is covered under the area of intelligent EID that is explained later in detail in this thesis.

Normally, a modern domestic refrigerator consists of an automatic defrost system, a cooling system, a temperature control system, lighting system, and an ice making system. In addition to these systems, there are door seals and hinges plus some additional installations. These systems are explained briefly.

Automatic defrost system of a refrigerator is a system that aids to prevent frost accumulation inside the refrigerator. Old refrigerators required manual defrost, however, modern refrigerators are equipped with an automatic defrost system that consists of three components, a defrost timer, a defrost heater, and a defrost thermostat. The defrost timer of a refrigerator acts like a clock. It functions 24 hours a day and after a particular period, it turns off the cooling system of refrigerator and turns on the defrost heater. The defrost heater works simply like an electric stove. It is situated below the cooling coils of the cooling system. As the defrost heater is situated near the cooling coils of the refrigerator, therefore, when the defrost timer turns on the electric heater it melts the ice or frost. The melted ice or frost that is actually water, is then drained and collected in the tray present in the lower portion of the refrigerator.

The thermostat, which is situated near cooling coil is responsible to terminate this defrost cycle by sensing that the coil temperature has reached to a particular limit or not. In the other case, the cooling timer is pre-programmed to terminate the defrost cycle after a particular period of time.

The cooling system of a typical domestic refrigerator consists of a compressor, a condenser and an evaporator. It also contains an expansion valve. The refrigerant is actually a liquid gas that creates the evaporation effect inside the refrigeration unit to create cooling.

The compressor is the heart of refrigeration system. In most of the refrigerators, it is situated in the bottom at the back of refrigerator. Figure 4.1 shows a refrigerator compressor. The compressor works when the thermostat of refrigerator turns it on for cooling. The basic task of a refrigerator compressor is to compress the refrigerant gas, which results an increase in refrigerant's pressure and temperature. This high-pressure refrigerant then enters into the condenser, which is actually a large framework of heat-exchanging pipes situated at the back of refrigerator. The heat-exchanging pipes dissipate the refrigerant's heat, thus causing the condensation of high-pressure gas into liquid form. This liquid then passes through an expansion valve that is actually a tiny copper tube. This expansion valve connects the end of condenser to the evaporator. The liquid refrigerant then enters from a high-pressure to a low-pressure zone. The expansion valve is responsible for controlling the flow and pressure of refrigerant when it enters into the evaporator. The evaporator is often situated inside the freezer compartment of refrigerator. Due to pressure drop inside the tubes of evaporator, the refrigerant gets back into the gaseous state that involves absorption of heat, thus causing a cooling effect. The gaseous refrigerant then enters again into the compressor. This is how a refrigeration cycle works.

Fig.4.1. A typical refrigerator compressor

As the process of heat absorption takes place in the evaporator, therefore, it is very cold. This coldness can cause the air to freeze on the evaporator as ice or frost, therefore, a fan inside the freezer compartment is responsible to circulate the air inside the freezer and the refrigerator compartment.

Temperature control is done by thermostat. Thermostat is a very simple device. When the temperature inside the refrigerator drops down to a particular limit, it disconnects the power from the compressor that results in absence of cooling, similarly, it turns on the compressor when temperature is increased up to a particular limit.

There is often a white push-button located inside, near the refrigerator's door, which is responsible for lighting inside the refrigerator. When refrigerator door closes, this button is pressed, causes the bulb inside the refrigerator compartment to turn off. Similarly, when someone opens the door the button is released, causes the bulb inside the refrigerator compartment to turn on.

Doors of a refrigerator are provided with a seal like rubber gasket. These seals are provided to avoid the escape of cool air from the refrigerator to the atmosphere. These seals are provided with a magnet lining throughout their perimeter, which actually helps to keep a firm contact with the body of refrigerator. In addition to gasket, doors are provided with hinges that are used to mount and aid the opening and closing of the door.

4.2 Experimental Setup

An experiment was carried out to demonstrate the implementation of smart EID system. For this purpose a Lec R-R106 refrigerator was used. An accelerometer was used to measure the vibration data of refrigerator compressor. For this purpose, Kistler 8636C10 PiezoBeam accelerometer was used that is shown in figure 4.2.

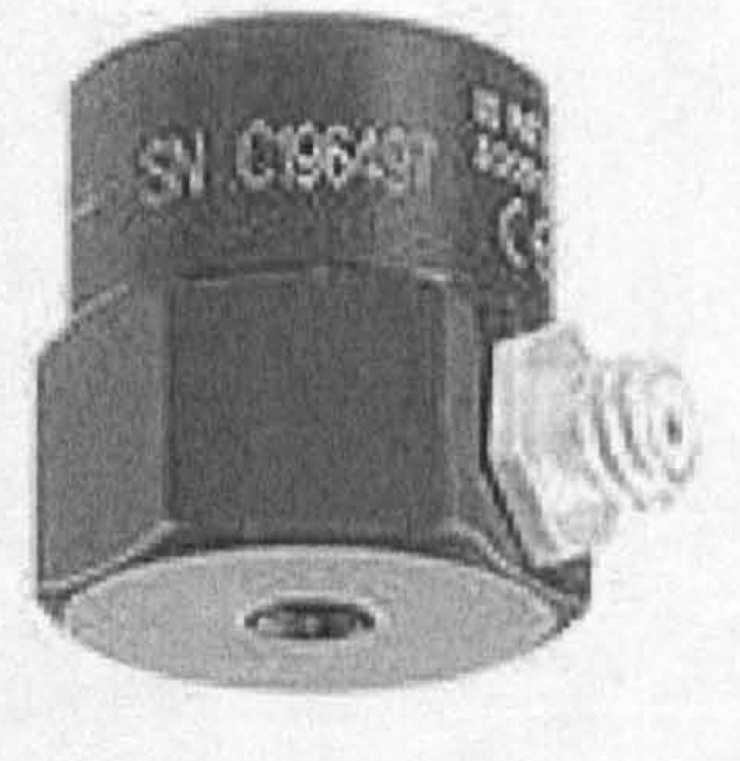


Fig. 4.2. Kistler accelerometer

The accelerometer was mounted on the surface of refrigerator compressor. As the output voltage of the accelerometer is in millivolts, therefore, a power supply/coupler was used to condition the output voltage in the range of 0 to 5 volts. For this purpose, Kistler Piezotron power supply/coupler was employed. Figure 4.3 shows the general experimental setup and figure 4.4 shows the tested compressor with mounted accelerometer.

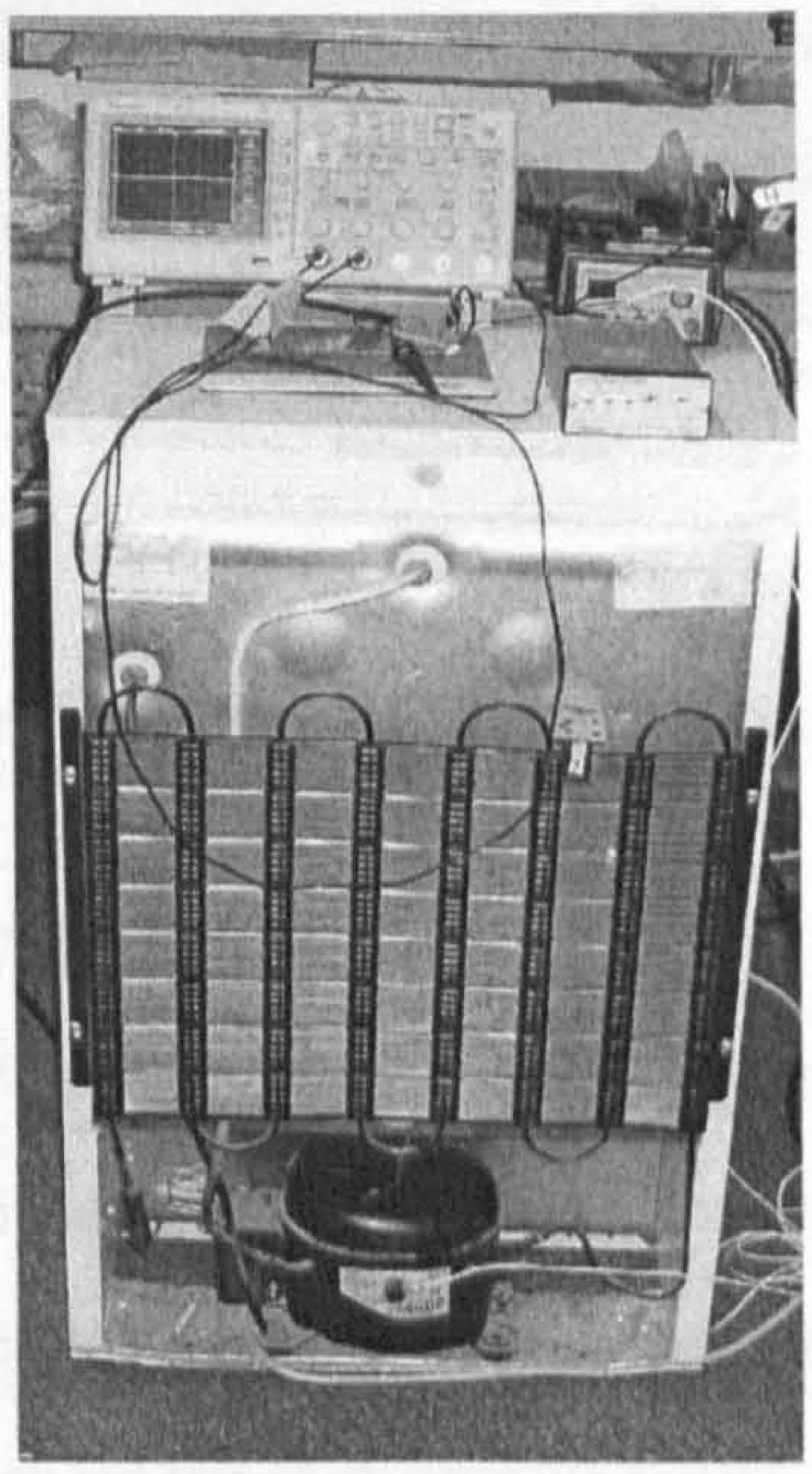


Fig.4.3. Experimental setup

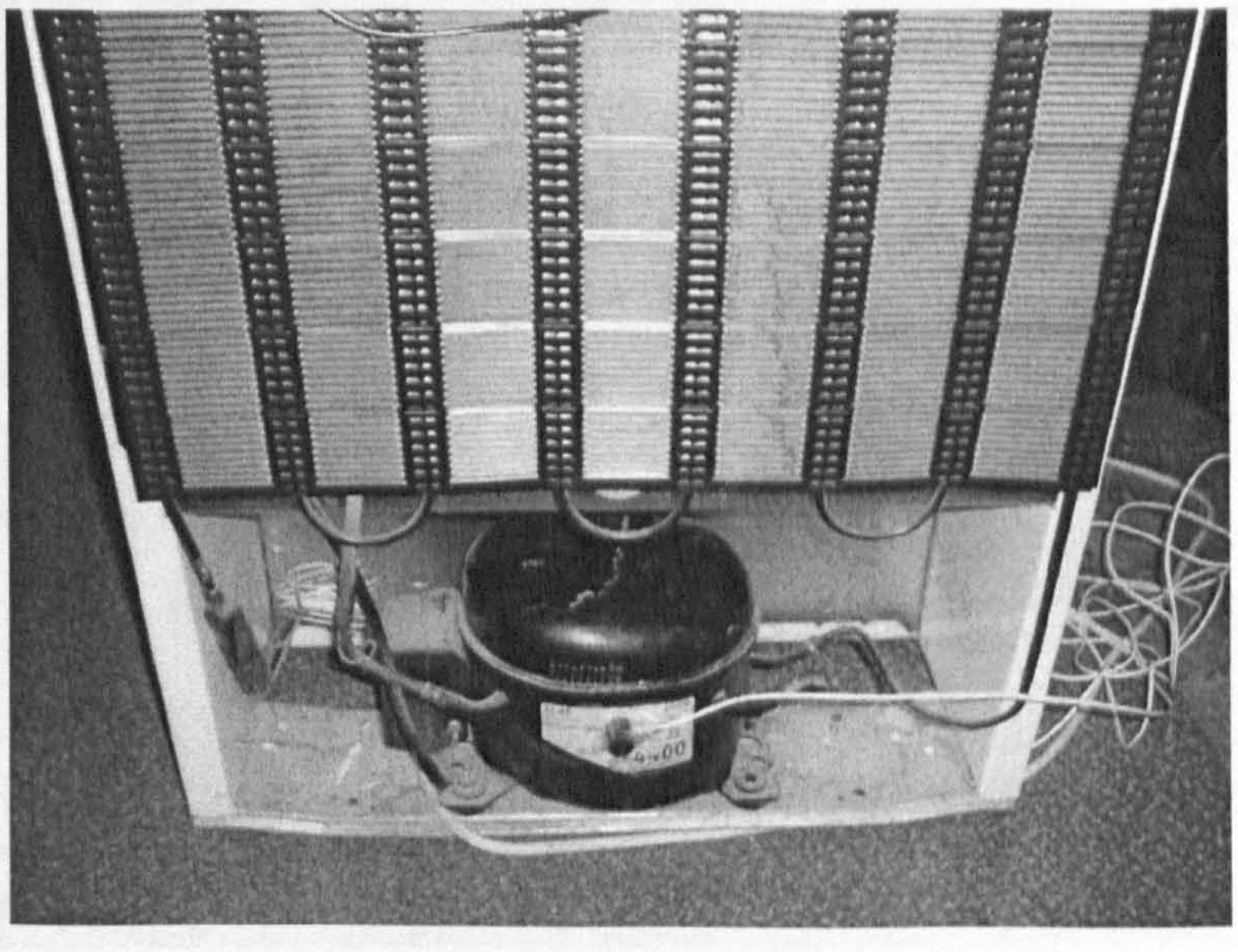


Fig.4.4. the tested compressor

Figure 4.5 shows the experimental data of compressor vibration. Next section explains the implementation of smart EID.

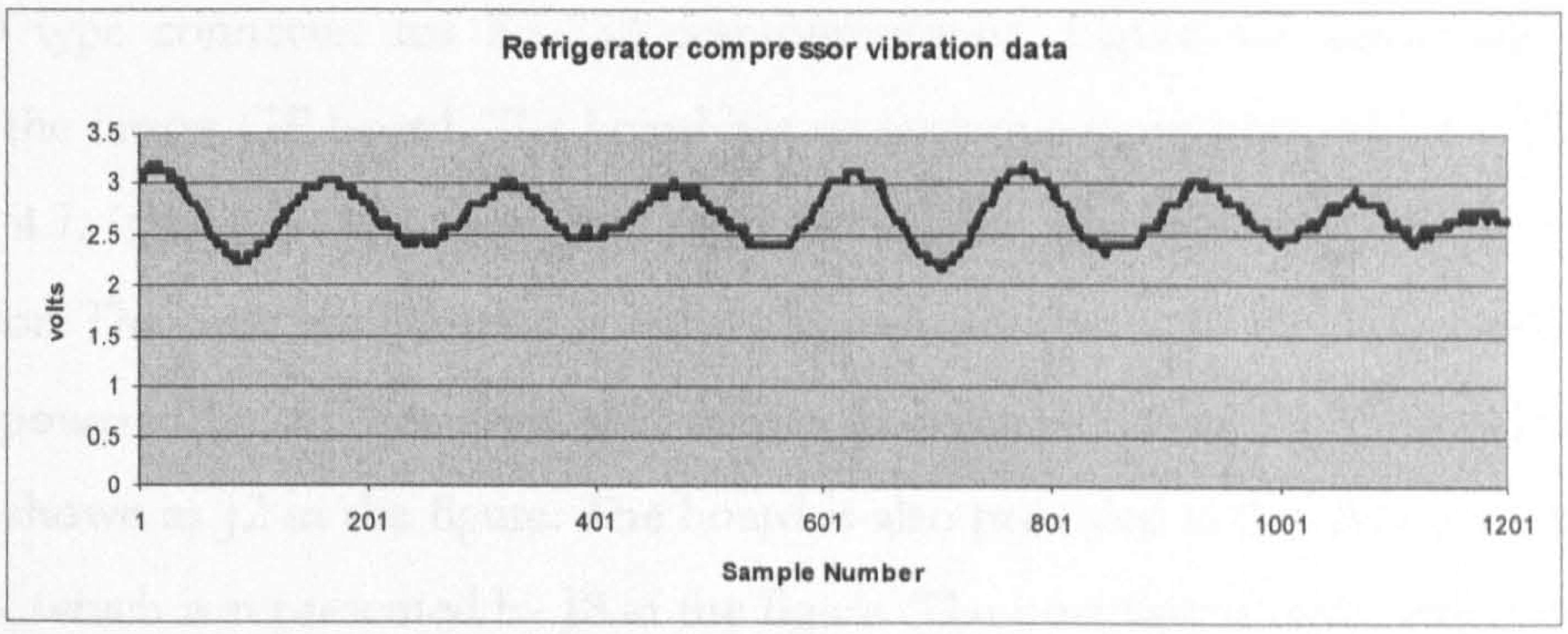


Fig.4.5. Compressor vibration graph

4.2.1 Implementation of smart EID

The implemented smart EID system consists of Iensys general purpose board and Axis 83+ device server. Iensys general-purpose board was used to acquire compressor vibration data. This data is then sent to the Axis device server, which acts as the central module of smart EID. The Iensys general-purpose board is shown in figure 4.6 .

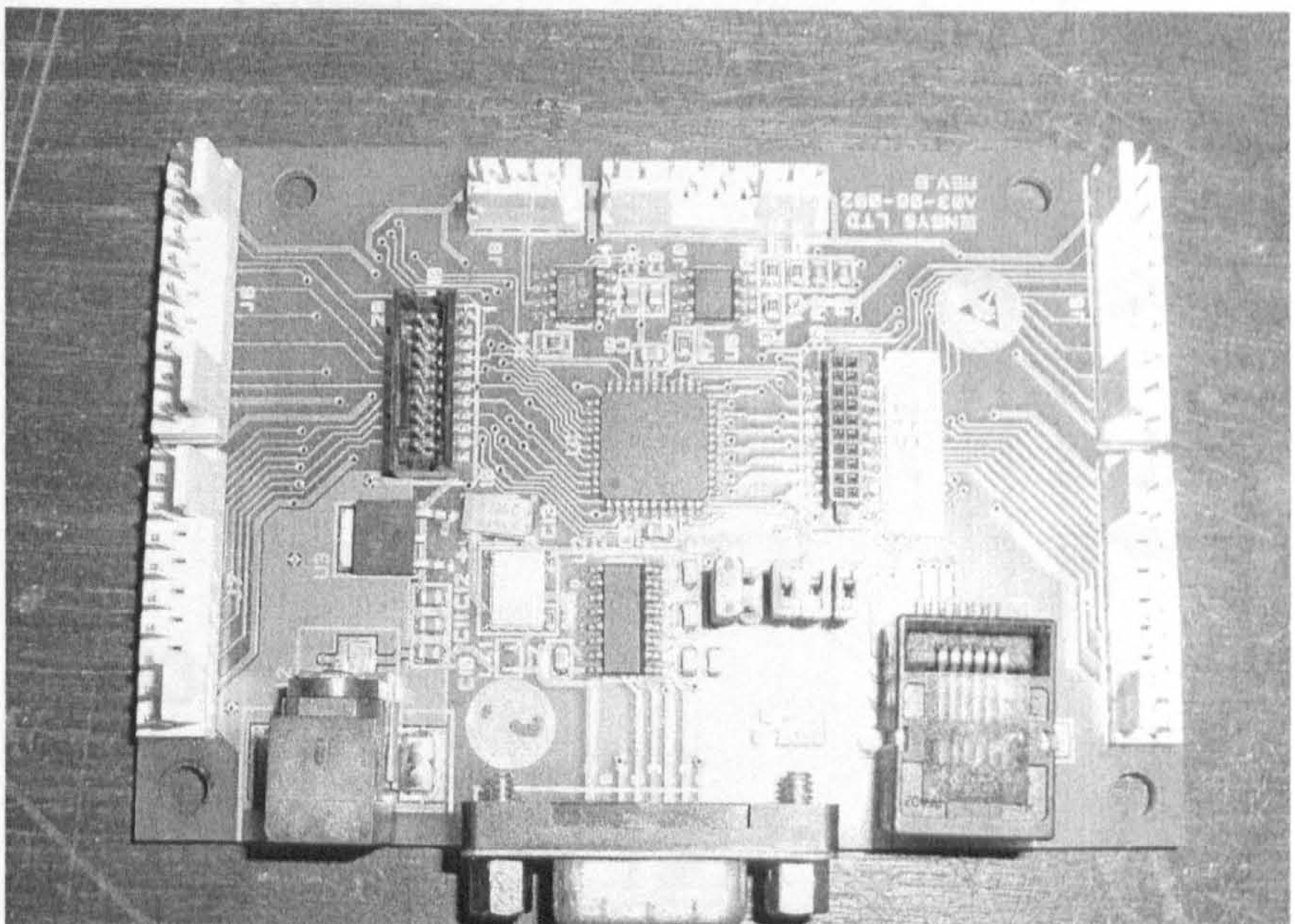


Fig. 4.6 Iensys general-purpose board

It consists of a microchip PIC 18F458 microcontroller. The board has 33 I/O lines but some are reserved for special tasks, therefore, not all of them are in use. It has RS-232 9 pin female D type connecter for RS-232 communications. Figure 4.7 shows the schematic layout of the Iensys GP board. The board has an analogue input port, which is shown as J5 in figure 4.7. This analogue port was used to acquire vibration data of the refrigerator compressor. The port has 8 analogue input channels and has a 10 bit A/D converter. The board is powered by a DC supply that ranges between 7.5 V to 24 V. The Jack for DC supply is shown as J2 in the figure. The board is also provided with CAN (Controller Area Network), which is represented by J8 in the figure. The port that is represented by J4 in the schematic diagram has all digital I/O pins except two pins that are reserved for CAN. Pins of the ports that are represented by J6 and J7 are also available as digital I/O except one pin from each port that is used by RS232 communication. The board is provided with a 20 MHz crystal.

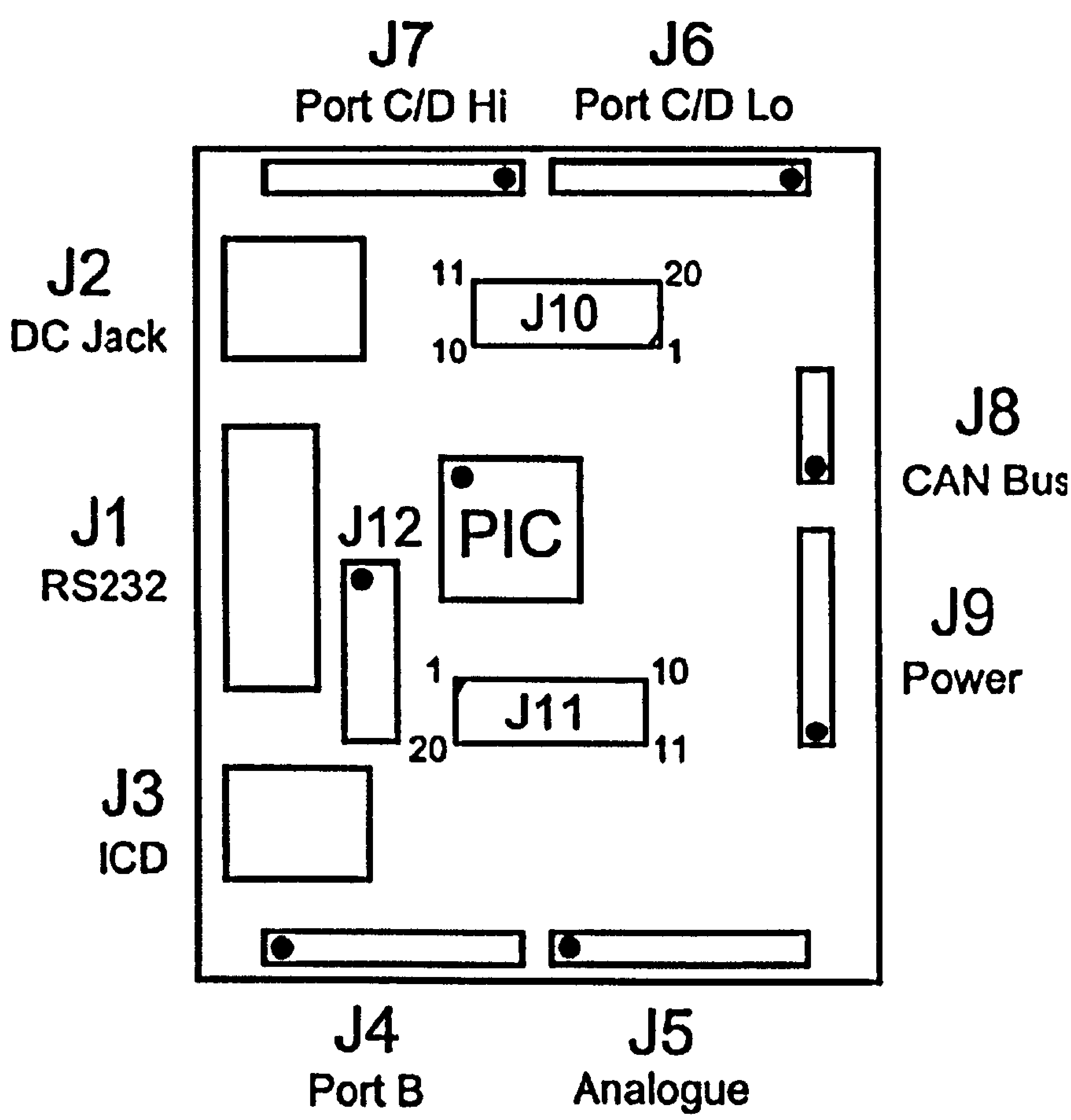


Fig. 4.7 Schematic layout of the Iensys general-purpose board

PIC 18F458 is the central module of the Iensys board. PIC 18F458 is a RISC microprocessor that has processing speed upto 10 MIPS (10 million of instructions per second). It has operating voltage of 4.2 to 5.5 V. This micrcontroller is suitable for the industrial temperature ranges between -40° C to +85° C. It has a program or flash memory of 32KB and an static RAM of 1536 Bytes. It also contains an EEPROM of 256 Bytes. The PIC 18F458 microcontroller takes 16 bit wide instruction and has 8 bit wide data bus. Special features of PIC 18F458 are CAN, watchdog timer, power saving mode and programmable code protection, etc. For more details, reader is referred to microchip website**[107]**. Output of the accelerometer signal conditioner is then connected to one of the analogue input channels of the Iensys board. The Iensys board was programmed to read the analogue input channel and to perform A/D conversion. After performing A/D conversion, the data is sent to the Axis 83+ device server via RS-232 terminal of the Iensys board.

Axis 83+ device server is an embedded linux server that uses Etrax 100 LX chip as the processing module. Etrax chip is a 32 bit, 100 MIPS RISC processor that is provided with preinstalled linux operating system. Therefore, enclosed in an aluminium casing, this server is a complete programmable device with Linux kernel 2.4/2.6. The Etrax chip has a flash memory of 8MB and has a RAM of 32 MB. Fig 4.8 shows the front and back view of the Axis 83+ device server.

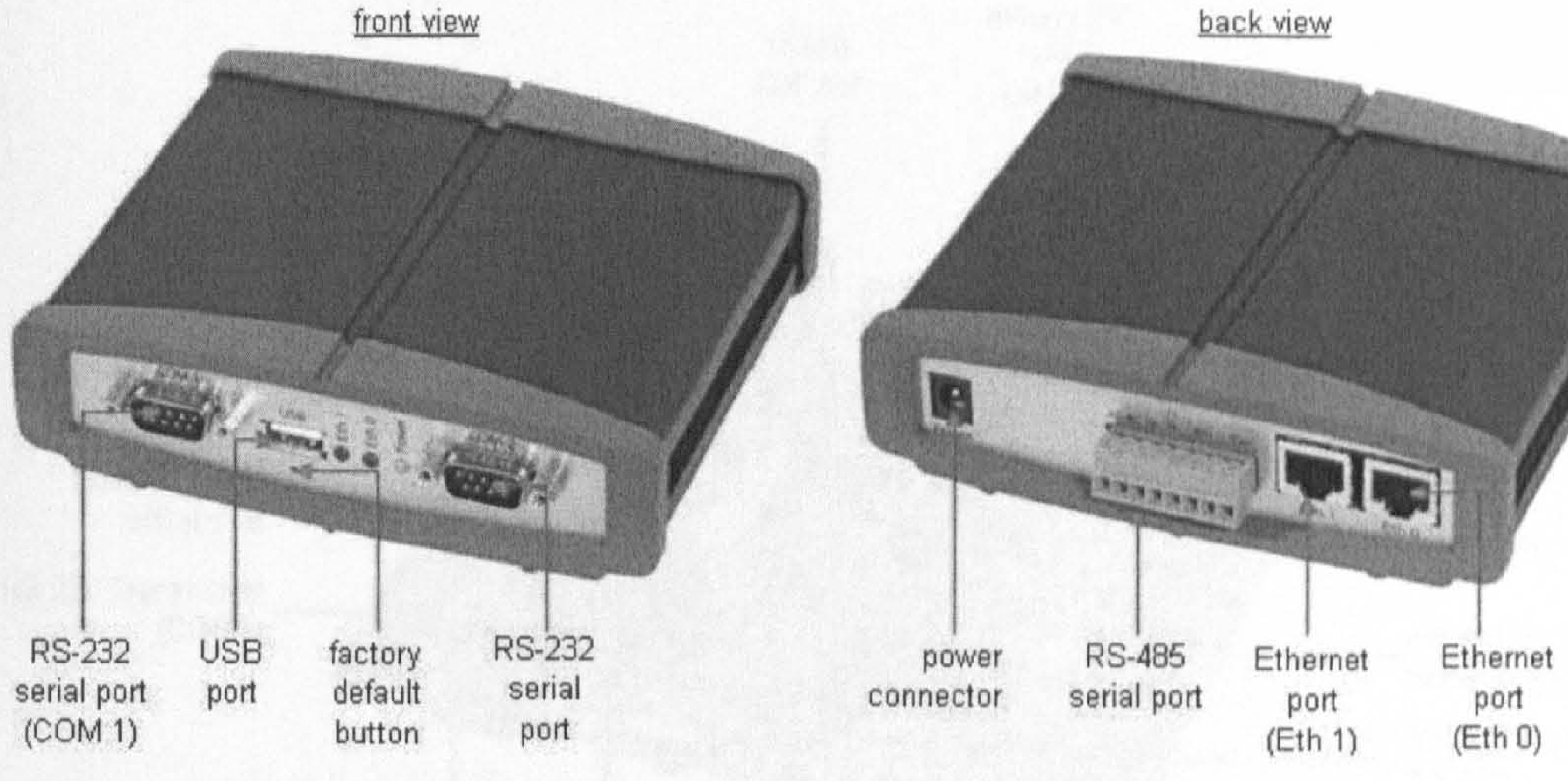


Fig. 4.8 The Axis device server

The Axis device server is provided with two ethernet ports and two RS-232 ports. In addition to these, there is one parallel port and one RS-485 port. One important feature of the Axis device server is the availibility of a USB port, so that USB cameras, barcode devices, bluetooth and other network devices such as Wifi can be easily connected. The USB port of the Axis device server can provide DC voltage upto 5 V. The Axis server can be powered by a 9 to 24V power supply. Figure 4.9 shows the inner construction of the Axis server.

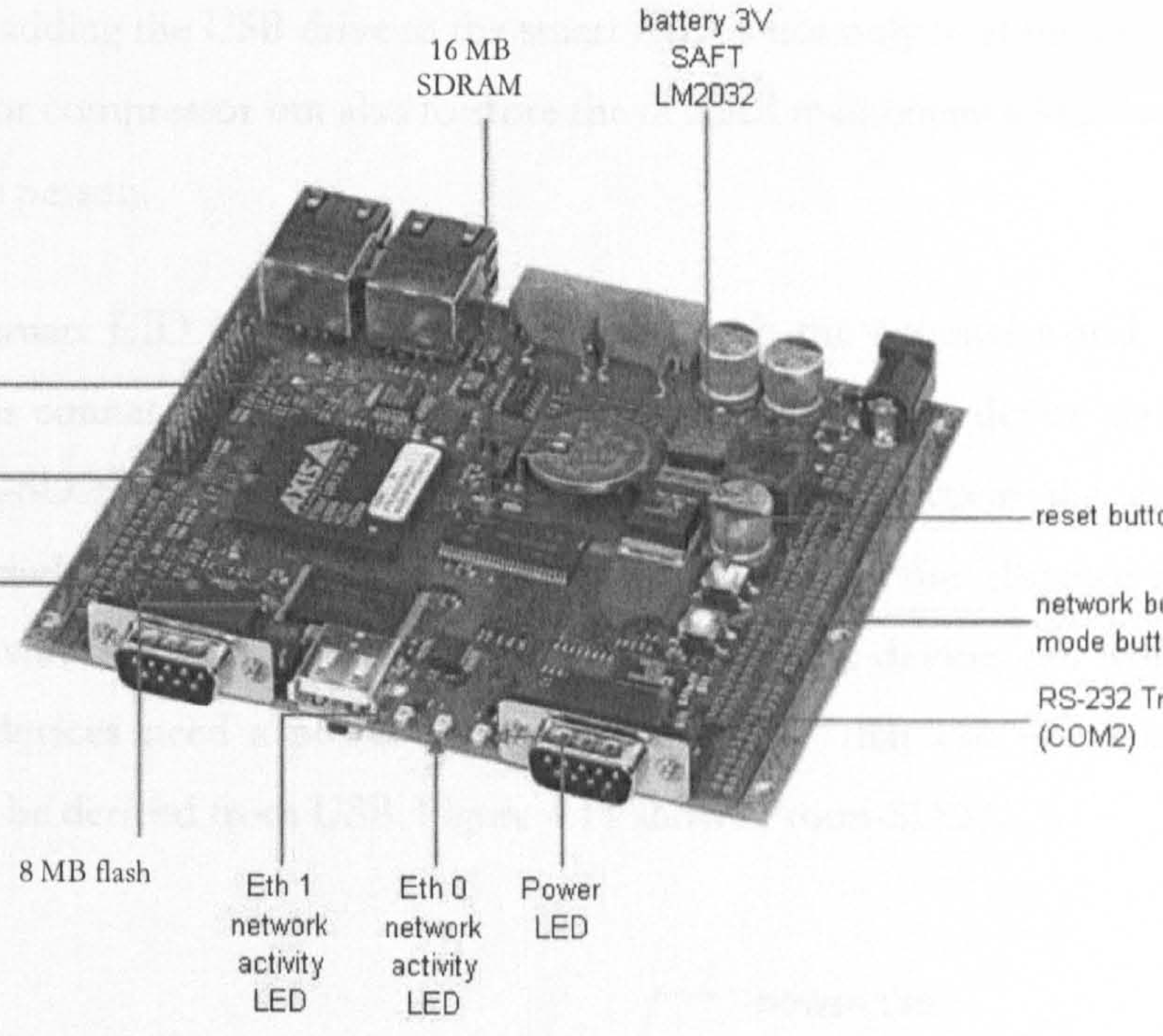


Fig. 4.9 Inner construction of the Axis device server

The Iensys general-purpose and device server are connected to each other via RS-232 communication cable. A USB mass storage device (see figure 4.10) of 1GB capacity is plugged to the Axis device server in order to store the sensory data of the refrigerator compressor.

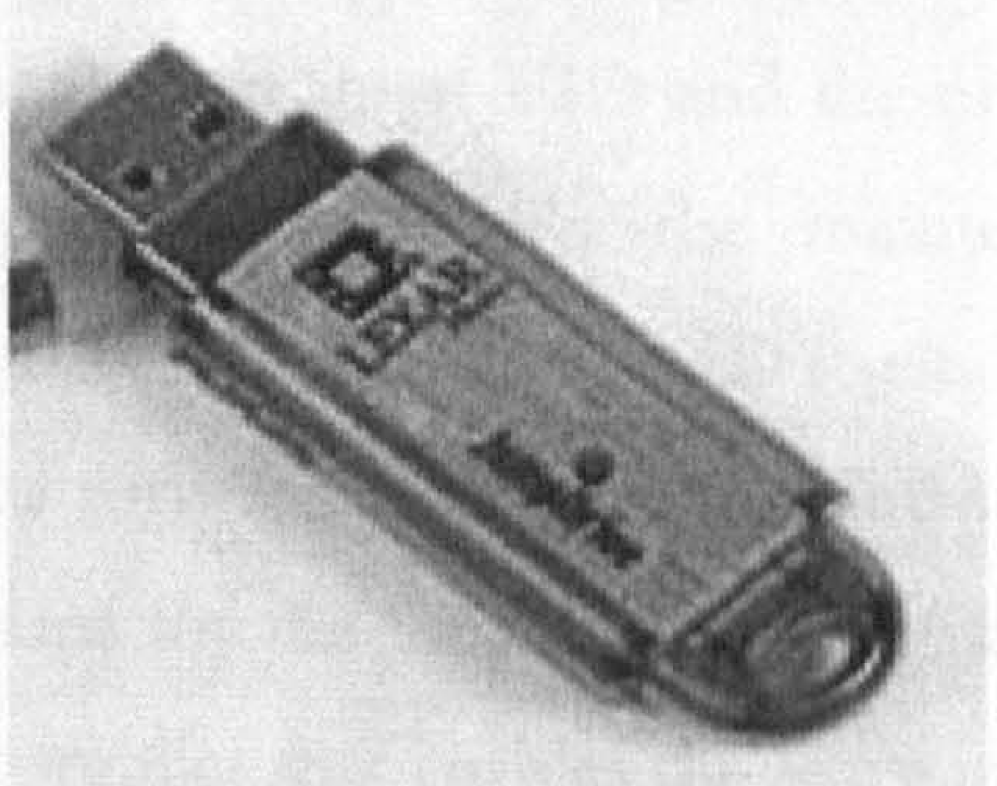


Fig. 4.10 USB mass storage device used in the smart EID

The purpose of adding the USB drive to the smart EID is not only to store the sensory data of the refrigerator compressor but also to store the detailed maintenance logs written by the maintenance person.

To enable the smart EID in order to communicate with the external world, a bluetooth wireless device is connected to one of the RS-232 ports of the Axis device server. For this purpose, Promi-SD202 bluetooth module is used. Depending upon the antenna type, Promi-SD202 wireless devices are capable to work finely across the distance ranges up to 1000 metres, however, with the default antenna, Promi-SD202 devices can work up to 100 metres. These devices need a power source of 5 to 12 V that can either be separately provided or can be derived from USB. Figure 4.11 shows Promi-SD202

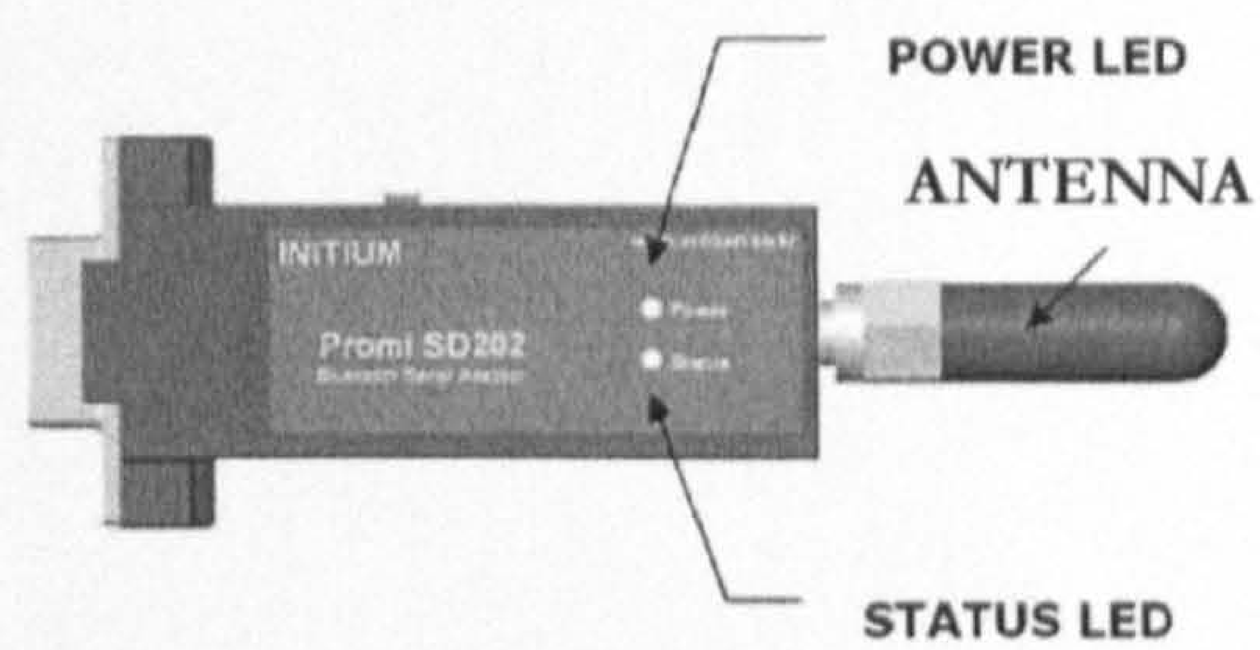


Fig. 4.11. Promi-SD202 Bluetooth module

module. Promi-SD devices can operate at baud rate of 1200 to 230400 bps. In the case of smart EID, one device is installed on smart EID and the other device is installed on the maintenance person's laptop or PC, so that the maintenance logs created by the maintenance person can be stored into the smart EID itself. To accomplish various tasks performed by the smart EID, a software is programmed and stored in the program memory of Axis device server. Programs for the ETRAX chip in Axis device server are compiled with the help of CRIS cross-compiler that enables the software to run under real-time linux environment. First the software is programmed in GNU C linux environment and then it is compiled with the help of CRIS cross-compiler that converts the source file into a binary executable file. This binary executable file is then tranferred to the program memory of Axis device server via FTP(File Transfer Protocol). The developed software for smart EID recieves data from Iensys board via RS-232 communication protocol. The software then stores the vibration data with date and time stamps in a separate file in the USB mass storage device. The software also serves to communicate with an external software interface that is developed to send and store maintenance data into the smart EID. This software is explained in the next section. The schematic diagram of smart EID is presented figure 4.12.

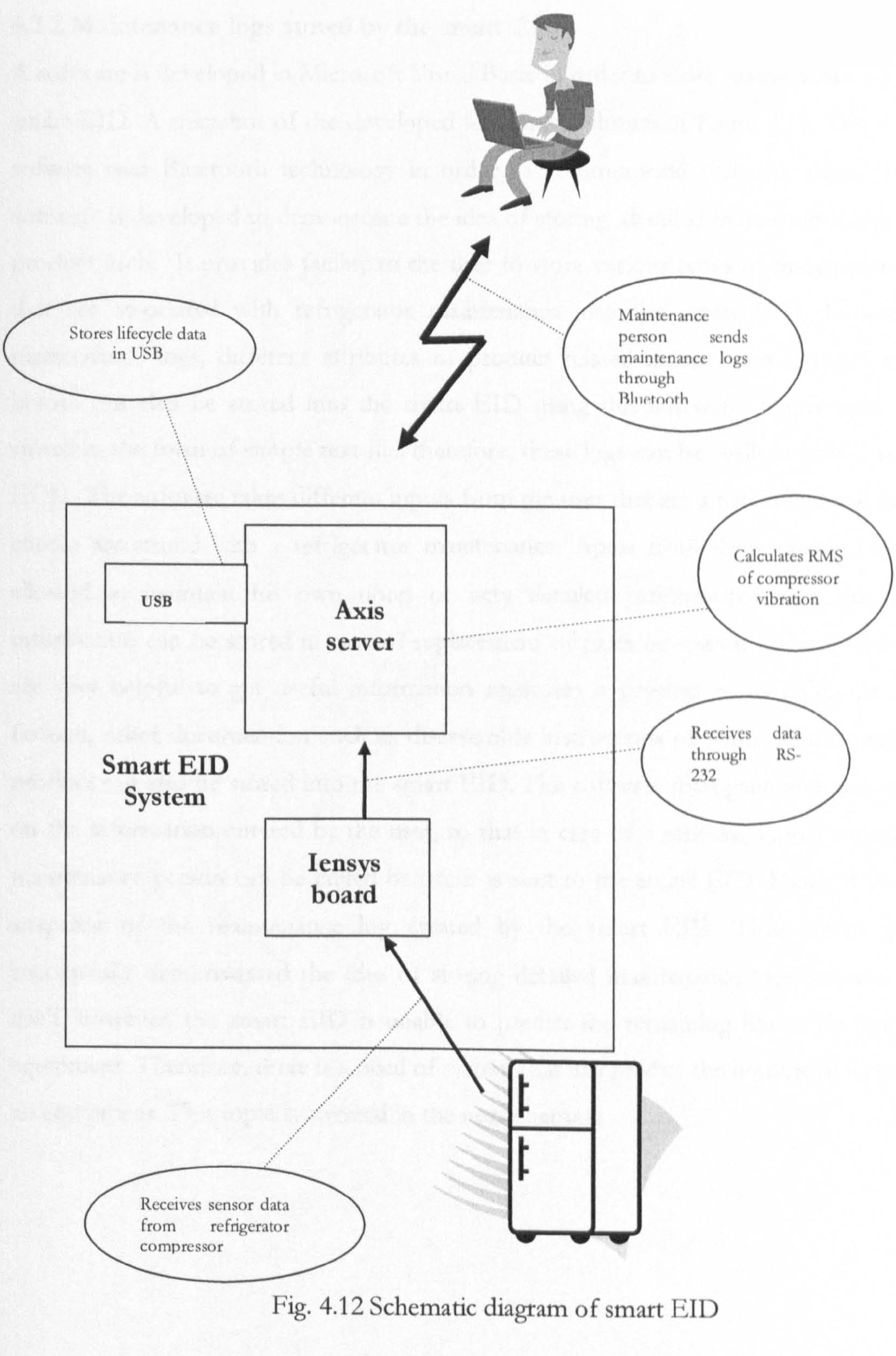


Fig. 4.12 Schematic diagram of smart EID

4.2.2 Maintenance logs stored by the smart EID

A software is developed in Microsoft Visual Basic in order to store maintenance log into the smart EID. A snapshot of the developed software is shown in figure 4.13. The developed sofware uses Bluetooth technology in order to communicate with the smart EID. The software is developed to demonstrate the idea of storing detailed maintenance logs into the product itself. It provides facility to the user to store various types of maintenance checks that are associated with refrigerator maintenance into the smart EID. In addition to maintenance logs, different attributes of product related information that are explained before can also be stored into the smart EID using this software. Mantenance logs are stored in the form of simple text file, therefore, these logs can be easily retrieved at product EOL. The software takes different inputs from the user that are a part of general maintence checks associated with a refrigerator maintenance. Apart from these checks, the user is allowed to maintain his own notes or very detailed maintenance logs. For example, information can be stored in case of replacement of parts or spares. These types of logs are very helpful to get useful information regarding a product at its EOL. In a similar fashion, other documention such as disassembly instructions or some drawing regarding a product can also be stored into the smart EID. The software then generates a report based on the information entered by the user, so that in case of a mistake, report created by the maintenance person can be edited before it is sent to the smart EID. Figure 4.14 shows a snapshot of the maintenance log created by the smart EID. Thus, smart EID has successfully demonstrated the idea of storing detailed maintenance logs into the product itself, however, the smart EID is unable to predict the remaining life of the machine or equipment. Therefore, there is a need of system that can predict the lifetime of a machine or an equipment. This topic is covered in the next chapters.

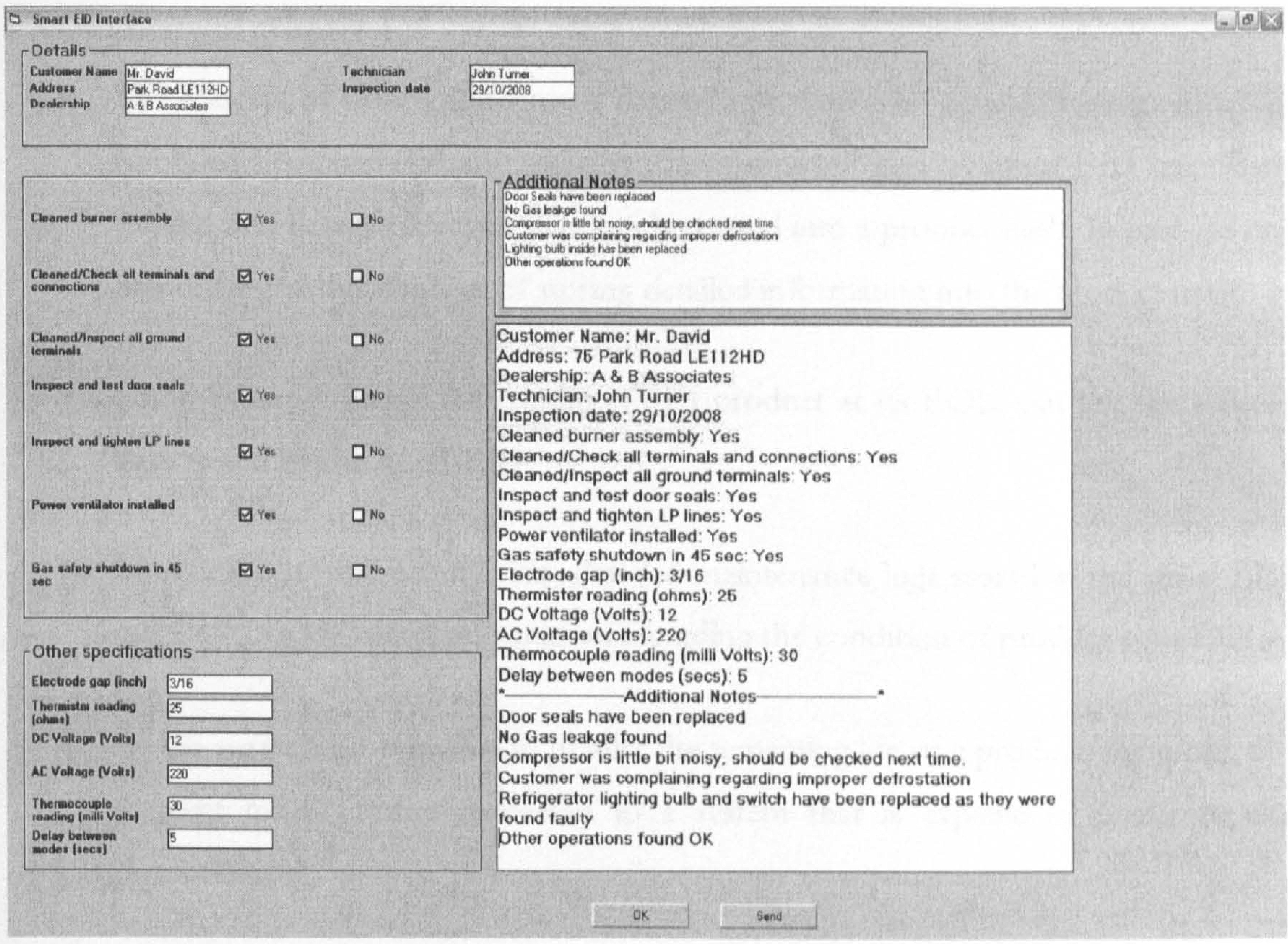


Fig. 4.13 Snapshot of the software interface for the smart EID

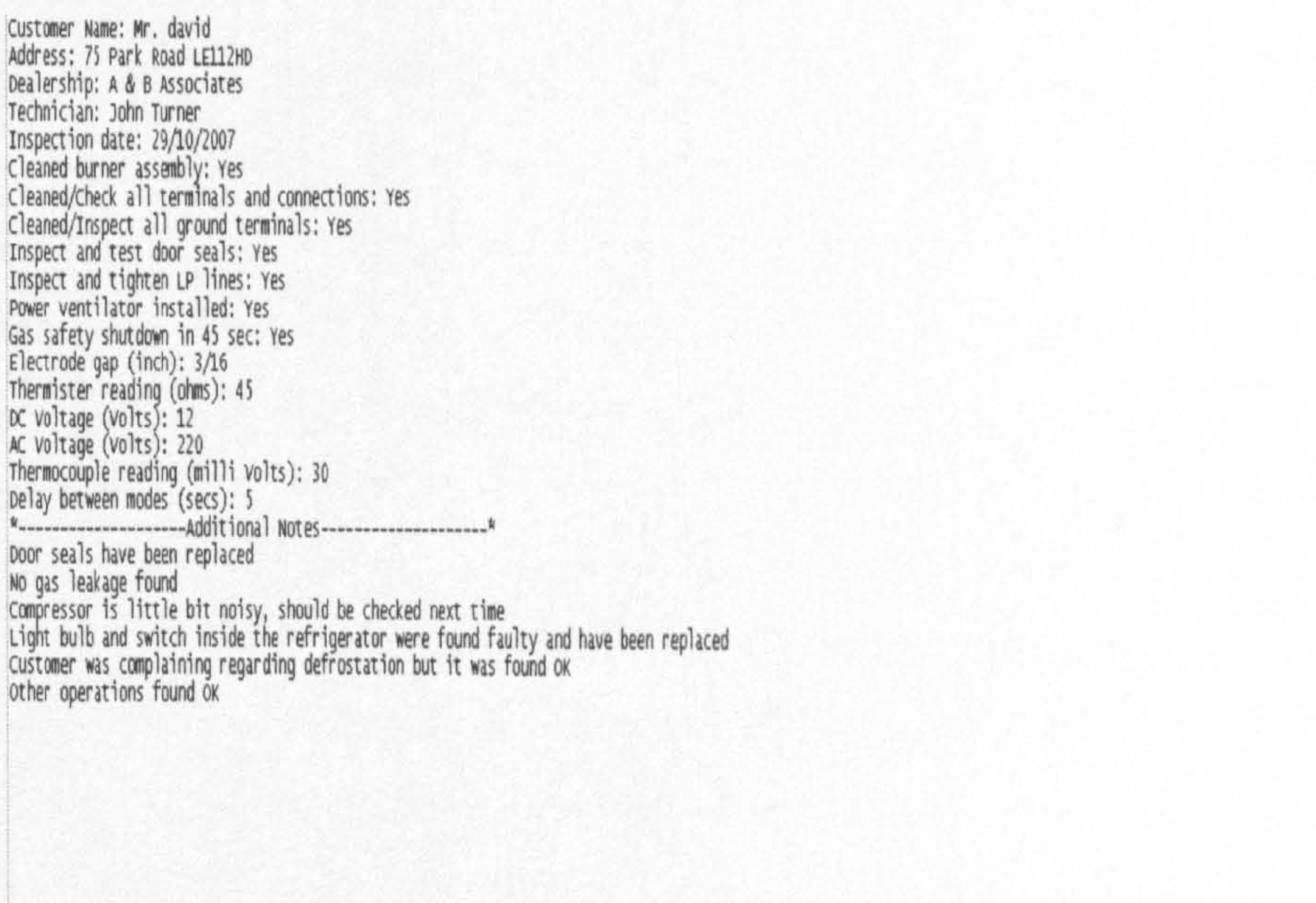

Customer Name: Mr. david
Address: 75 Park Road LE112HD
Dealership: A & B Associates
Technician: John Turner
Inspection date: 29/10/2007
Cleaned burner assembly: Yes
Cleaned/Check all terminals and connections: Yes
Cleaned/Inspect all ground terminals: Yes
Inspect and test door seals: Yes
Inspect and tighten LP lines: Yes
Power ventilator installed: Yes
Gas safety shutdown in 45 sec: Yes
Electrode gap (inch): 3/16
Thermister reading (ohms): 45
DC voltage (Volts): 12
AC voltage (Volts): 220
Thermocouple reading (milli volts): 30
Delay between modes (secs): 5
-------------------Additional Notes-------------------
Door seals have been replaced
No gas leakage found
Compressor is little bit noisy, should be checked next time
Light bulb and switch inside the refrigerator were found faulty and have been replaced
Customer was complaining regarding defrostation but it was found OK
Other operations found OK

Fig. 4.14 Snapshot of the maintenance log created by the smart EID

4.3 Summary of chapter 4

- The concept of storing the sensory data of a product with detailed maintenance logs has been demonstrated successfully. The proposed idea of smart EID has clearly proved that detailed lifecycle data can be stored into a product itself. In past, no one demonstrated this concept of storing detailed information into the product itself.

- Some expert to judge the condition of a product at its EOL, can use the sensory data stored by the smart EID.

- In addition to the sensory data, detailed maintenance logs stored in the smart EID can also provide useful information regarding the condition of product at its EOL.

- As the smart EID is unable to predict the remaining life of a product, therefore, this concept needs further extension to a system that is capable of predicting the product life.

Chapter 5

INTELLIGENT EID TEST RIG SETUP

The previous chapter explains the implementation of a smart EID. This chapter now explains the target application for intelligent EID, that is a gearbox. Different types of gears and the gearbox environment are introduced and the different modes of gear failure are explained. The chapter then presents the demonstration rig setup for an intelligent EID that is designed to conduct an accelerated life test for a gearbox.

5.1 Subject for the application of an intelligent EID

According to the proposed definition of an intelligent EID in the introductory chapter, one of the functions of an intelligent EID is to predict a machine's remaining life. The basic attribute of machine life prediction is the mapping of machine degradation with respect to time. In addition to this, intelligent EID should be a device that has capability of bi-directional communication in terms of information exchange. Figure 5.1 depicts the schematic diagram of the intelligent EID. The proposed intelligent EID contains an on-chip life prediction algorithm for machine life prediction. The intelligent EID receives sensory data from the product. The life prediction algorithm then processes the data in order to predict the machine's lifetime. In addition to this, the intelligent EID has capability to communicate with its external environment in terms of knowledge exchange. For this purpose, intelligent EID uses bi-directional communication software that enables it to connect to the external world. The details of this software are described in chapter 7. With the help of this software, the intelligent EID gets intelligence updates and provides the feedback of product lifecycle data to the external world that can be stored into some external database.

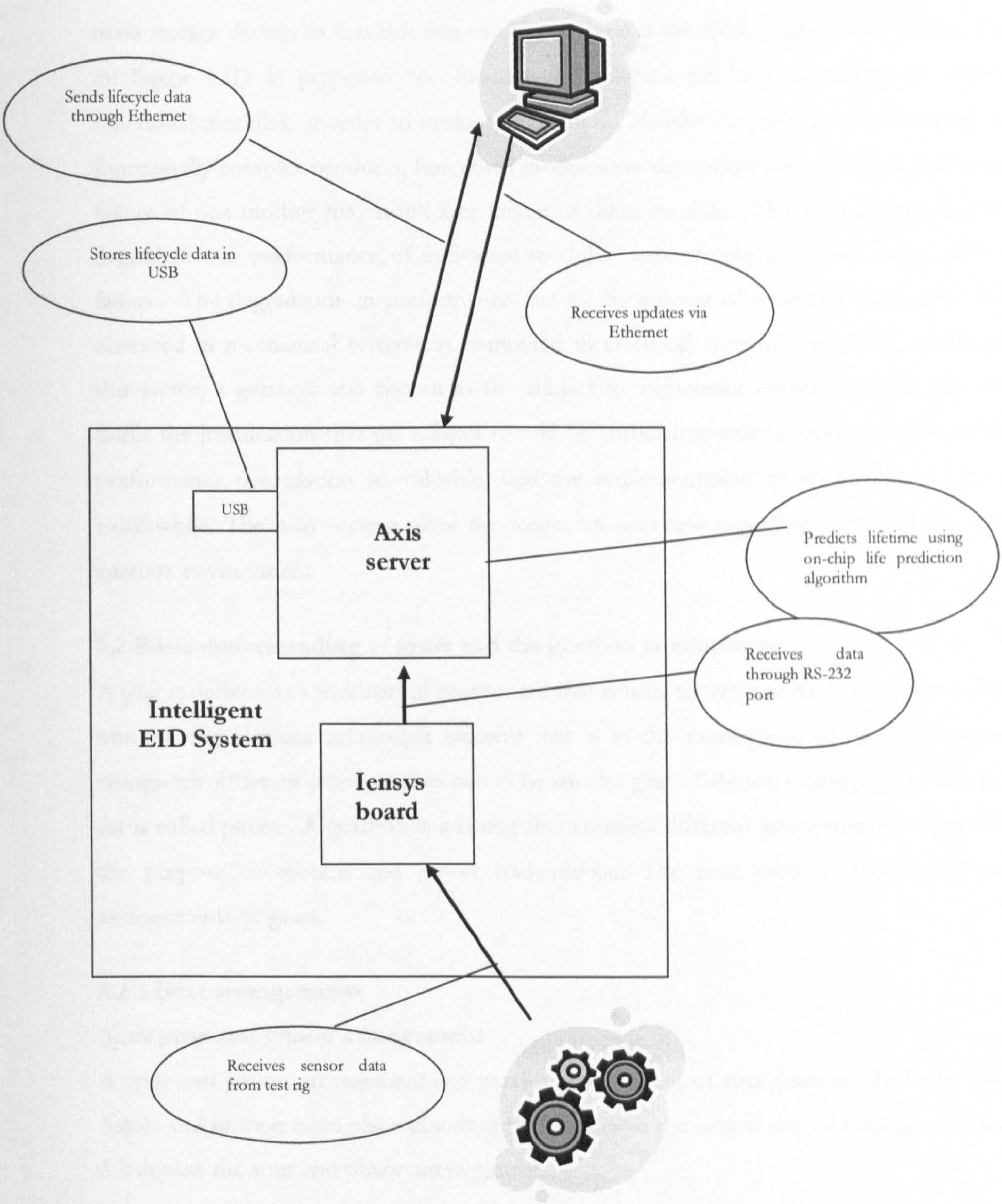


Fig. 5.1 Schematic diagram of the intelligent EID

Like smart EID, the proposed intelligent EID also stores product lifecycle data into a USB mass storage device, so that this data can be retrieved at the EOL stage of the product. The intelligent EID is proposed for functionally complex products consisting of various functional modules, in order to prolong their useful lifetime via predictive maintenance. In functionally complex products, functional modules are dependent on each other, therefore, failure of one module may result into failure of other modules. Therefore, monitoring the degradation in performance of individual modules can prevent a product from ultimate failure. The degradation in performance due to the process of wear and tear can be well observed in mechanical systems as compared to electrical systems, therefore, considering this factor, a gearbox was chosen as the subject to implement intelligent EID. This also fulfils the justification that the subject should be sufficiently worthy, and awareness of the performance degradation so valuable, that the implementation of an intelligent EID is worthwhile. The next section gives the reader an overview regarding gears and the basic gearbox environment.

5.2 Basic understanding of gears and the gearbox environment

A gear is defined as a mechanical component that is used to transmit motion or power from one moving element to another element that is in the same plane or direction or in a completely different plane or direction. The smaller gear of the two mating gears in a gear set is called pinion. A gearbox is a casing that contains different arrangements of gears for the purpose of motion and power transmission. The next section explains different arrangements of gears.

5.2.1 Gear arrangements

Spur gear and pinion arrangement

A spur and pinion arrangement is a parallel arrangement of two gears in which the tooth forces and motion takes place exactly at right angles to the central axis of both gears. Figure 5.2 depicts the spur and pinion arrangement.

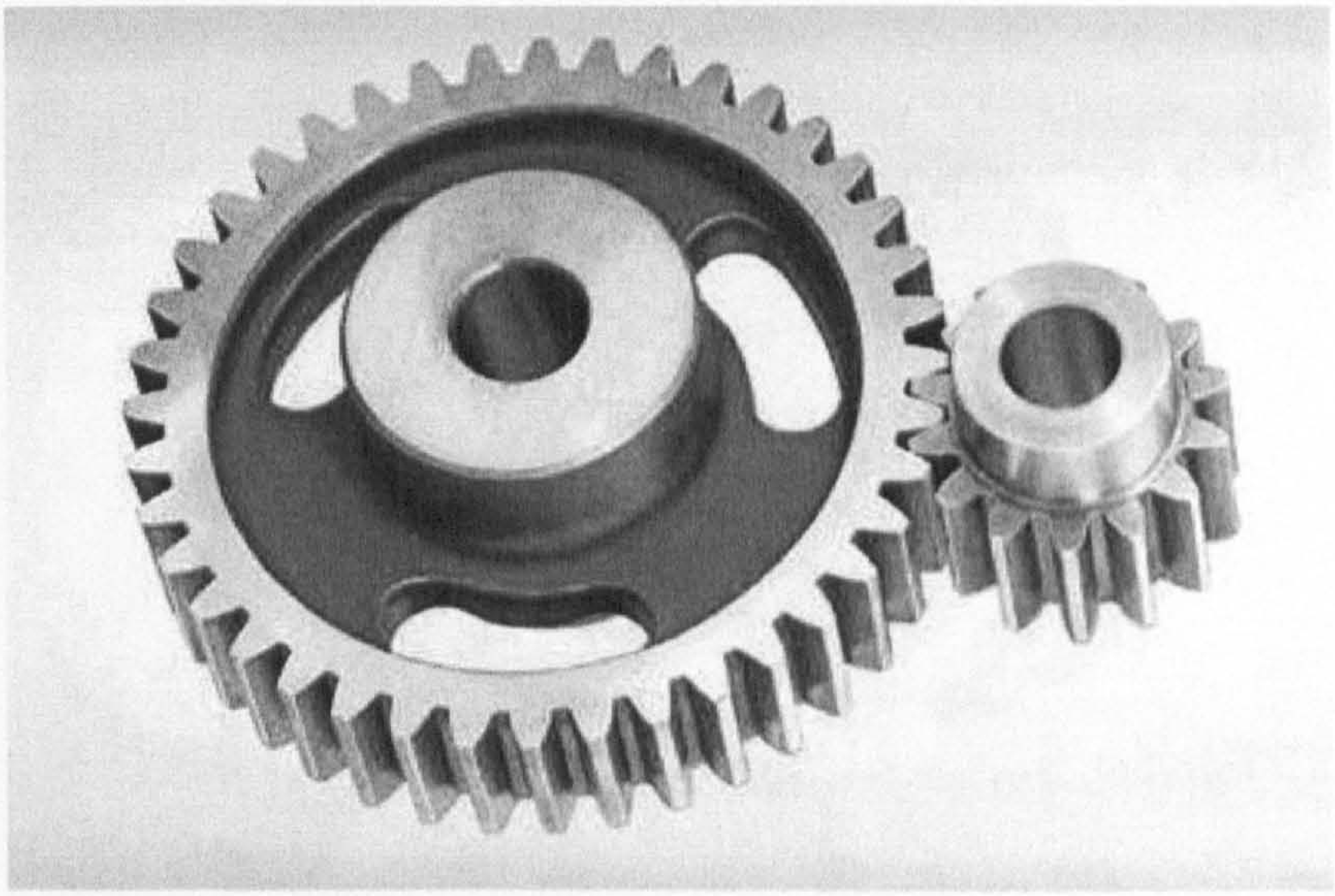


Fig. 5.2. Spur gear and pinion arrangement

Helical gear and pinion arrangement

This type of arrangement is another parallel axis arrangement that involves power transmission along a straight line, however, the direction of force exerted by the meshing teeth is angular in direction because the teeth are helical in shape or we can say they follow some angle of helix. As the teeth of a helical gear are curved, therefore the engagement of these teeth with their opposite teeth is much better than the engagement of the teeth in spur gears. This type of arrangement gives helical gears a smoother motion as compared to spur gears. Though the parallel axis arrangement of helical gears is mechanically sound, they can also be used in a non-parallel arrangement known as a crossed configuration. In a crossed configuration, there is no tangential meshing and the contact takes place at the tooth surfaces only. As the area of contact in the crossed arrangement is small, therefore, this type of arrangement is suitable only for light loads. There is another type of helical gears, called double helical gears, which contain two opposite sets of helical teeth that are machined around the same periphery having an opposite helix angle. The two sets of opposite teeth are separated by a machined surface between them. Figure 5.3 shows the helical gear arrangement.

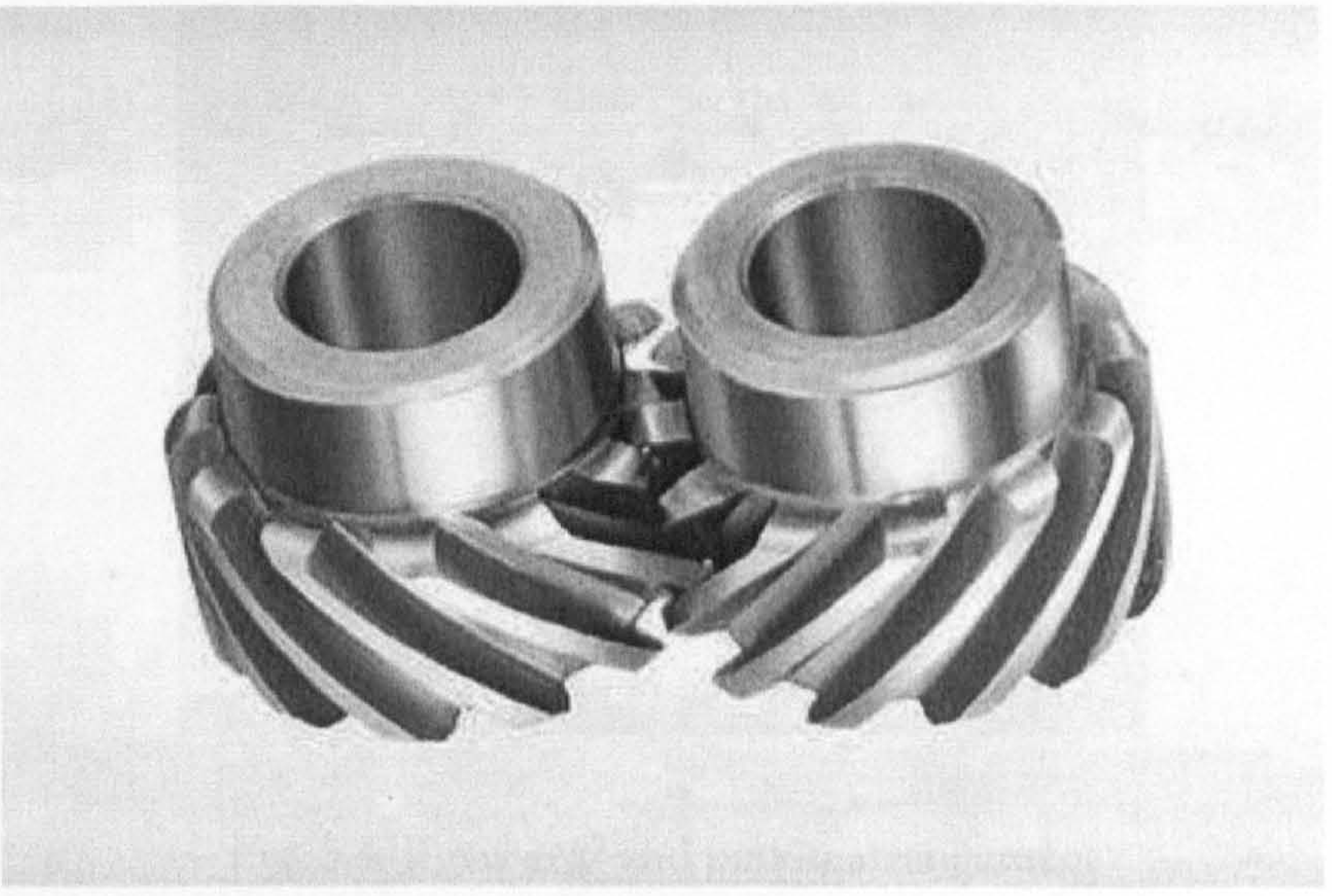


Fig. 5.3. Helical gear arrangement

Bevel gear and pinion arrangement

Bevel gears are conical shaped gears. Such a type of arrangement is used to transmit power in an angular direction. The speed and angle of motion change with the change in the number of meshing teeth. Contact forces between the meshing teeth are responsible for giving a push to the opposing teeth as well as creating a lateral slide along the surface of every tooth. Another type of bevel gear is a spiral bevel gear that acts as a bevel and a helical at a same time. As in helical gears, the teeth have an angle of helix, which confirms a smooth motion. In spiral bevel gear sets, the off angle teeth are given an angular displacement; therefore they naturally assume a spiral shape. Figure 5.4 shows a bevel gear and pinion arrangement.

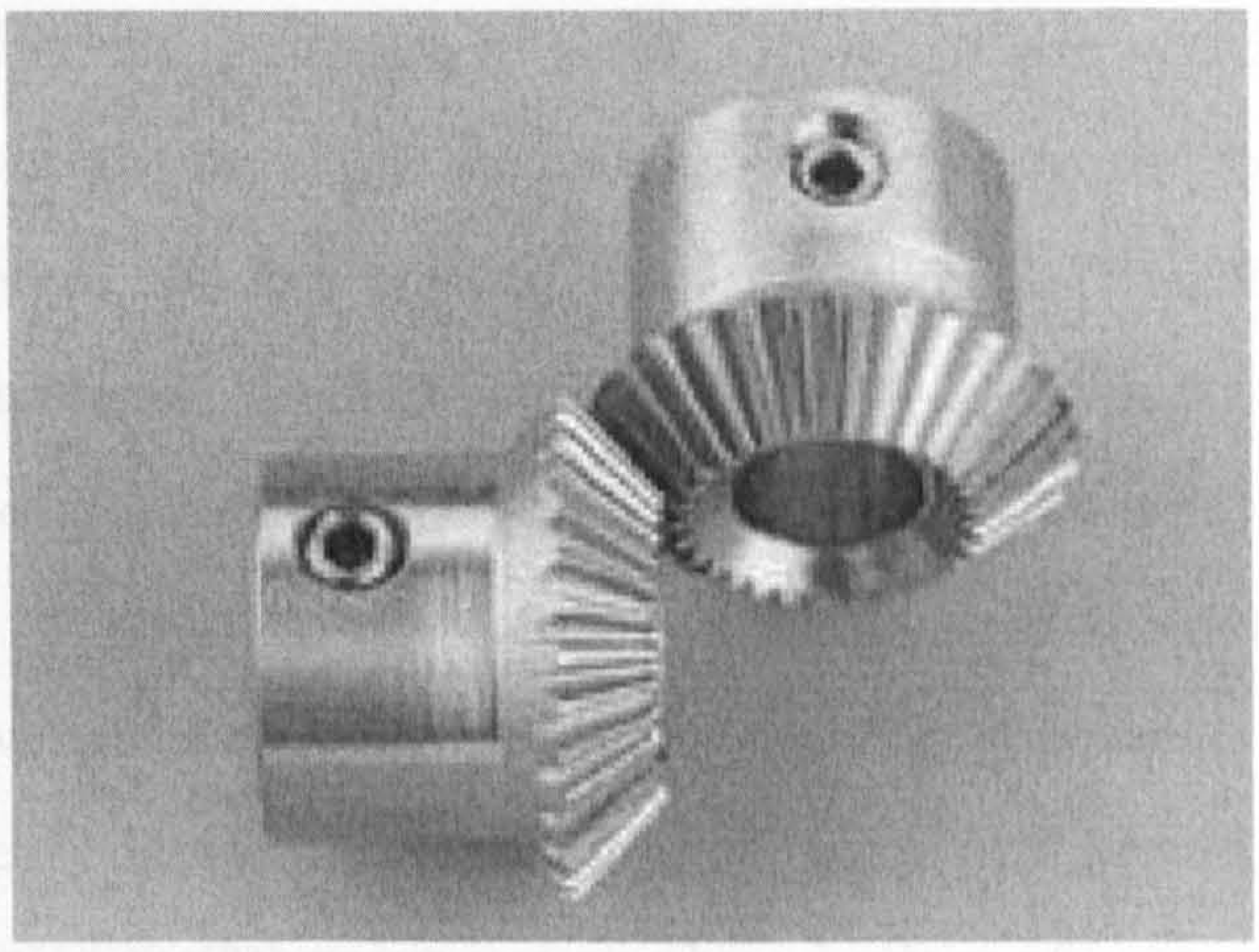


Fig. 5.4. Bevel gear and pinion arrangement

5.2.2 The gearbox environment

To understand gearbox failure it is necessary to understand the basic environment of a gearbox, which is the set of factors or conditions that are present inside or around the gearbox. To understand the failure mechanism of a gearbox the factors mentioned below must be understood.

Lubrication is one of the most important factors responsible for gearbox failure. Insufficient, excessive, incorrect and contaminated lubricant may lead a gear to fail. Lubrication is basically carried out on the teeth of a gear and it creates two types of oil films: one is called the reaction film and the other one is called the elastohydrodynamic film. The reaction film, which is also called the boundary lubricant, is created as a result of physical absorption or some chemical reaction, this film is soft and of low shear-strength but on the other hand this layer is hard to remove from the surface of the teeth. The other film, the elastohydrodynamic film, which is produced as a function of surface speed, is a thin but very strong film, as it is not disturbed even under high compressive loads, as long as the temperature remains constant. Actually, the lubricant film is responsible for transferring the load from a gear tooth to its meshing tooth, the absence or breaking of the film results in the gear deterioration. There is a specific value for the equilibrium temperature of the gear tooth at which the lubricant film tends to break. The gear tooth equilibrium temperature is reached when the heat absorbed by the lubricant is equal to the heat dissipated by the lubricant. In other words, we can say that the lubrication plays an important role in gear failure. If we use a lubricant of incorrect specification, and the type of lubricant that is suitable for one type of gearbox may not be suitable for another type, then the gearbox may be damaged within a short period. Insufficient lubrication increases the operating temperatures due to which remaining lubrication runs out, this brings the mating gears into direct contact and hence results in deterioration. On the other hand, excessive lubrication results in solidification of the lubricant as a combined effect of heat and the churning of oil, which also causes damage to the gearbox. Thus, we can say that temperature is another important factor in the gearbox environment. Another factor that is a part of the gearbox environment is the integration of the gearbox with the system. Mechanical stability of a gearbox should be given considerable importance because any misalignment, deflection, or instability may result in an improper tooth contact of the mating gears, which may result in a gear failure. Personnel-related activities are also a part of environment and should be considered. For example, while assembling a gearbox unit, if an assemblyman does not care about alignments and tolerances then this negligence may subject a gearbox and the associated assembly to work under excessive stress. This excessive stress may result in a gearbox failure. If cleanliness during assembly process is not maintained, then any contamination or impurity can be easily added during the process. This can also result in some sort of deterioration. Operation related activities are also very important, as operating an equipment properly and carefully ensures longer life. On the other hand, operating a product in an improper manner causes an early failure. Similarly, activities related to maintenance play an important role as well in gearbox failure. Use of recommended replacement parts and spares, scheduled maintenance practices, and again careful assembly after repair, ensure a healthy operation of gearbox. Next section explains different modes of gear failure.

5.2.3 Modes of gear failure

A gear can fail in various modes. One mode of gear failure can give rise to another mode of failure. A failure mode of a gear is a special type of failure that has a signature of its own.

Most gears fail due to fatigue or due to impact that is either tensile or shearing, or due to abrasive or adhesive wear. Alban reports that in an analytic study of more than 1,500 gears, tooth bending fatigue, tooth bending impact and abrasive wear were found to be the most common modes of failure **[108]**. Some of the important modes of gear failure are explained below:

Fatigue failure

Fatigue failure occurs when a gear is subjected to cyclic stresses at a load much lower than its ultimate tensile strength. Normally, there are three phases of fatigue failure. The initial phase starts with a fracture, then, in the second phase, this fracture increases and finally, the third stage results in the breakage of the part.

One of the most common modes of fatigue failure is tooth-bending fatigue. Normally, it originates on the root radius when one tooth fails and then the fracture progresses. Because of the fracture, the deflection of the tooth continues until the top corner of the next tooth picks up the load. Overloading is one of the main causes of fatigue failure. Figure 5.5 shows tooth-bending fatigue.

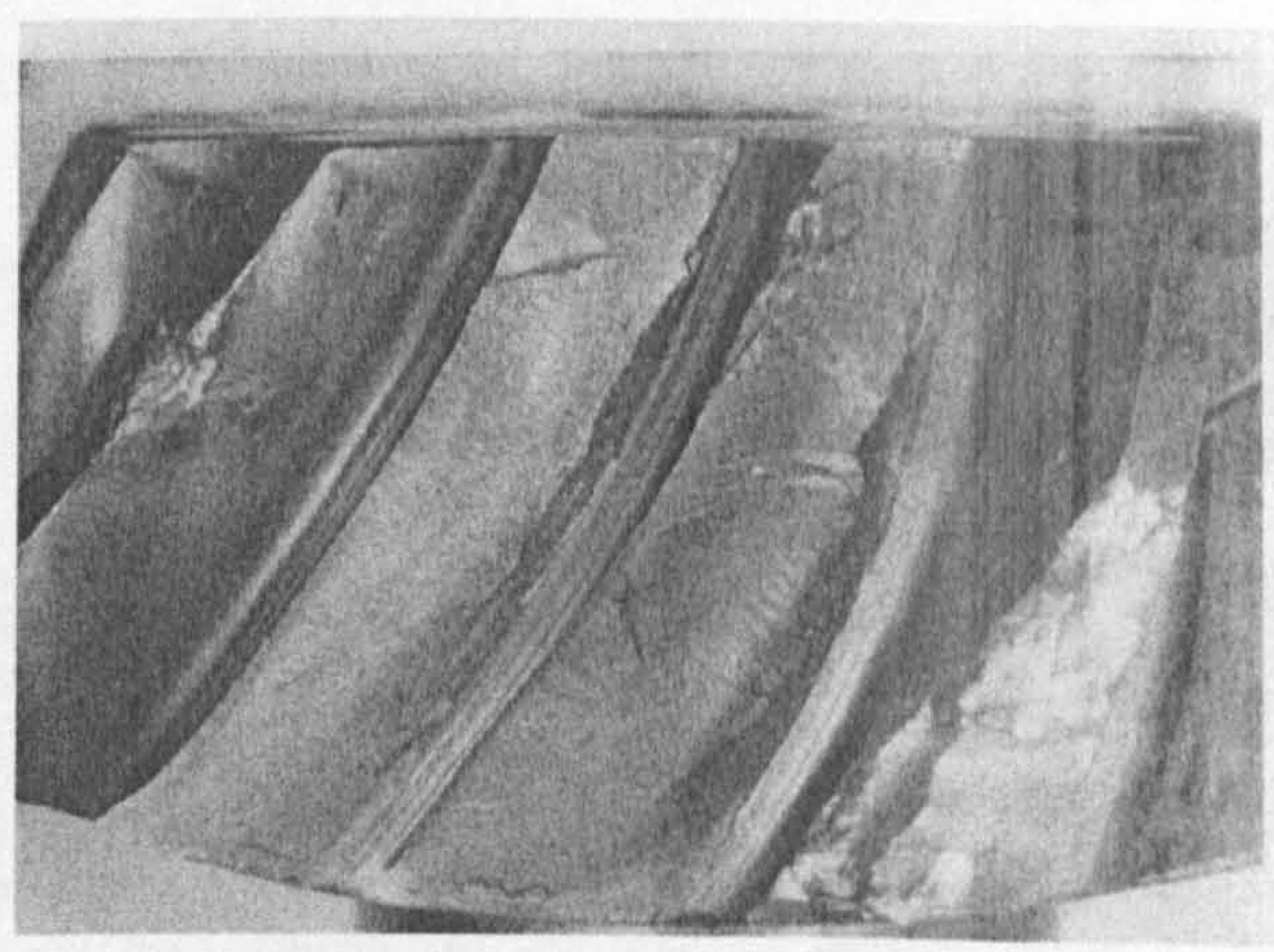


Fig. 5.5. Tooth-bending fatigue **[108]**

Contact fatigue, which is also known as spalling, is one of the causes that can initiate some basic mode of gear failure. Spalling is a type of failure that produces a subsurface at the point of intersection of the total stresses that are applied and misapplied and the net strength of the gear. The fracture grows under the carburised case of the gear. Figure 5.6 shows contact fatigue.

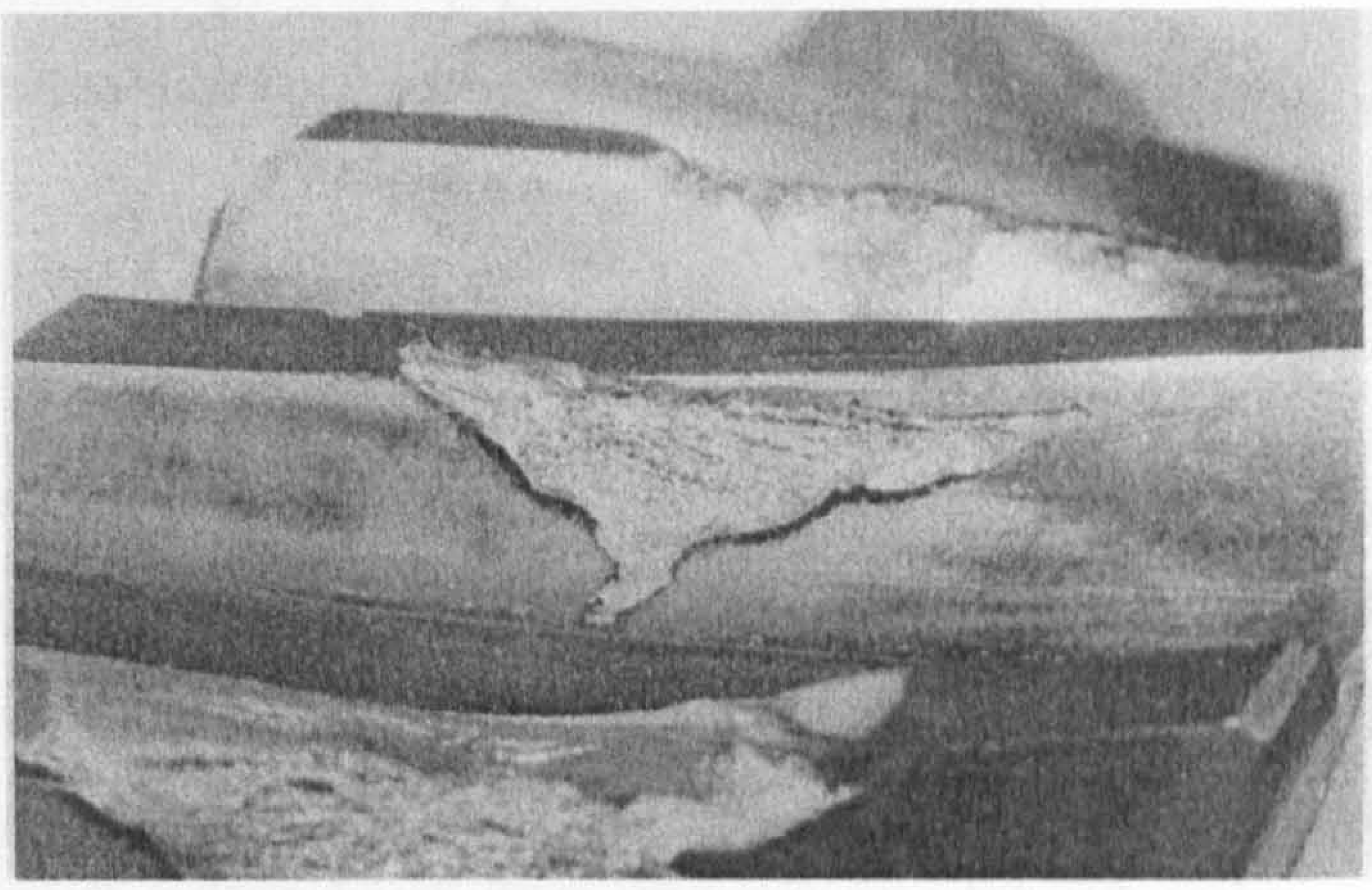


Fig. 5.6. Contact fatigue **[108]**

Another type of fatigue is surface contact fatigue or pitting. In gear engineering it is considered as a material-fatigue mode of failure. In the case of surface contact fatigue, the surface elements are deformed plastically due to compressive stresses that are cyclic in nature. Because of these stresses, grains of the structure are subjected to random plastic deformation that results in fatigue cracks. Figure 5.7 shows contact fatigue or pitting.

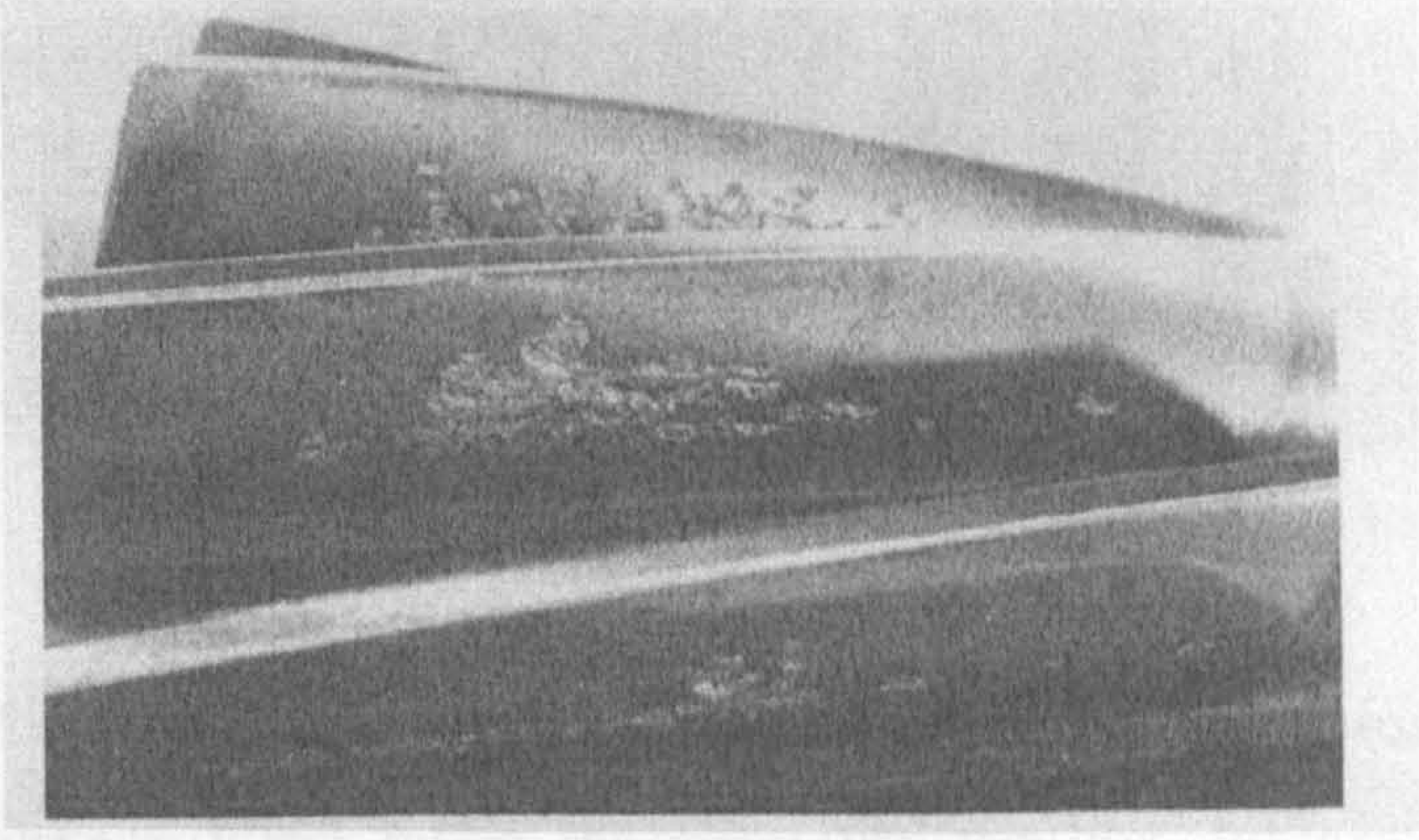


Fig.5.7. Contact fatigue or pitting **[108]**

One type of fatigue failure that is observed in gears is rolling contact fatigue. The main reason for rolling contact fatigue is the sliding of surfaces under rolling contact. If the sliding of surfaces takes place in the same direction as the rolling then this results in an increase in the shear stress. This increase in the shear stress causes pitting. This results in crack propagation if rolling is taking place at high loads. This crack continues to develop until and unless it turns into spalling or pitting of a severe nature.

Impact failure

Tooth shear is one of the modes of gear failure that is observed when a gear is subjected to a very high impact load within a very short contact time. If the gear material is ductile, then it results in shearing. Fracture appears in the form of a shiny, convex surface that appears as a combination of both shearing and bending. However, bending is dominant over shearing, therefore, the direction of impact can be judged clearly. Figure 5.8 shows impact failure.

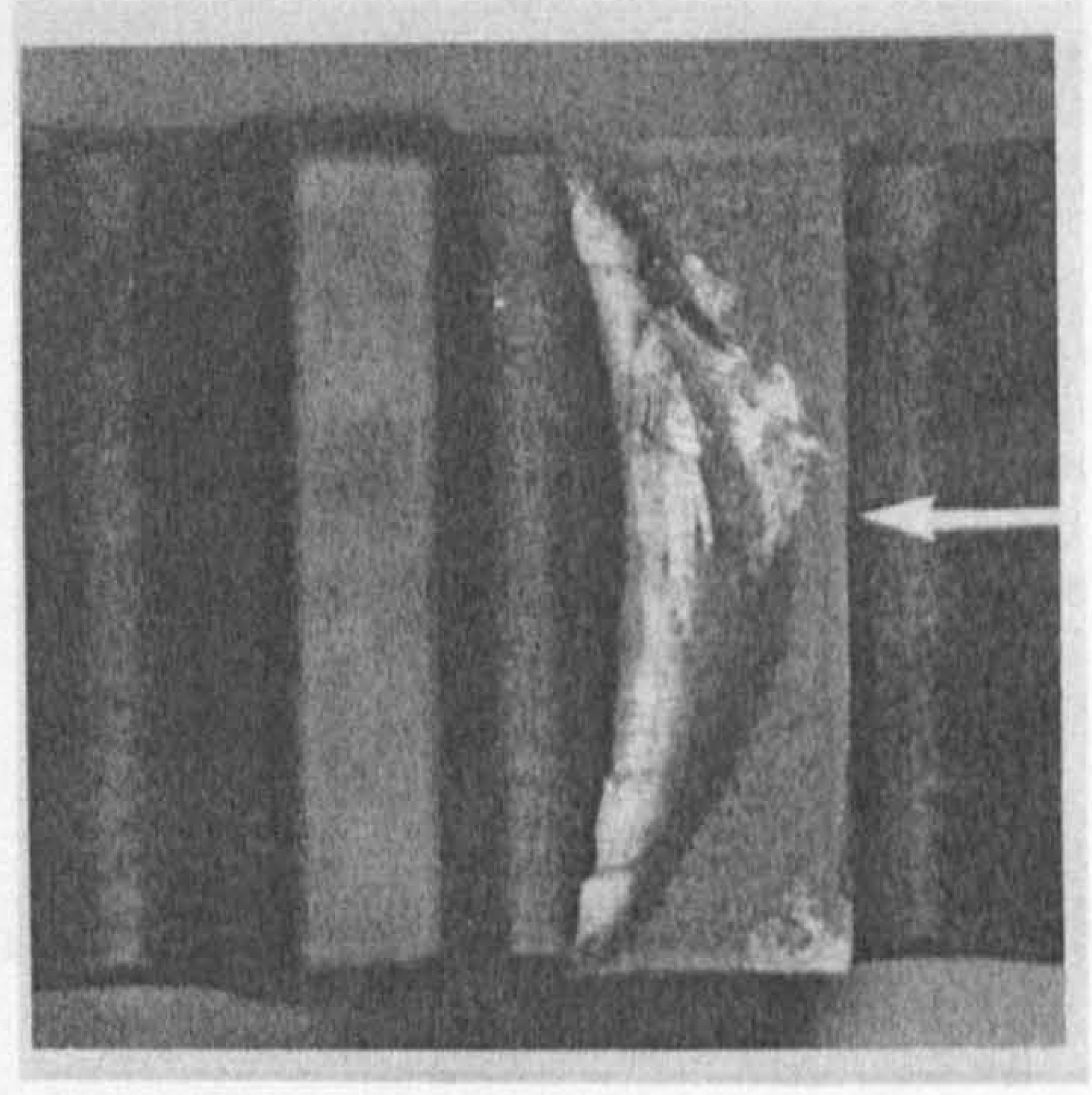


Fig.5.8. Impact failure **[108]**

Another mode of impact failure is tooth chipping. The main reason for tooth chipping is some sort of a foreign object inside the assembled gearbox, for example, a loose bolt striking the gear tooth or sometimes a broken particle from some other tooth. Sometimes, mishandling during assembly or transportation is a reason for tooth chipping.

Case crushing is another mode of gear failure that occurs because of overloading. Case crushing in gears is observed when the carbon case in the gear structure is subjected to overloading up to a very high level. Due to this overloading, a fracture is developed which continues to grow inside the material core and is directed towards the gear surface. Figure 5.9 shows case crushing.

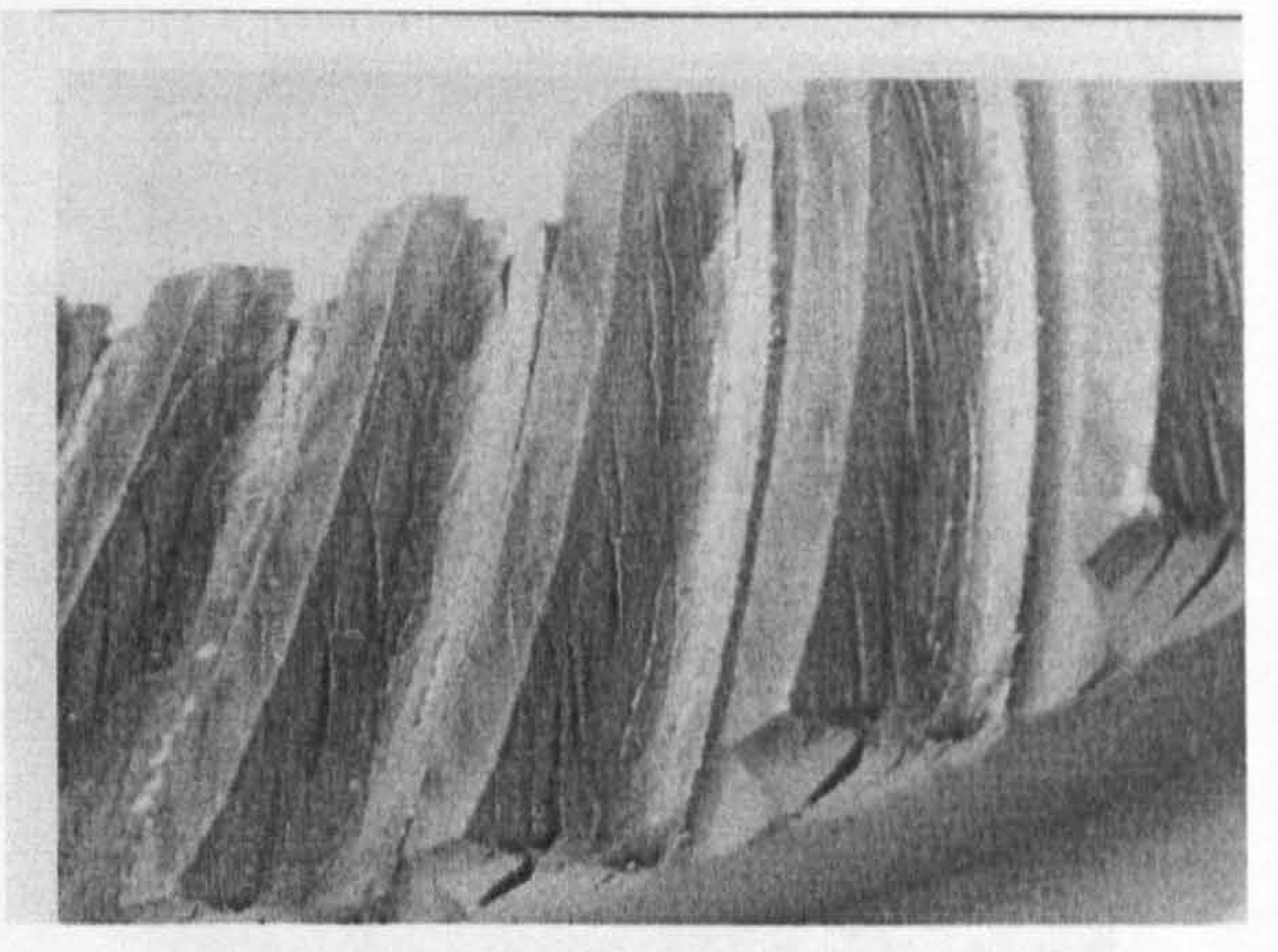


Fig.5.9. Case crushing **[108]**

Wear

Wear is basically defined as surface worsening of the gear teeth profile. It can be classified into two types:

- Abrasive wear
- Adhesive wear

Abrasive wear in gears takes place when material from the gear teeth profile is removed by solid abrasive particles as a result of sliding contact between the surfaces. Initially, abrasive wear appears in the form of light scratches over the surface, which then turns into scuffing and then scoring. One of the main reasons of abrasive wear is contamination of an abrasive nature from the lubricant. This contamination affects more or less all the moving parts inside the gearbox assembly, including the gears. Figure 5.10 shows abrasive wear.

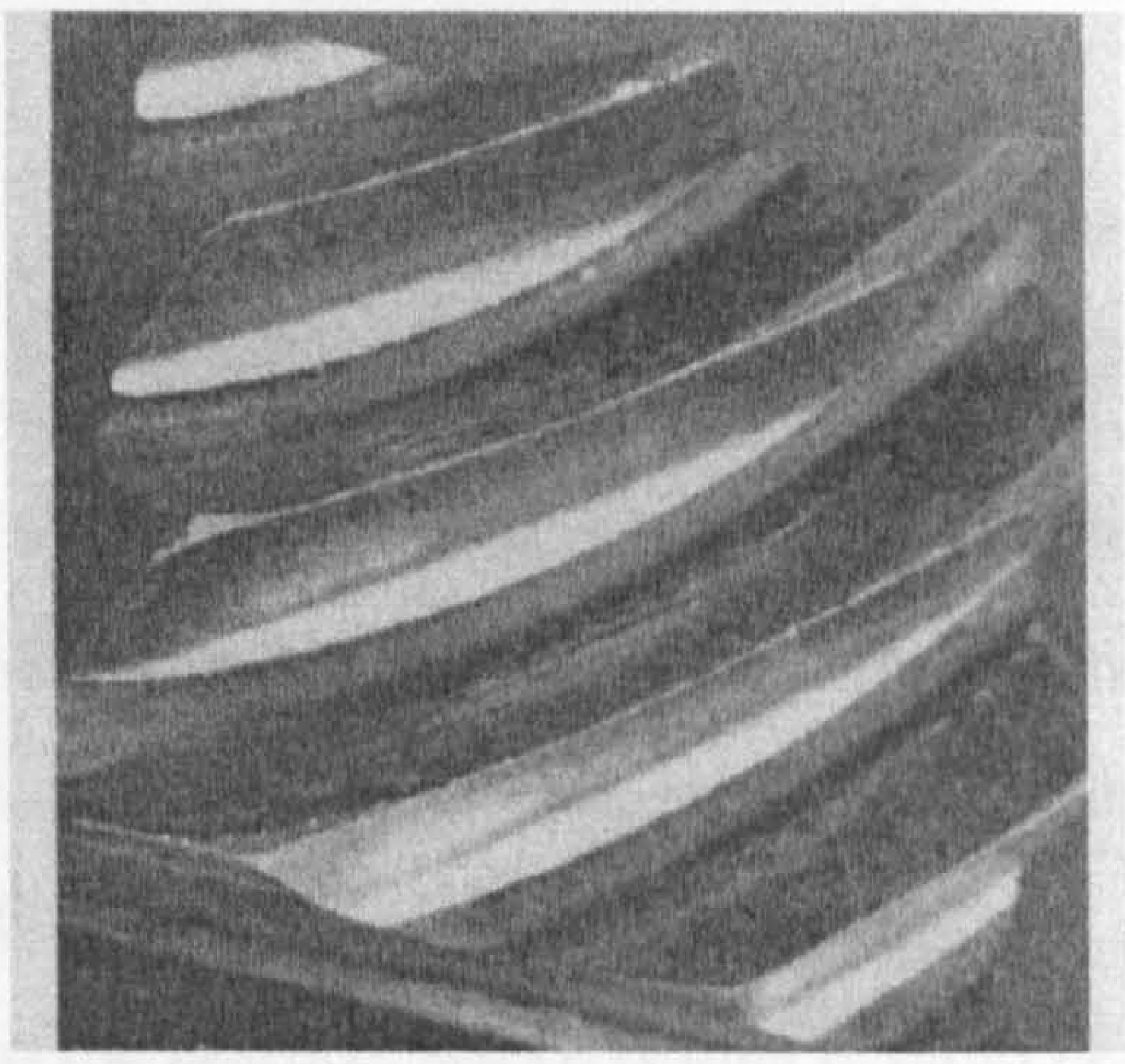


Fig.5.10. Abrasive wear **[108]**

Adhesive wear is a form of wear that occurs because of sliding contact between two surfaces under a load that is high enough to create plastic deformation in the material. Because of this plastic deformation, frictional energy is absorbed in the form of heat. This frictional heat causes the bulk movement of surface material. Initially it starts with the formation of a glazed surface, which then converts into galling and finally the seizure. Due to an increase in the frictional heat, the surface of the material tends to soften and also the material becomes increasingly adhesive. This results in an increase in plastic deformation of the material and then the galling takes place. This galling increases further and results in a welding between the sliding surfaces. Therefore, large movement of material from the surface can be seen. Figure 5.11 shows adhesive wear.

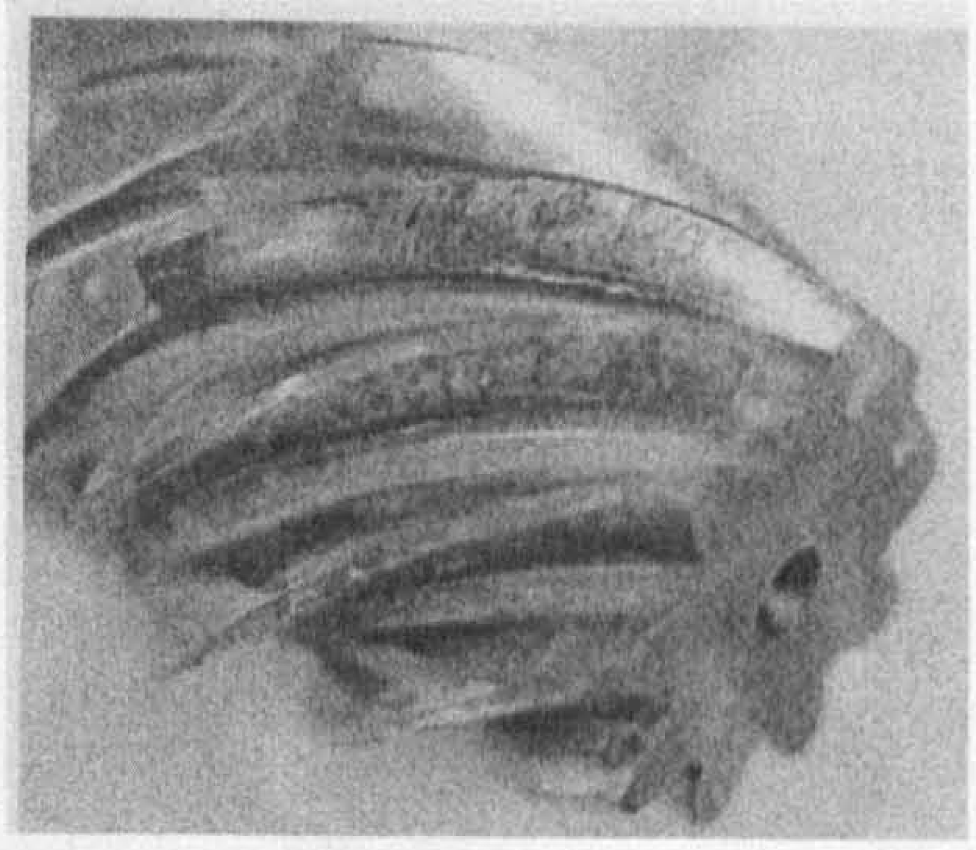


Fig.5.11. Adhesive wear [108]

5.3 Test rig

A test rig, which is shown in Figure 5.12, was developed to monitor the gradual degradation in the performance of the gearbox. It is designed with the intention of performing an accelerated life test and to create a rough-usage mode scenario, so that the degradation phenomenon can be clearly monitored. This is done by applying an excessive torque greater than the designed torque of the gearbox, which results in rapid degradation.

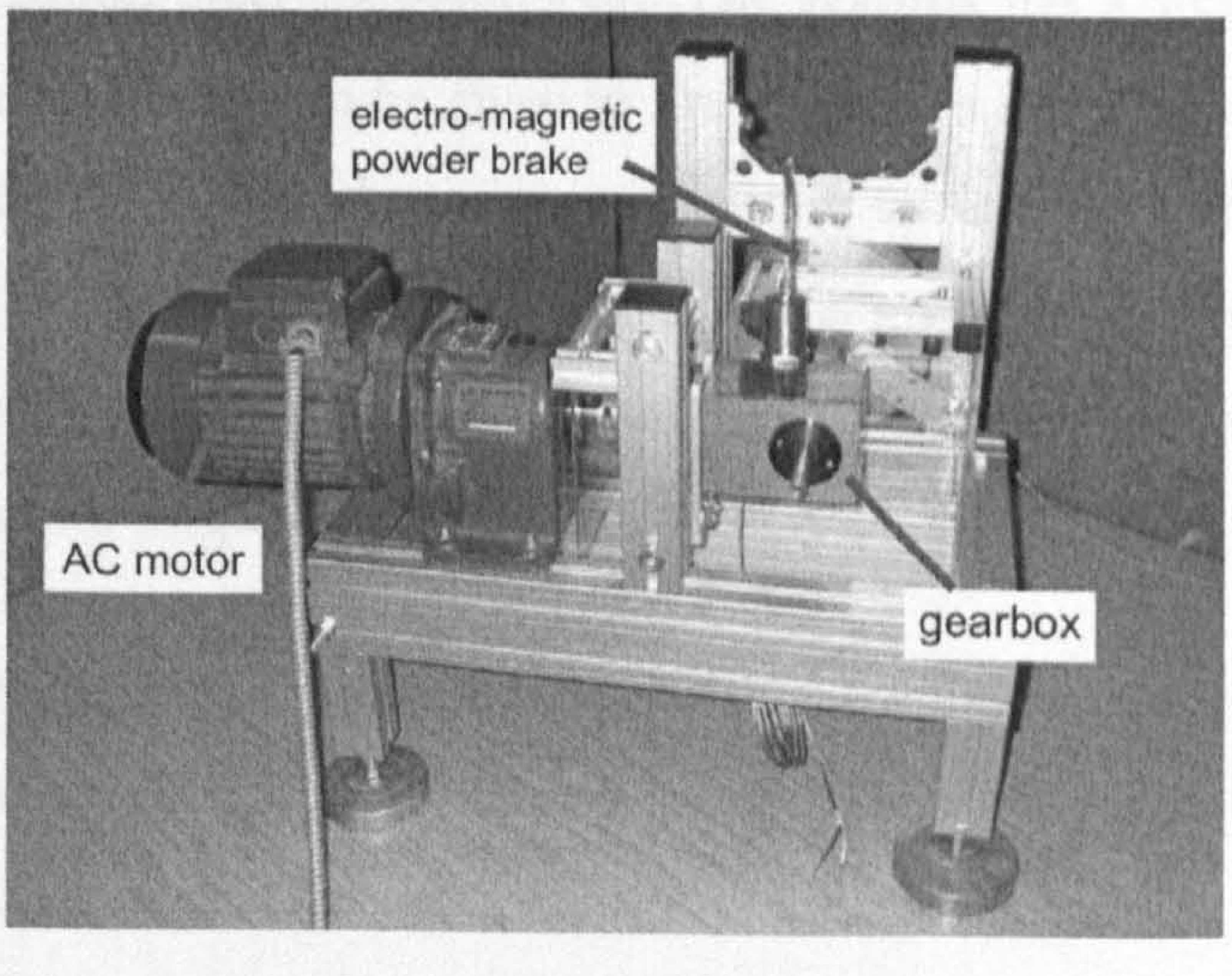


Fig. 5.12. Intelligent EID test rig

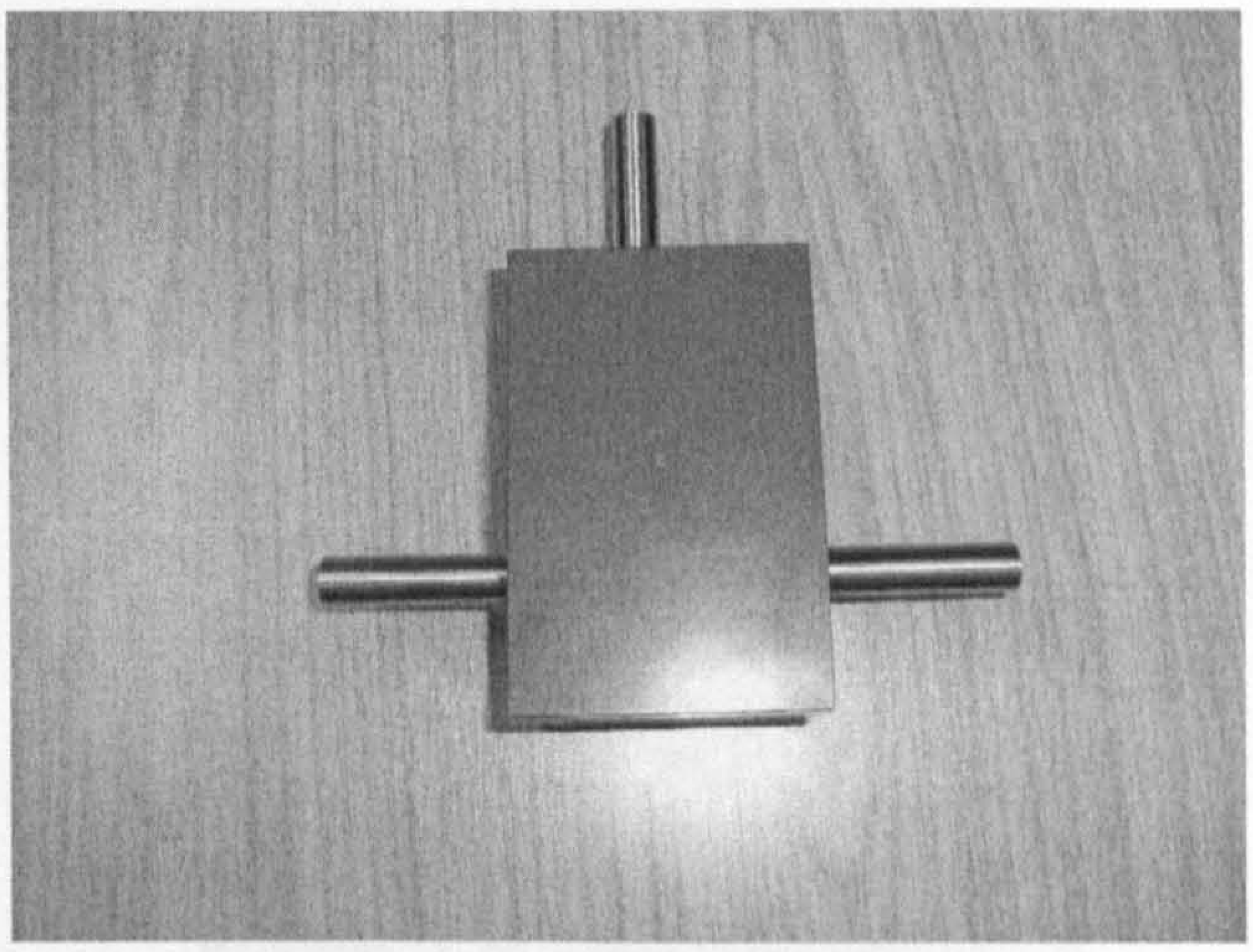


Fig. 5.13 .The tested gearbox

The test gearbox is a right angle bevel gearbox. Figure 5.13 shows the tested gearbox. The outer casing of the gearbox is made of Red Anodised Aluminium (6082-T6) and the gear is made of Medium Carbon Steel 080M40(EN8). The gearbox has a weight of 1.75 Kg and the maximum input speed that can be given to the gearbox is 2,000 rpm. The gearbox has a reduction ratio of 2:1, therefore the maximum output speed delivered by the gearbox is 1,000 rpm with an efficiency of 88%. The gearbox is greased for life with Shell Alvania grease, number HDX2. However, during the test, the gearbox was operated at a speed of 40 RPM at which its output torque was 2.2 N.m.

A 3-phase AC motor having a power of 250 Watts is connected to the gearbox with the help of a mechanical coupling. The maximum speed of the motor is 1,400 rpm. Figure 5.12 shows the motor that is used in the rig.

The motor is provided with a speed controller that controls the motor at different operational speeds. With the help of this speed controller, the motor can be operated within the speed range from 1 rpm to 60 rpm. Fig. 5.14 shows the speed controller that is provided with the motor.

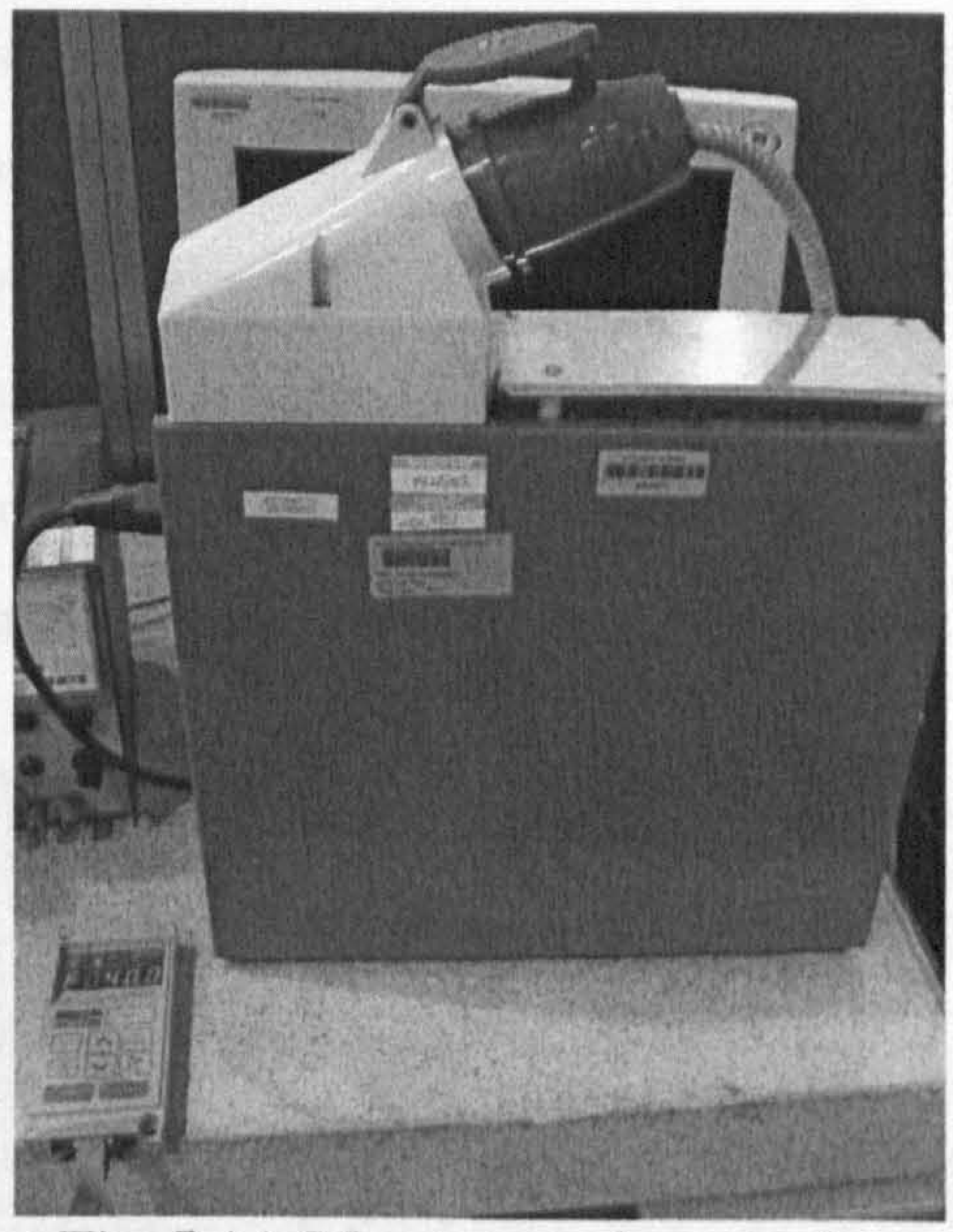


Fig. 5.14. Motor speed controller

As previously described, the gearbox used in the rig is a right angle bevel gearbox, which is coupled with the motor at its input and is overloaded with the help of an electromagnetic powder brake at its output. Electromagnetic powder brakes are used in a variety of applications like card readers, sorting machines and labelling equipment. Electromagnetic brakes consist of magnetic particles that are located in a cavity. When voltage or current is applied to the coil that is present inside the powder brake, then the powder particles become energised from their state of rest. The electromagnetic flux that is produced in the coil tends to bind the powder particles. The relationship between the input voltage or current and the output torque of the electromagnetic powder brake is almost linear. Therefore, with the gradual increase in the input voltage or current, the binding force of the powder particles becomes stronger and stronger. The output of the brake is coupled to a rotating machine element. The rotor of the brake passes through these powder particles, therefore, the binding force tends to create resistance that initially slows down and finally stops the coupled machinery at the output shaft of the powder brake. When the voltage supply is stopped, the brake then turns free and disengagement takes place. Due to their fast response, accurate control, long life and extremely fast engagement, powder brakes have found their use in various applications where accuracy and control play an important role.

The electromagnetic powder brake used in the rig has an operational voltage of 24 V. At this voltage along with a current rating of 1.3 Amps, the maximum output torque produced by the electromagnetic powder brake is 5.5 Nm. This output torque is twice greater than the output torque produced by the gearbox. The power dissipation of the electromagnetic powder brake is 70 Watts and it weighs about 1.8 Kg. Figure 5.15 shows the electromagnetic powder brake used in the rig.

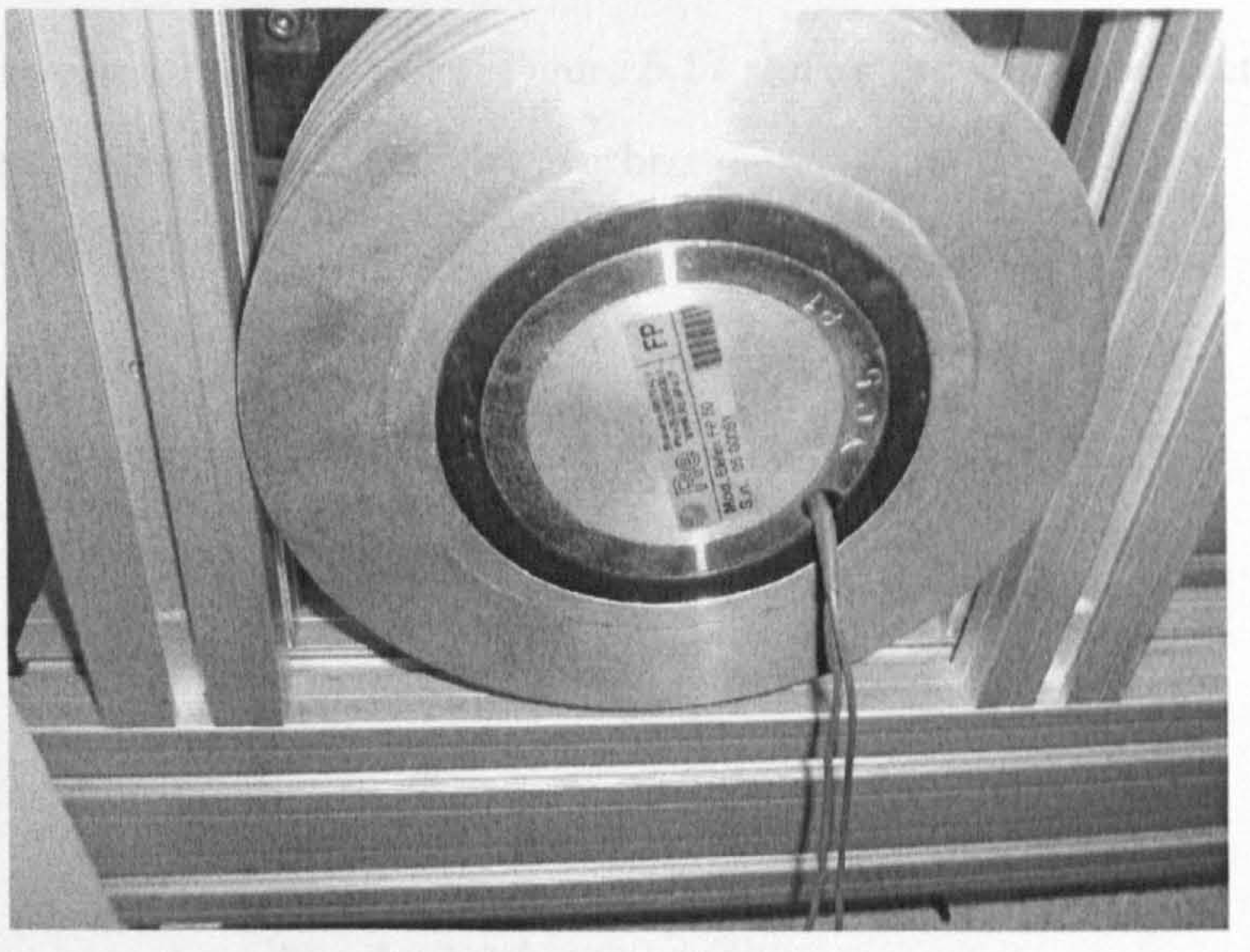


Fig. 5.15. Powder brake attached to the rig

The brake is coupled to the output shaft of the gearbox with the help of the flexible coupling shown in figure 5.16.

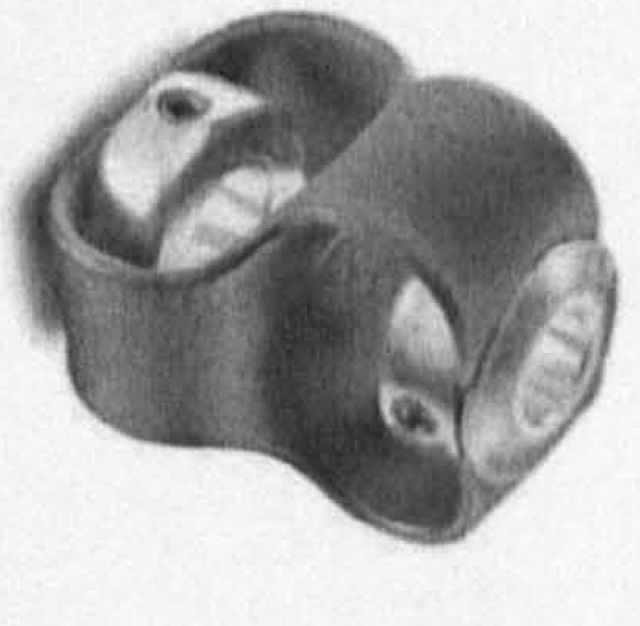


Fig. 5.16. Flexible coupling

When the voltage is applied to the powder brake, it produces torque and tries to stop the gearbox driven by the AC motor, thus the gearbox tends to degrade rapidly. A vibration sensor is mounted on the gearbox to measure its vibration level during the accelerated life test. The accelerometer that is used in the rig has a maximum current output of 20 mA and a minimum current output of 4 mA. The accelerometer is made of stainless steel and weighs 150g. The maximum operating temperature at which it can work is 80 ^{0}C and the minimum operating temperature is -25 ^{0} C. Its sensitivity is 0 to 10 mm/s and it operates in the voltage range between 10 and 32 Volts. Figure 5.17 shows the accelerometer and figure 5.18 shows the accelerometer mounted on the gearbox.

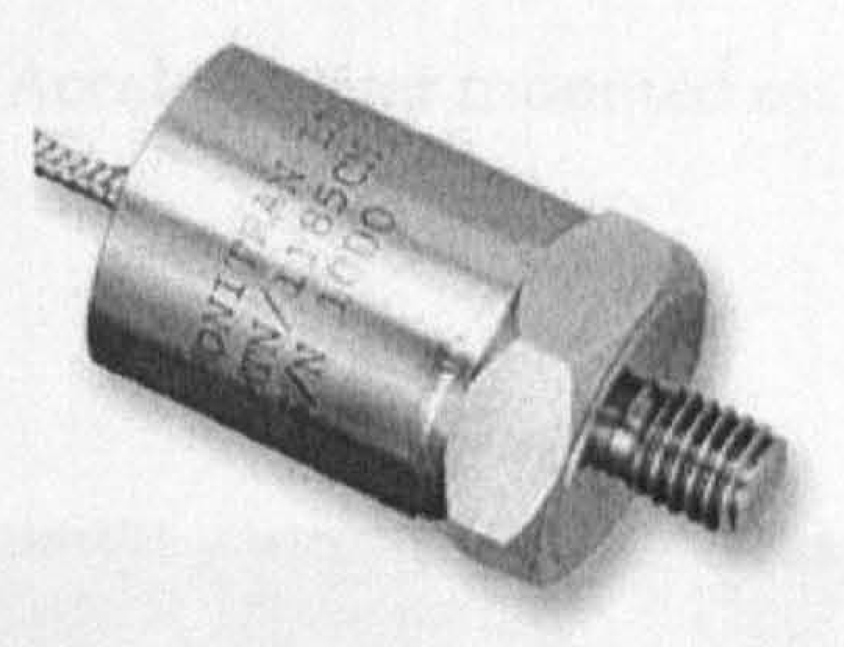


Fig. 5.17. Monitran accelerometer

The output of the accelerometer is connected to the intelligent EID that employs a life prediction algorithm in order to predict the life of the gearbox. Life prediction algorithms will be discussed later in this thesis. The complete experimental setup is shown in figure 5.19.

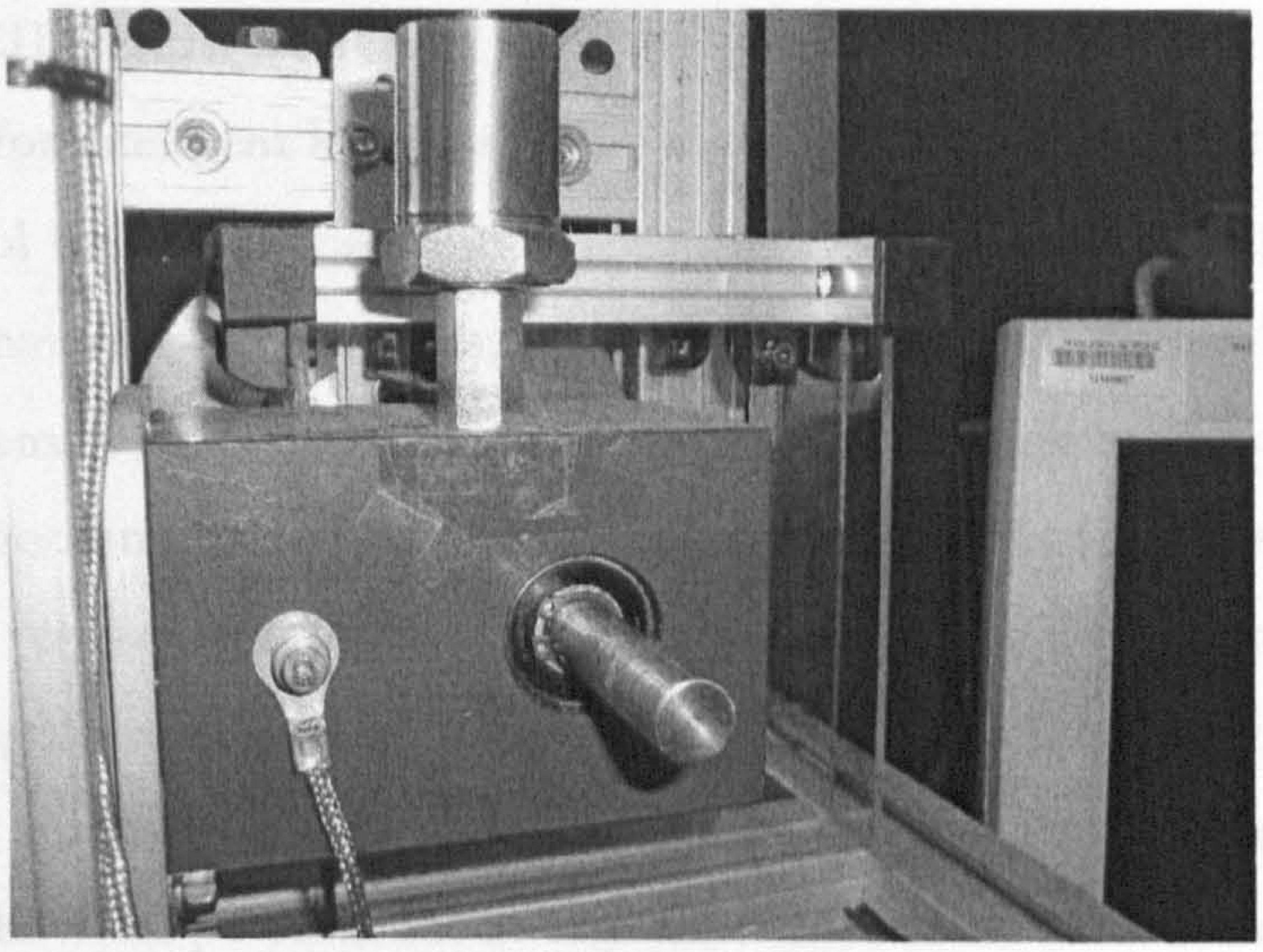


Fig. 5.18. Accelerometer mounted on the gearbox

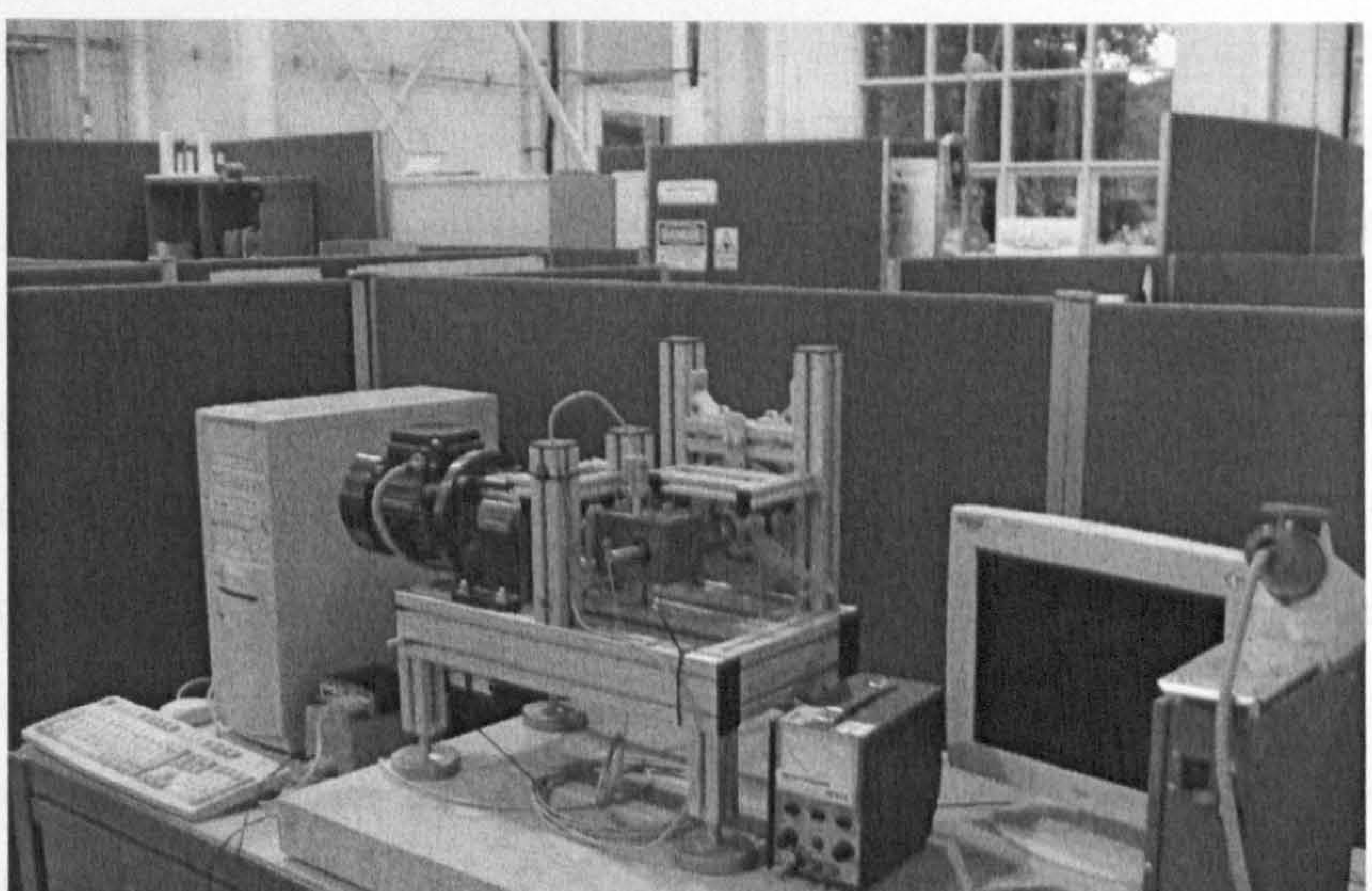


Fig. 5.19.The experimental setup

5.4 Intelligent EID hardware setup

Hardware setup for intelligent EID is same as that for smart EID but intelligent EID uses Ethernet protocol for communication as compare to smart EID, which uses Bluetooth protocol for communication purposes. However, intelligent EID is totally different from smart EID in a sense that it employs a novel life prediction algorithm for life prediction of a gearbox This algorithm is explained in chapters 6 and 7. Though for the purpose of experimentation, results were displayed on a PC terminal, however, the intelligent EID has capability to integrate an LCD display into it. In addition to this, intelligent EID can be accessed over internet, as it contains an internal web server. These features of the intelligent EID show the potential for its implementation in an industrial environment. The proposed intelligent EID can be implemented in three ways. For example, in a manufacturing environment consisting of various machine tools, proposed intelligent EID can be implemented as standalone unit into the machine itself. In this case, an LCD screen can be integrated into the intelligent EID to display the machine's lifetime. The MOL data of machine will then be stored only into the USB mass storage device. The other way to implement intelligent EID is that every machine tool should be connected individually to a PC, so that the MOL data of every machine can be collected into individual PCs as well as into the USB mass storage device and the performance data can be displayed on the monitor or terminal. However, in an industrial environment that consists of several machine tools, the intelligent EID of every machine can also be connected to local intranet of the company and can be accessed via its internal web server. This type of arrangement with the intelligent EID seems suitable because in this case, data can also be maintained in a centralised company database. This database then can be integrated with some other MIS software manage by the company. Also, it can be integrated or shared by the concerned parties such as recyclers, maintenance persons, suppliers, etc., in a peer-to-peer networking fashion. In addition to this, the USB mass storage device will also store the MOL data.

The Iensys general-purpose board that is used in the active EID (both smart and intelligent EIDs) costs under 150 pounds, whereas, the cost of the central module i.e. Axis device server, is also about 150 pounds. This makes the proposed embedded information device little bit expensive for the purpose of product lifecycle management. However, if we consider the system from the perspective of MOL management i.e. predictive maintenance of high value industrial equipment, then the cost of the proposed system is much lower than the breakdown and maintenance cost of the such equipment. On the other hand, breakdown of machinery also results in terms of production loss, which in turns results in monetary loss. As the main function of the proposed embedded information devices is the MOL management of an equipment through predictive maintenance, therefore, as compared to the preventive maintenance strategy that is in normal practice for high value equipments, like CNC machine tools, predictive maintenance enables us to know that when the machine or equipment will fail. Thus, by predicting the possible failure, the proposed system allows to plan the maintenance accordingly. On the other hand, preventive maintenance is the scheduled maintenance that requires machine shutdowns at regular intervals without knowing that whether the machine requires maintenance or not. In addition to this, preventive maintenance results an increase in the frequency of parts replacement when it is not required, which results an increase in the maintenance cost. The proposed system aims the predictive maintenance of the equipment by reducing the probability of unexpected machine failure, which will result in less production losses. With the help of the proposed system, maintenance is only required when the early signatures of degradation in performance are detected, therefore, this ensures reduction in maintenance activities and hence reduction in labour costs. This will result in reduction of inventory costs as well because then parts will be ordered as per requirement. As dismantling a machine at frequent periods decreases its life, therefore, the proposed system is advantageous in the sense that it will minimise the frequency of dismantling, thus, it will increase the machine life. Implementation of such type of a system will ensure the safe operation of a machine, as early detection of degradation in machine performance reduces the probability of ultimate machine breakdown that may result in a safety hazard. Briefly, various savings can be made in terms of saving scheduled outage cost, forced outage cost, etc., which justifies the cost of the proposed embedded system.

In addition to this, when we see in terms of mass production, the costs are generally reduced down. The cost of Iensys general-purpose board is high because of additional features, such as on-board socket for programming and other additional humidity and temperature sensors, however, PIC18F458 microcontroller that is the processing unit of

Iensys general-purpose board, is available with all its features for only 5 pounds. Similarly, the manufacturers of Axis device server provide the boards at low prices when boards are ordered according to economic order quantity. Hence, the cost can be reduced further when considerations are made from the perspective customisation and mass production.

5.5 Summary of chapter 5

- Gearbox is chosen as a subject to implement the intelligent EID concept.
- Most common types of gears are spur gear, helical gear, and bevel gear.
- Major modes of gear failure are fatigue failure, impact failure, and failure due to wear.
- Some important factors that play an important role in satisfactory performance of a gearbox are lubrication, operating temperature, mechanical stability, operational activities, and maintenance-related activities.
- A test rig has been explained, which is developed to conduct an accelerated life test in order to monitor gearbox degradation via intelligent EID.

Chapter 6

TOOLS AND TECHNIQUES FOR LIFE PREDICTION

This chapter will explain the tools that are being used for life prediction in the intelligent EID system. It will provide the reader with a general understanding of artificial neural networks (ANN), especially the back propagation neural networks that are used as an intelligent tool to identify the faulty or good behaviour of a gearbox. Moreover, this chapter will explain the methods or probability distributions that are being employed in reliability practice to predict the life of a system. The practical implementation of a life prediction technique is explained in Chapter 7.

6.1 Neural Networks

The artificial neural networks or ANN are the analytical tools that are used to predict the behaviour of a system whose behaviour is difficult to describe mathematically. The idea of artificial neural networks is basically adapted from the working of the human brain. The human brain can be considered as a nonlinear, parallel-processing unit of high functional complexity with neurons as the basic functional units. These functional units or neurons have the capability to emit or fire an electrochemical signal. Each neuron has an input that is called the dendrite; an output called the axon and a basic cell body. A structure called a synapse connects the axon of one neuron to the dendrite of another, which means that all neurons are interconnected through these synapses. In the active state, the neuron fires an electrochemical signal from its axon. The synapse transmits this signal to the dendrite of another neuron. The emission of an electrochemical signal from a neuron is totally dependent upon a threshold value. A neuron is activated or triggered only when a signal received at the cell body is equal to, or above, the particular threshold value. The power of the received signal at the cell body is purely dependent upon the efficiency of the synapses. Research suggests that the efficiency of the learning process is dependent upon the strength of these synapses. Therefore, we can define neural networks as bearing a resemblance to the human brain [109]:

"A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1) Knowledge is acquired by the network through a learning process.

2) Interneuron connection strengths known as synaptic weights are used to store the knowledge."

The next section describes the artificial neuron model.

6.2 The Artificial Neuron Model

An artificial neuron (see figure 6.1) is the fundamental information-processing unit in artificial neural networks. The artificial neuron model consists of three elements:

6.2.1 Synapses

An artificial neuron has synapses or links, and each synapse is assigned a weight. The weight is basically the strength with which a synapse amplifies or decreases the intensity of a signal. These synaptic weights are multiplied by the signal in order to increase or decrease its intensity. A positive weight increases the intensity of the signal, whereas, a negative weight decreases the intensity or strength of a signal.

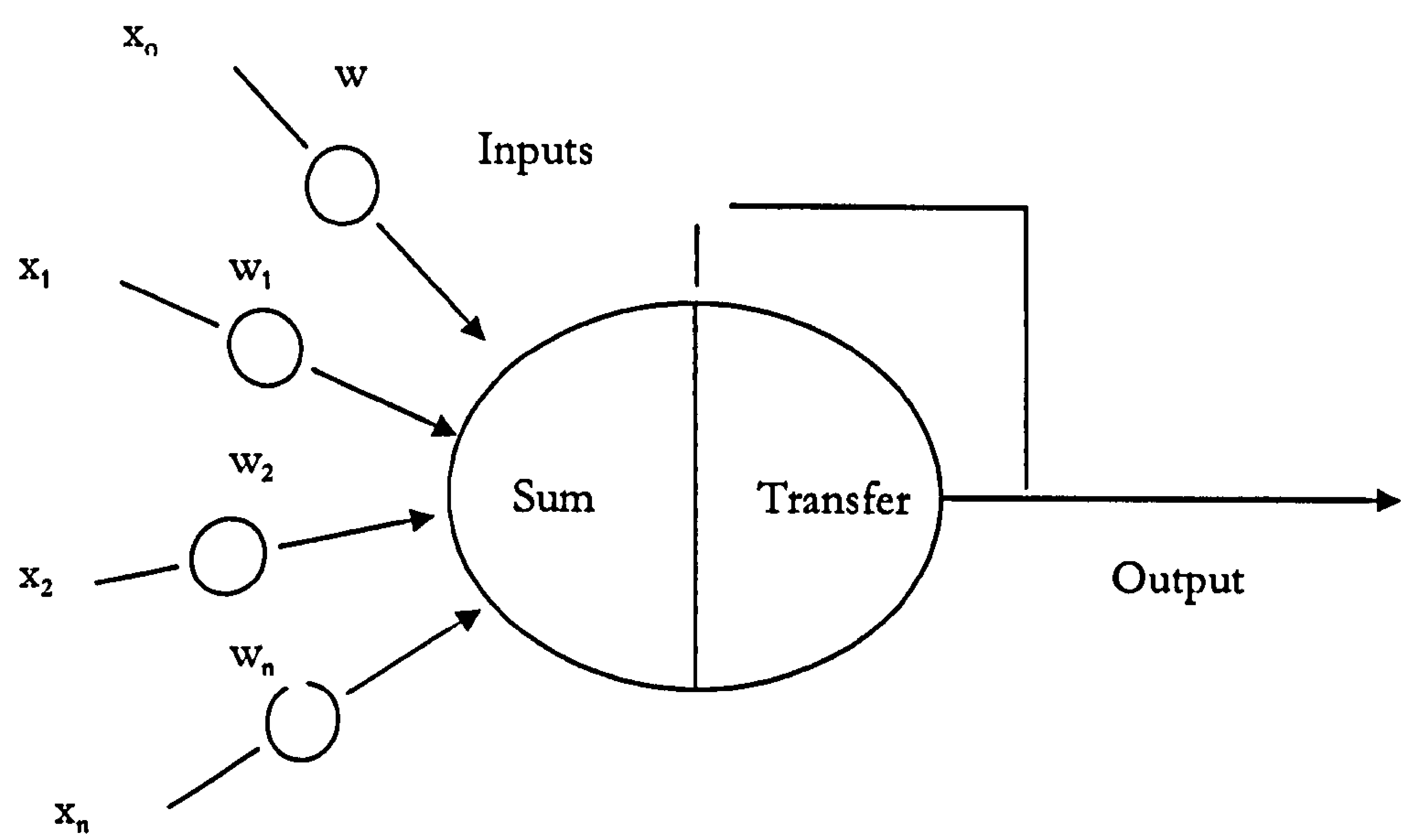


Fig.6.1. Artificial neuron

6.2.2 Adder

An adder is used to sum various signals or inputs that arrive at the cell body. The adder basically serves as a linear combiner. If x_1, x_2................, x_n are the inputs and w_1,w_2........, w_n are the corresponding weights associated with them, then the weighted inputs will be $i_1 = w_1*x_1$, $i_2 = w_2 * x_2$, and so on. The adder will add all these weighted inputs (i_1+i_2+..................$+i_n$) and the result will be a single number.

6.2.3 Activation or transfer function

An activation or transfer function is used to control or limit the neuron's output. It is also called a squashing function because it limits the output of a neuron, usually into the range of –1 to +1 or between 0 and 1. There are various types of transfer functions. In its simplest form, a transfer function can be a function that fires 0 or 1 depending upon the whether the output of the adder is positive or negative. Such a function is called a hard limiter or step function. Another form of transfer function can be one which, in a given range, produces the same output as the input and acts as a hard limiter outside this range. Such a function is called a threshold or ramping function. Another form of transfer function is a sigmoid or S-shaped function. Normally, the function is called sigmoid if the function is defined to produce an output between 0 and 1. If the function is defined to produce an output between -1 and 1 then it is called a hyperbolic tangent. If x is the input then the sigmoidal output, S, is given as:

$$S = \frac{1}{1+e^{x}}$$

The next section explains the training process of neural networks.

6.3 Training a neural network

All decisions and outputs that are made by a human brain depend upon past experience, since the human brain learns by examples or experience. In a similar manner, like a human brain, neural networks also require experience or examples to produce a desired output in response to a given input. This process is called training a neural network i.e. the process by which neural networks learn to produce the desired output. There are two methods of training a neural network: one is called supervised learning and the other is called unsupervised learning. Most of the neural networks use a supervisory mode of learning. Supervised and unsupervised learning are explained below:

6.3.1 Supervised learning

In supervisory mode, sets of inputs and desired outputs are fed into the neural network. The set of inputs and outputs is called the training set. During supervised learning, the neural network processes the input to produce an output and then compares the produced output with the desired output. The network then calculates the error between the produced and desired output. The calculated error is then fed back to the system, the system then adjusts the weights that are associated with the inputs in order to minimise the error. This process continues until all the weights are perfectly adjusted to produce the desired output. With this method of training, the network must be trained properly before it is ready for use. Supervised learning of a neural network is a time-consuming process because during training each input and desired output is fed into the system. Therefore, the training data sets are often very large and often consist of actual data. For good results, it is necessary that the network should be trained with a broad range of data so that it covers or learns as many examples as possible. As artificial neural networks can deal only with the numeric set of data, therefore, the raw data must be scaled or normalized before feeding it into the neural network.

6.3.2 Unsupervised learning

The second type of learning is unsupervised learning. In this method of training, the network is fed with the inputs but not with the desired outputs. The network itself judges the best classification of data. Therefore, this type of learning is also called adaptive learning and the networks are called self-organised maps. These types of networks are capable of identifying a change in the trend of data, the networks then adjust their weights according to their own performance. The unsupervised learning often involves the cooperation between different groups of nodes or processing elements that work together. Any change caused by an external input to an individual node or processing element in a group will affect the entire group of nodes. Because of this, the activity of the whole group of nodes can be increased or decreased. The network has some information in its learning rules about how to organise itself.

The next section explains the different types of learning rules that are being employed by neural networks.

6.3.3 Learning rules

There are various types of learning methods that are being employed by neural networks. Most of these methods are a somewhat changed or improved version of each other.

The very first learning rule was introduced by Donald Hebb in 1949. According to Hebb, if two neurons are interconnected and one neuron receives an input from the other, the synaptic weight between the two neurons will have strength if they are both in the active state. Mathematically it can be said that if both have a positive sign then the weight between the two neurons will be stronger. The Hopfield Law says the same thing with the slight modification that, if the neuron input and the desired output are both in the same state, that is both are active or both are inactive, then the associated weight is incremented by the learning rate. If the desired output and neuron input are in different states, that is one is active and the other is inactive, then the associated weight is decremented by the learning rate. The Delta Rule is the most common rule that is being employed for learning. According to the Delta Rule, the weights of the input connections should be modified continuously till the difference between the desired output and the produced or actual output is minimised to an acceptable level. The Delta Rule involves changing the synaptic weights in order to minimise the mean squared error of the network. Therefore, this rule is also called the least mean square or simply the LMS learning rule. The Delta Rule transforms the error by the derivative of the transfer function, which is then fed back to the previous layer for the adjustment of the connection weights in order to achieve the desired output. The Gradient Descent Rule is somewhat similar to the Delta Rule with slight modifications. In addition to the use of a derivative of transfer function to modify the calculated error, this rule also uses a proportional constant that is associated with the learning rate.

Inspired by biological learning, Teuvo Kohonen proposed his learning rule. This rule is used for unsupervised learning. According to this rule the processing nodes are in competition with each other for learning by changing or updating their weights. The processing element that produces the largest output or whose output is closest to the input is considered as the winning element. Only the output of the winning element is considered. Only the winning node and its neighbours that normally work in the form of a cluster or a group are allowed to update their weights.

6. 4 Types of neural networks

There are different types of neural networks that are in common use for different applications. The author has used back propagation neural networks in the life prediction algorithm. These networks are explained below, along with a description of some other types of neural networks.

6.4.1 Back propagation neural networks

Feed-forward, back-propagation, neural networks are one of the most commonly used neural networks for prediction and classification. A simple back propagation neural network consists of three layers: an input layer, an output layer and a hidden layer. The number of hidden layers is not fixed but there must be at least one hidden layer in a back propagation neural network. The input layer is used to feed data to the back propagation neural network, whereas the output layer is used to get the output from the neural network. The number of layers and the number of processing elements are totally dependent upon the complexity of a back propagation neural network. The more complex the relationship between the input and the required output, the more processing elements in the hidden layer will be required. Back propagation neural networks use the Delta Rule or one of its variants for learning. Initially, random weights are assigned to the nodes or processing elements. In the learning process, a forward pass is made, it means that the output of each layer is passed to the next layer. This process continues until the output layer is reached. The difference in the output of the final layer and the desired output is fed back to the previous layer. This difference between the actual output and the desired output is normally transformed by the derivative of the transfer function. The error is continuously back-propagated until it arrives at the input layer. The weights are then adjusted according to the back-propagated error depending upon the type of learning rule employed. This process of learning is continued until the error is minimised or adjusted to a particular level. Transfer functions that are normally used by back propagation neural networks are described above. However, for the life prediction algorithm, sigmoid transfer is used. A back propagation neural network is shown in the figure below:

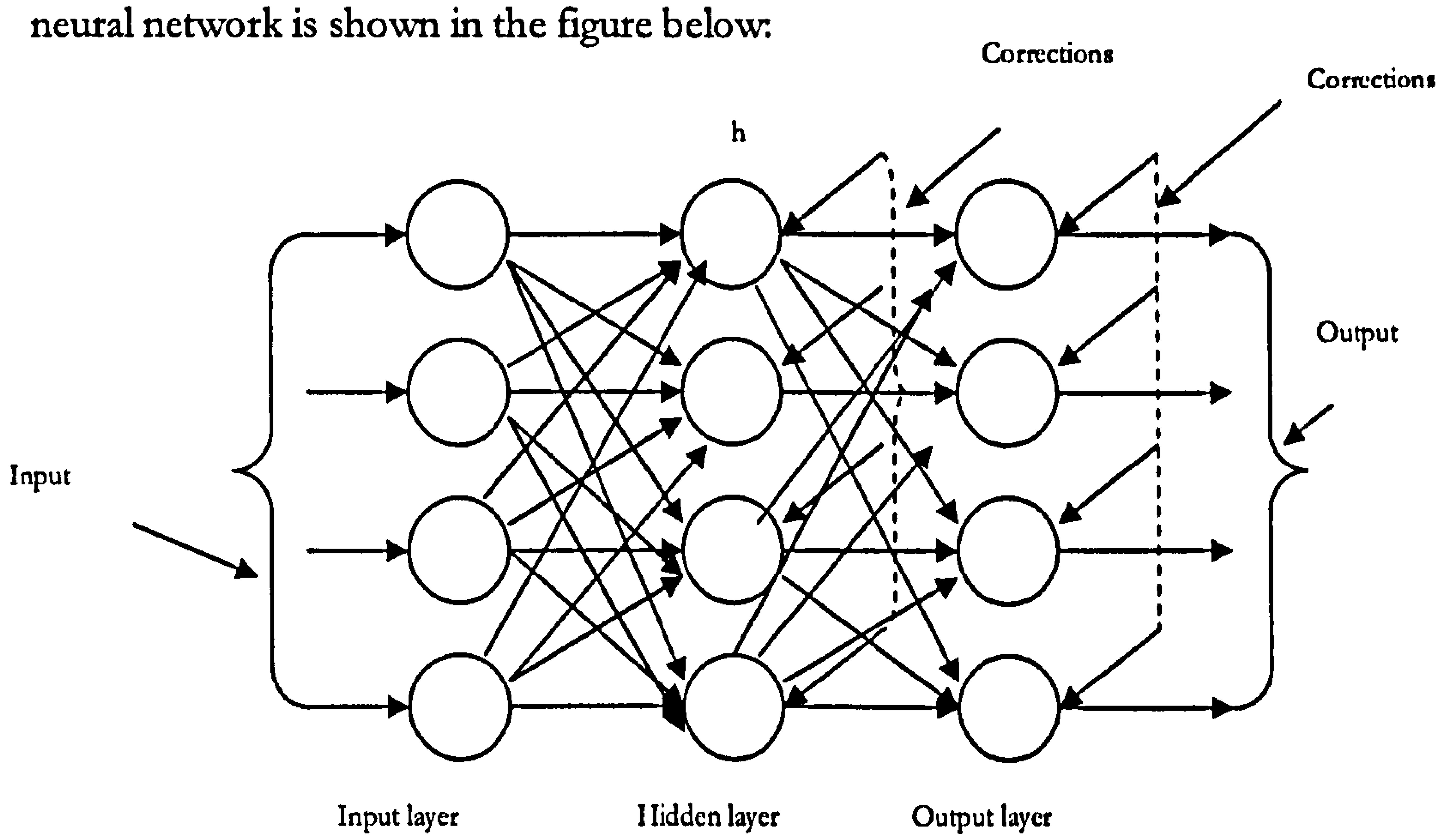


Fig. 6.2. A back propagation neural network

6.4.2 Probabilistic neural network

Probabilistic neural networks classify inputs on the basis of the probability that an input can be a member of a learned class. A probabilistic neural network consists of three layers. An input layer, a pattern layer and an output layer. The input layer is used to feed data to the neural network, whereas the output layer is the layer that is used to get results from the neural network. The pattern layer is used to determine the probability that a particular input belongs to a particular learned class or not. This is done with the help of a class estimator that uses training data to classify the input pattern correctly. The class estimator estimates the probability based on Bayes Theorem that predicts the probability of an event provided the prior information is given. In a probabilistic neural network, a neuron produces a high value if the input matches with the trained value. The element that produces the highest value is considered to be the winning element and only the winning element is allowed to produce the output.

6.4.3 Hopfield Network

The Hopfield Neural Networks are neural networks that have binary inputs and outputs. These networks consist of three layers: an input layer called the input buffer, a Hopfield layer and an output layer. The number of neurons or processing elements in each layer is equal. The network is constructed in such a way that the inputs of the neurons in the Hopfield layer are connected to the outputs of the neurons in the buffer layer via synaptic weights. The outputs of neurons in the Hopfield layer are connected to the inputs of every neuron in the Hopfield layer except that neuron itself. The neurons of the Hopfield layer are also connected to the neurons of the output layer. The network receives data via the input buffer layer, the data is then send to the Hopfield layer via learned synaptic weights. The Hopfield layer then processes the data for a particular period of time and then the resulting state of the Hopfield layer is sent to the output layer. The resultant state is the state that has already been taught to the network during the training process. During the training process, the training patterns are applied to both input and the output layers at the same time. The learning is carried out according to Hopfield's Law (see above in the section on learning rules).

6.5 Basic measures of reliability

Basic reliability measures are the reliability measures that are used to predict the system performance without any support from maintenance and logistics **[110]**.

The failure function is one of the basic reliability measures and it is basically the probability that a system will fail before or at a particular time t. The failure function is normally denoted as F(t).

F(t) = Probabilty that a system will fail in a period $0 \leq x \leq t$

Another function is called the reliability function. This is defined as the probability that 'a' will not fail during a particular period of time 't' under particular operating conditions. The reliability function is denoted as R(t).

R(t) = P(System will not fail during time period t) = 1 – F(t)

The hazard function is another important measure of reliability and is defined as the ratio of the probability density function and the reliability function. The probability density function is explained later in this chapter.

6.6 Probabilistic models or distributions to predict lifetime

This section describes the probabilistic models or distributions that are commonly used in reliability practice to predict the lifetime of a system. These distributions are explained below, but before explaining them, a few terms must be understood:

6.6.1 Sample space

When a statistical experiment is performed, the set S of all possible outcomes is called the sample space. For example, if S is a sample space that consists of all possible outcomes of an experiment to test 2 electric bulbs then S can be given as S = {GB, BB, GG, BG}. Where G denotes the good condition of the bulb and B denotes the bad condition of the bulb.

6.6.2 Random variable

A random variable can be defined as a function, which represents a real value for each element of a sample space. If X is defined as a random variable, then each value of X, say x, will represent an outcome of the sample space. For example, in the above sample space S, if GB is assigned a real value, such as 1, then the value x=1 of random variable X will represent the outcome GB of sample space S. A random variable can be continuous or discrete. A random variable is said to be continuous if it is used to define an infinite number of values, whereas it is said to be discrete if it used to define a countable or finite number of values. The probability P(X) of a possible outcome in a sample space, which is basically the probability of a random variable X for a particular value x or a range of values, can be best described with the help of a formula or function. In the case of a discrete random variable, the set of values (x, f (x)) is known as the probability function or discrete probability distribution. The probability of a discrete random variable can be presented in tabular form as a set of values. However, in the case of a continuous random variable, the probability distribution cannot be presented in tabular form as it can take an infinite range of values. Therefore, the probability of a continuous random variable is always described in terms of a function. This function is called the probability density function (PDF) or density function of the random variable X and the distribution is called the continuous probability distribution. All of the distributions that will be discussed later in this chapter from the perspective of life prediction and reliability are continuous in nature. Therefore, the rest of the terms that are going to be explained further are normally used to describe the properties of a continuous probability distribution.

Generally, a probability density function for a continuous distribution can be defined as:

$$P(a < X < b) = \int_a^b f(x)dx$$

The probability P(X) of a random variable X between two real values x=a and x=b can be seen as the shaded area under the curve of the probability density function. This is shown in figure 6.3 and the probability density function f(x) is valid for all values of x that belong to real numbers provided that f(x) >=0 and the total area inside the probability density function curve should be equal to 1. This indicates that the total probability of a sample space cannot be greater than 1. Mathematically, these conditions can be written as:

$f(x) \geq 0$ for all values of x

and $\int_{-\infty}^{+\infty} f(x)dx = 1$

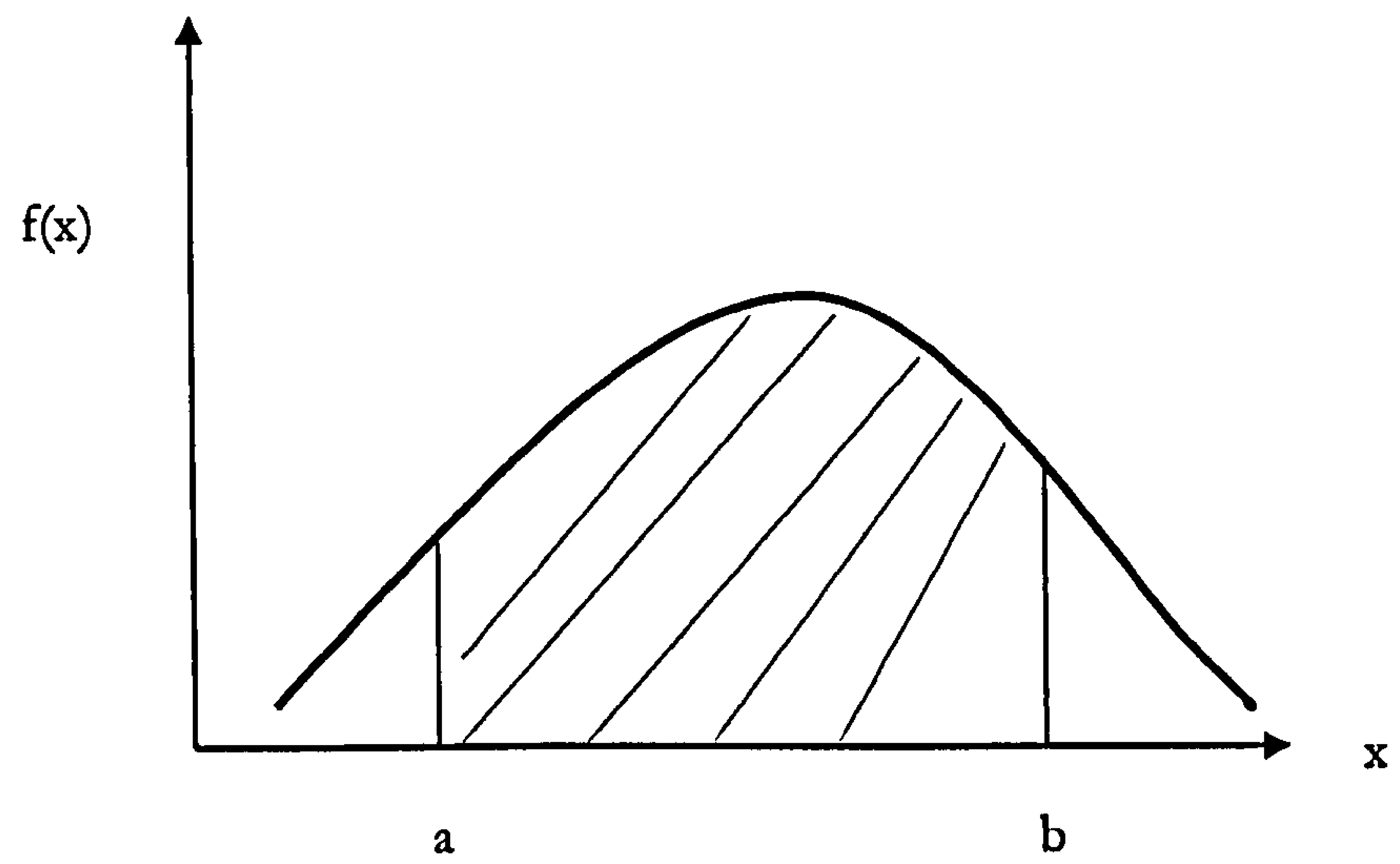


Fig.6.3 Probability density function of a hypothetical distribution

The function F(x) that is used to measure probability below a particular number, say x = a, is called the cumulative distribution function and it is given as:

$$F(a) = P(X \leq a) = \int_{-\infty}^{a} f(x)dx$$

The graph of a cumulative distribution function for a continuous random variable is shown in figure 6.4.

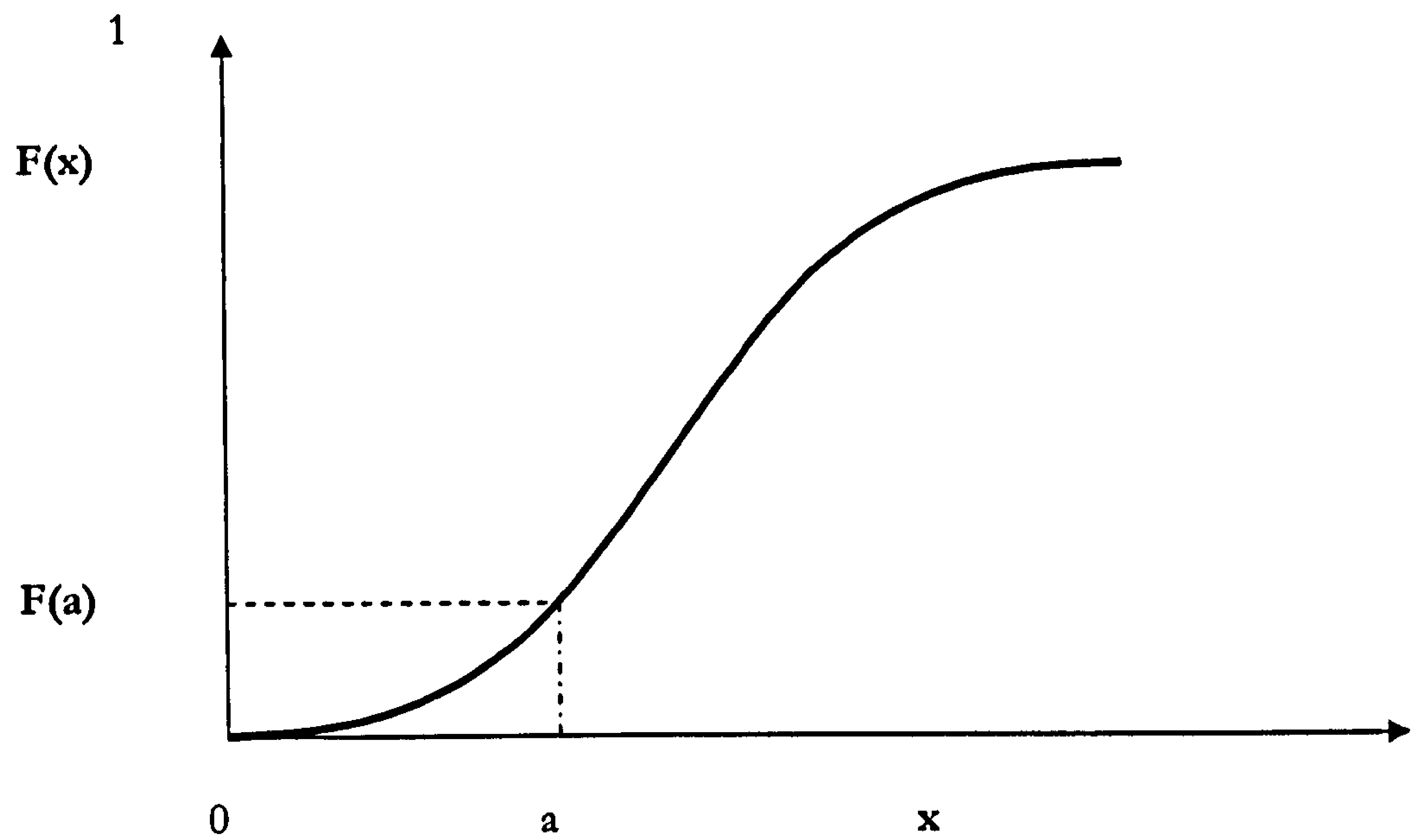


Fig.6.4 Cumulative distribution function of a random variable

6.6.3 Scale parameter

The scale parameter is the parameter that is used to control the range of probability distribution over the horizontal scale.

6.6.4 Shape parameter

The shape parameter is the parameter that is used to describe the shape of the curve of a particular distribution.

6.6.5 Source or location parameter

The source or location parameter is used to describe the point of location of a distribution on the horizontal axis.

Now we come to an explaination of the various probability distributions:

6.6.6 Exponential distribution

Exponential distribution is one of the commonly used distributions that are employed in reliability practice. Reliability measures, such as time to failure or life of electrical equipment, are mostly modelled well using exponential distribution [111]. The probability density function of the exponential distribution can be given as:

$$f(x) = \lambda e^{-\lambda x} \text{ for } x > 0$$

Where λ is called the rate parameter and is measured in units like failures/hour, shocks/hour and revolutions/min. But for exponential distribution, it is normally called the failure rate. The rate parameter, λ, which is also the scale parameter, is given as:

$$\lambda = \frac{1}{\beta} \text{ where } \beta \text{ is the scale parameter}$$

So, the PDF of an exponential distribution can also be written as:

$$f(x) = \frac{1}{\beta} e^{-\frac{x}{\beta}} \text{ for x>0}$$

The PDF of an exponential distribution is shown in figure 6.5.

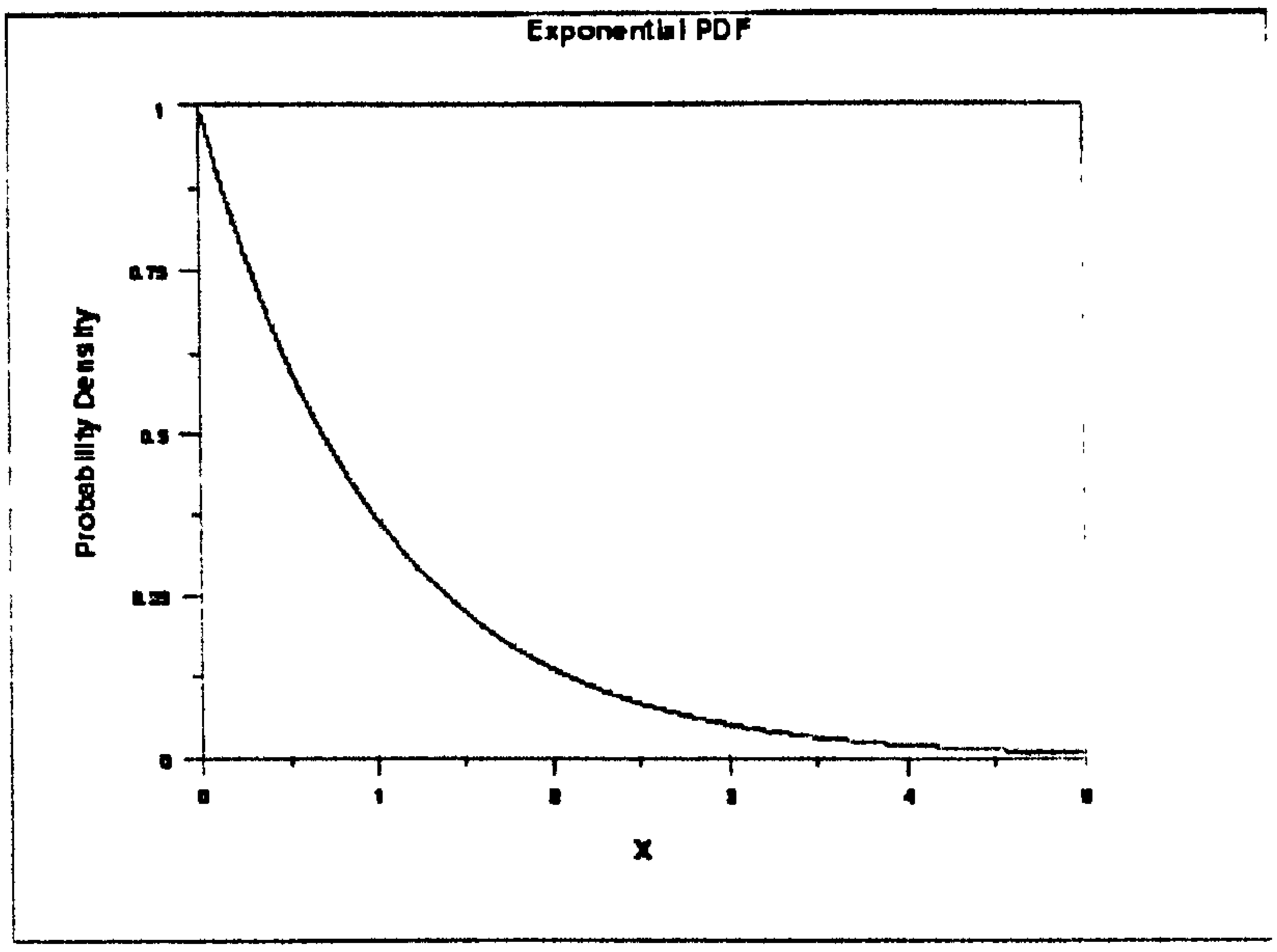


Fig.6.5. Probability density function of an exponential distribution

The cumulative distribution function of an exponential distribution can expressed as:

$$F(x) = P(X < x) = 1 - e^{-\lambda x} \quad \text{for } x \geq 0;\ \beta > 0$$

The CDF of an exponential distribution is shown in figure 6.6.

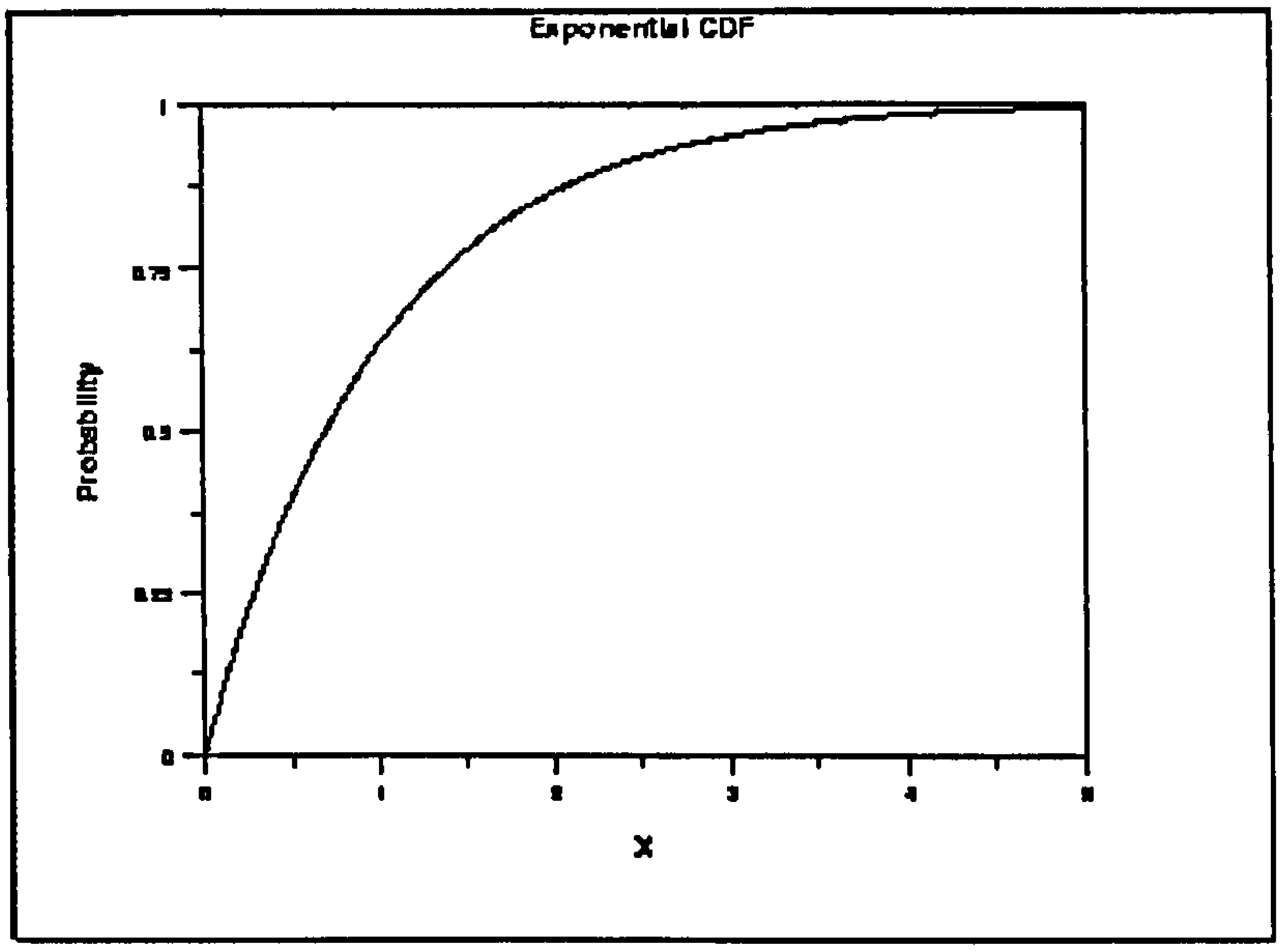


Fig.6.6 Cumulative distribution function of exponential distribution

If t is the operating time, then for x=t the CDF of the exponential distribution can be expressed as the failure function and the probability for time to failure (TTF) less than, or equal to, t can be given as follows:

$$F(t) = P(TTF \leq t) = 1 - e^{-\lambda t} \text{ for } t \geq 0; \beta > 0$$

Now the reliability function R(t) used to compute the probability that the system will not fail beyond TTF will be given as:

$$R(t) = 1 - F(t)$$

$$\text{or } R(t) = e^{-\lambda t}$$

The hazard function for exponential distribution is given as:

$$h(t) = \frac{1}{\beta}$$

$$\text{or } h(t) = \lambda$$

The mean and standard deviation of exponential distribution are given by:

Mean = standard deviation = β

6.6.7 Gamma distribution

The gamma distribution is one of the important distributions that are used in reliability practice. It is called the gamma distribution because it uses the gamma function. The PDF of the gamma distribution is defined as:

$$f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \quad \text{for } x \geq 0,\ \beta > 0,\ \alpha > 0$$

Where β is the scale parameter and α is the shape parameter. For the value $\alpha = 1$, the gamma distribution changes into exponential distribution. The gamma function is given by:

$$\Gamma(\alpha) = \int_{0}^{\infty} x^{\alpha-1} e^{-x} dx \quad \text{for } \alpha > 0$$

Different shapes of gamma distribution for different values of α are shown in figure 6.7.

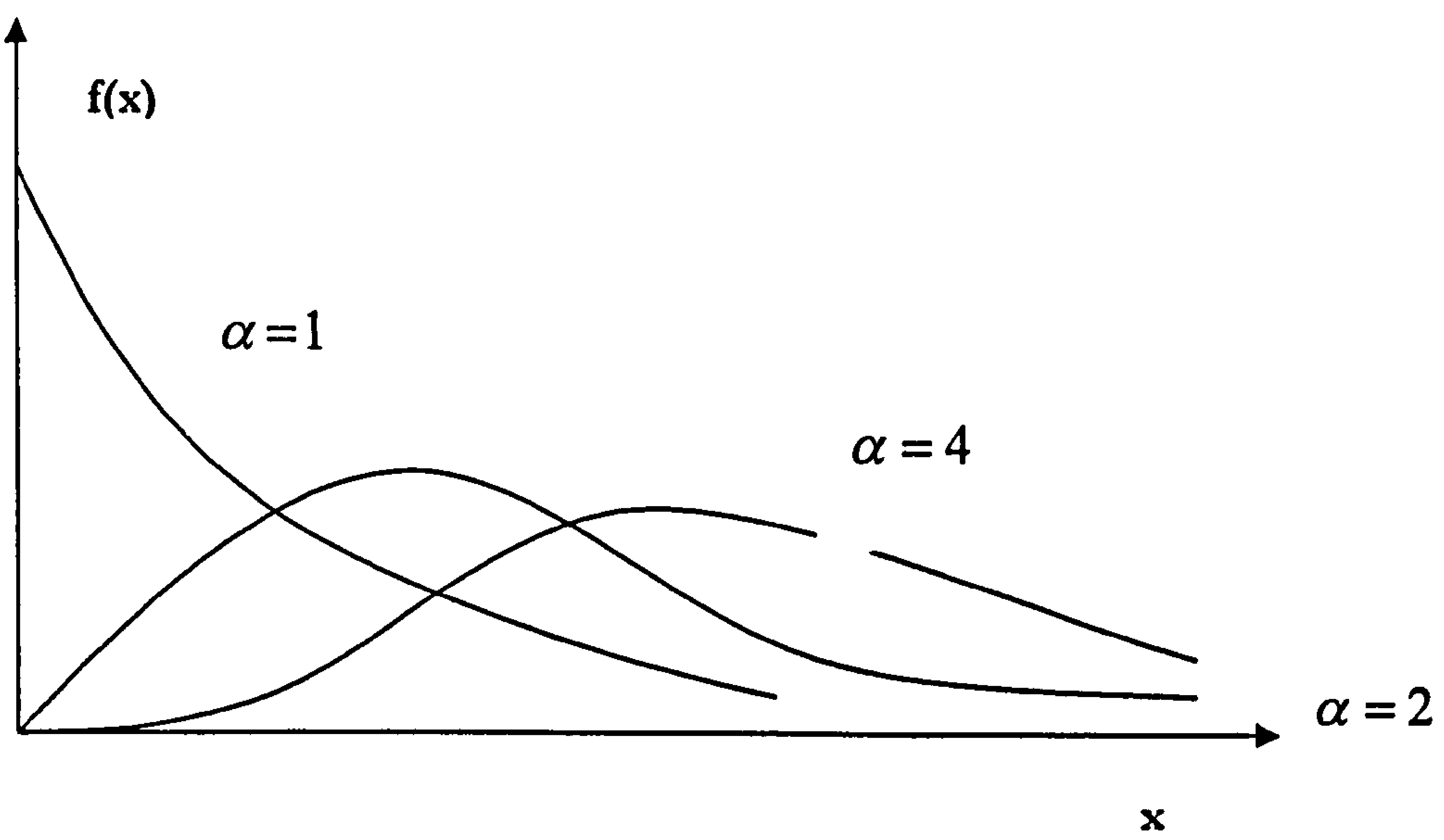


Fig.6.7. Probability distribution function of the gamma distribution

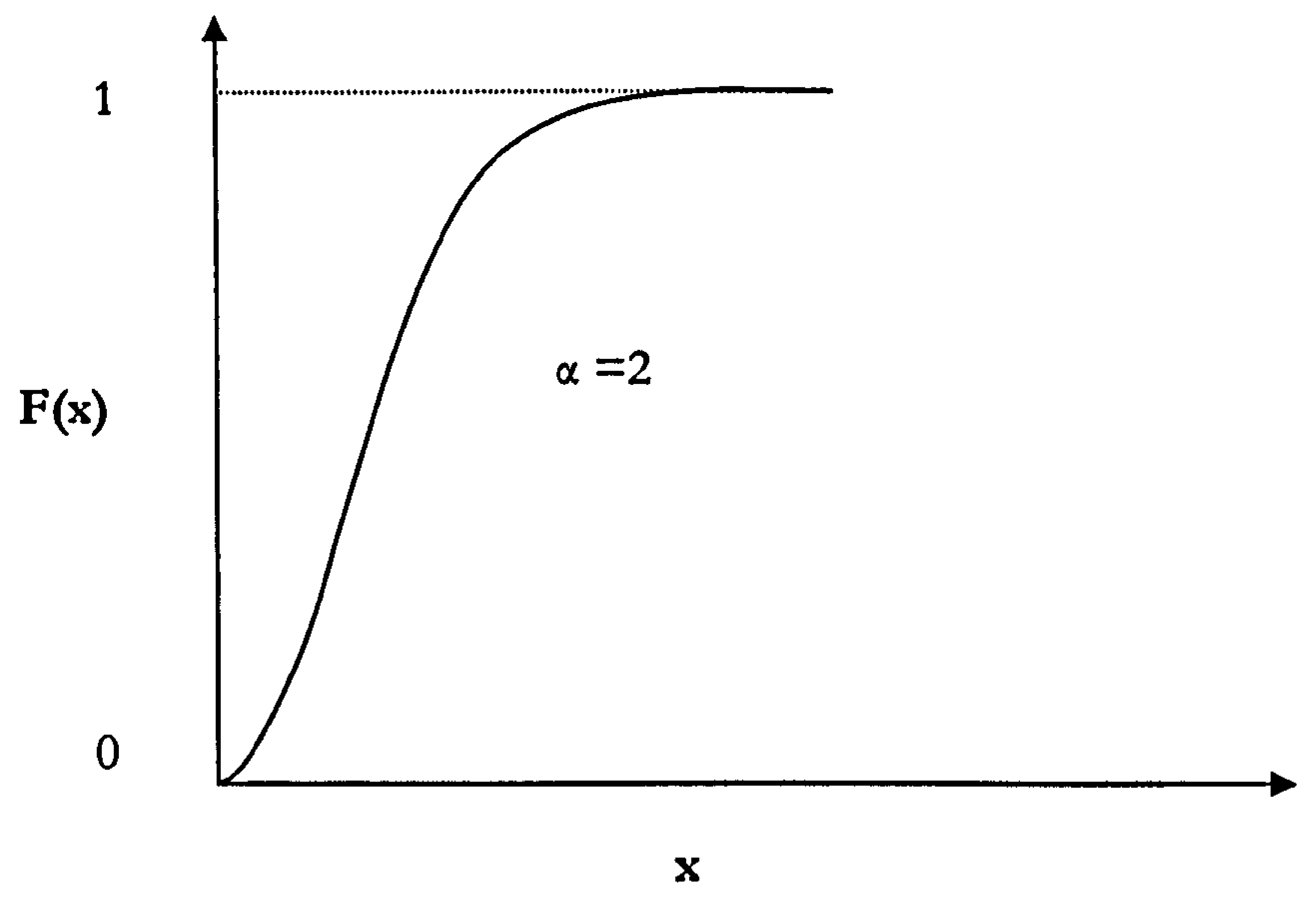


Fig.6.8. Cumulative distribution function of the gamma distribution

The cumulative distribution function (see figure 6.8) of the gamma distribution is given by:

$$F(x) = \frac{\Gamma_x(\alpha)}{\Gamma(\alpha)} \quad \text{for } x \geq 0, \alpha > 0$$

Where $\Gamma_x(\alpha)$ is called the incomplete gamma function and is given as:

$$\Gamma(\alpha) = \int_0^x x^{\alpha-1} e^{-x} dx$$

Therefore, the reliability function for time $x \leq t$ for gamma distribution can be given as:

$$R(t) = 1 - F(t)$$

$$R(t) = 1 - \frac{\Gamma_t(\alpha)}{\Gamma(\alpha)}$$

Now the hazard function can be given as:

$$h(t) = \frac{t^{\alpha-1} e^{-t}}{\Gamma(\alpha) - \Gamma_t(\alpha)} \quad \text{for } t \geq 0, \alpha > 0$$

The mean and standard deviations of the gamma distribution can be given as:

$$\text{Mean} = \alpha$$

$$\text{Standard Deviation} = \sqrt{\alpha}$$

6.6.8 Weibull Distribution

The most popular distribution for failure time modelling is the Weibull distribution. The PDF of the Weibull distribution is given as:

$$f(x) = \frac{\gamma}{\alpha}\left(\frac{x-\mu}{\alpha}\right)^{\gamma-1} e^{-\left((x-\mu)/\alpha\right)^{\gamma}} \quad \text{for } x \geq \mu,\ \alpha > 0,\ \gamma > 0$$

Where μ is the location parameter, α is the scale parameter and γ is the shape parameter. If $\mu=0$ and $\alpha = 1$, then the above equation becomes:

$$f(x) = \gamma x^{\gamma-1} e^{-x^{\gamma}} \quad \text{for } x \geq 0,\ \gamma > 0$$

This is called the standard form of the Weibull distribution. The PDF of Weibull distribution for different values of γ is shown in figure 6.9.

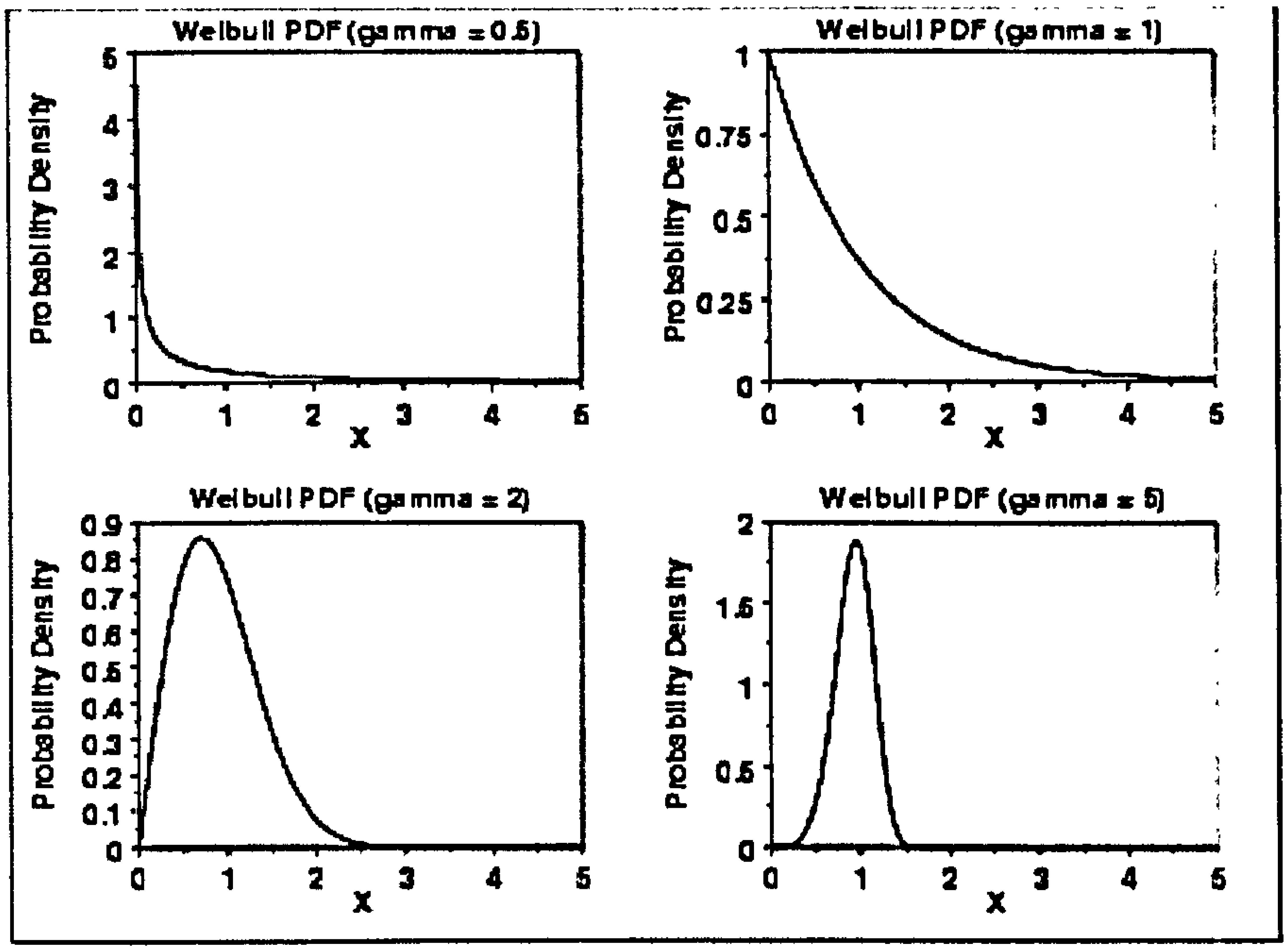


Fig.6.9. PDF of Weibull distribution

The cumulative distribution function (CDF) of the Weibull distribution can be given as:

$$F(x) = 1 - e^{-x^{\gamma}} \text{ for } x \geq 0, \gamma > 0$$

The cumulative distribution function of the Weibull distribution for different values of γ is shown in figure 6.10. For the shape parameter $\gamma = 1$, the Weibull distribution changes to an exponential distribution. For time to fail (TTF) less than, or equal to, time t, the failure function of the Weibull distribution is given by:

$$F(t) = P(TTF \leq t) = 1 - e^{t^{\gamma}}$$

The hazard function of the Weibull distribution is given as:

$$h(x) = \gamma x^{(\gamma - 1)}$$

The mean and standard deviations of the Weibull distribution are given as:

$$Mean = \Gamma(\frac{\gamma+1}{\gamma})$$

Where Γ is the gamma function.

$$\text{Standard deviation} = \sqrt{\Gamma(\frac{\gamma+2}{\gamma}) - (\Gamma(\frac{\gamma+1}{\gamma})^2)}$$

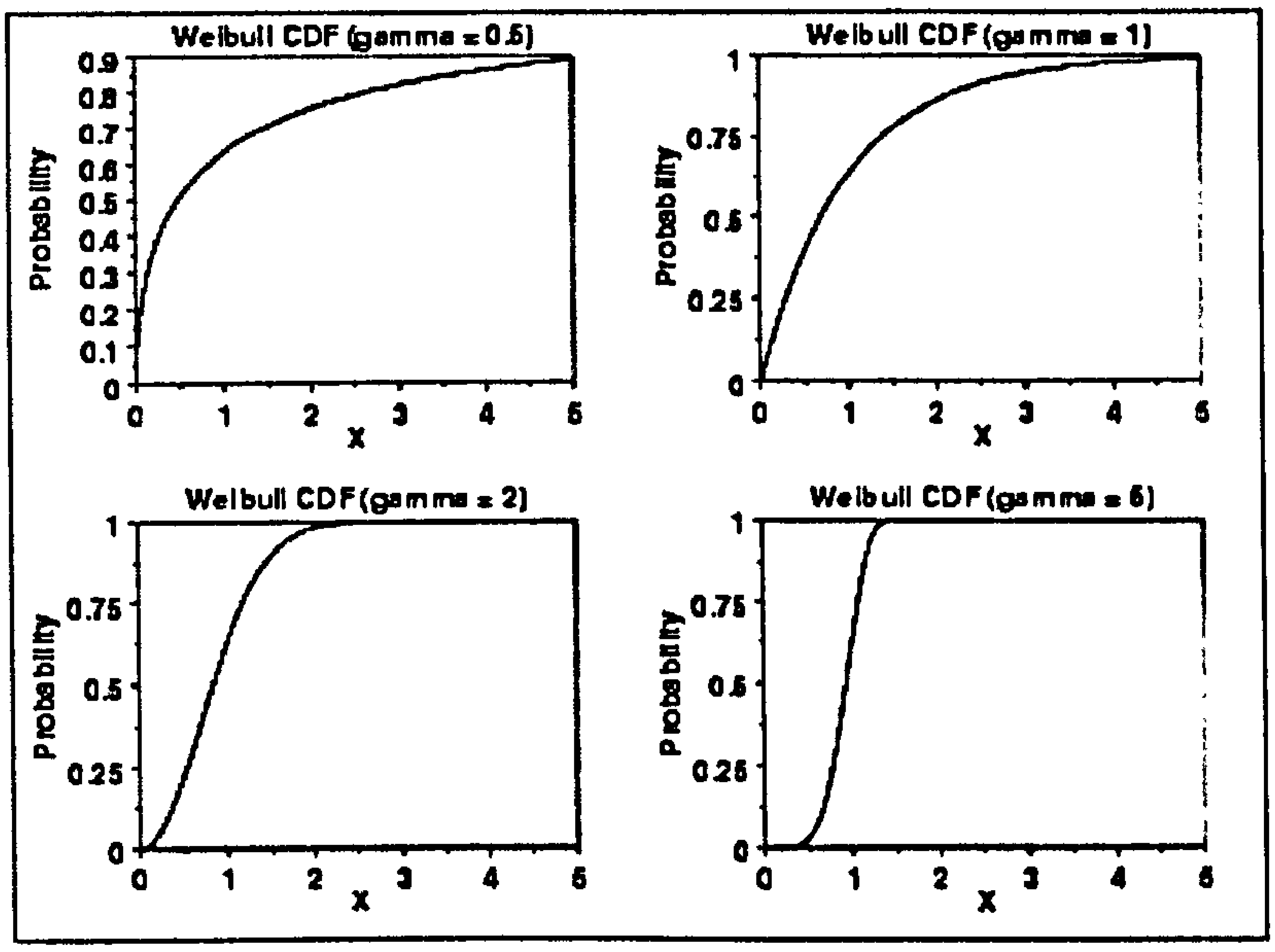


Fig.6.10 CDF of the Weibull distribution

6.6.9 Techniques for life prediction

The technique of using neural networks to identify the faulty or good behaviour of a machine is not very new. Various researchers have employed this technique to identify machine behaviour under different conditions. On the other hand, the probability distributions that are explained above are common in reliability practice. However, the idea of training neural networks with the probability of failure and using this probability of failure with some appropriate life distribution to calculate the time to failure based on the usage mode seems to be novel. The proposed technique for life prediction involves the merger of two techniques: firstly, using neural networks to classify the different behaviours of a gearbox under different probabilities of failure and secondly, using this probability with some appropriate, widely used, reliability distribution in order to predict the possible time of failure. In condition base monitoring, neural networks are typically trained with the faulty or good behaviour of a machine or to classify faults under different circumstances to predict the state or condition of equipment or a machine.

Vachtsevanos and Wang [112] used neural networks as an intelligent tool to detect the good or faulty states of bearings. They proposed a diagnostic and prognostic system to determine the intensity of crack growth in the bearing and thus the bearing failure. The proposed system consists of two modules, a diagnostician and a prognosticator. The diagnostician receives the sensory data. Using this sensory data, the diagnostician detects the sign of a possible failure, this sign or indication of failure then activates the prognosticator. The diagnostician uses a new type of neural network that employs wavelet transforms, therefore it is called a wavelet neural network. The diagnostician performs two tasks; it serves as a feature extractor as well as working as the classifier. The diagnostician performs a windowing operation on the incoming signal and extracts different features, such as the height and width of the windowed signal. Some other features like energy, area and periodicity are also recommended to be extracted in order to classify them under different fault categories for the prediction of possible failure. All the extracted features are combined together in order to define a feature vector. This feature vector is then used for fault identification. The diagnostician then acts as a classifier and uses the wavelet neural network as a classifier to classify faults into different categories. Any possibility of fault occurrence triggers the prognosticator. The prognostic module has two functions: it acts as a virtual sensor as well as a predictor.

The prognosticator also uses a wavelet neural network and acts as a virtual sensor in order to evaluate the fault in terms of fault dimensions, location, etc. The predictor then predicts the possible time to failure in terms of fault growth as a function of time using dynamic wavelet transforms. As the life prediction technique needs to be implemented on an embedded system, therefore, this technique cannot be implemented as wavelet transforms require powerful computation and memory. The proposed system uses vibration signals from the faulty and good bearings to predict the fault growth or failure. Lin and Zuo [113] also proposed wavelet transforms for fault diagnosis of a gearbox through vibration monitoring, however, they did not use neural networks. Many other examples can be seen regarding the use of neural networks to predict machine faults. Javadpor and Knapp [36] proposed a fuzzy neural network approach for machine condition monitoring. They used fuzzy ARTMAP neural networks to predict machine fault diagnosis using vibration signals. They used Fast Fourier transforms to process the raw vibration data from the machine and then fed it to a ARTMAP neural network for predictive maintenance purposes. Neural networks are employed in civil engineering for the health monitoring of structures [114]. It is clear that techniques involving wavelets and Fourier transforms cannot be implemented with neural networks on an embedded system due to their limited memory and calculation capacity. Wavelets and Fourier transforms are the techniques that are normally used in signal analyses to extract important features from a raw signal. However, one of the main advantages of using neural networks is that they can work well even with the raw data. Lee [35] proposed a very simple technique to measure machine performance degradation. Lee used CMAC (Cerebellar Model Articulation Controller) neural networks to measure the degree of machine degradation and fault detection. CMAC neural networks are supervised neural networks in which the inputs are mapped randomly to different memory locations and where these inputs are multiplied by weights associated with these memory locations in the weight table and are summed together to give an output. Similarly, training is the process that involves the adjustment of weights by judging the differences between the produced and desired output. Lee proposed a pattern discrimination model which calculates a confidence value based on the output of a CMAC neural network. For normal behaviour, the data in the weight table produces a value equal to 1 during a training session, which is stored in another table called the confidence table. During operation, any change in normal behaviour will change the mapping location in the weight table thus causing a 0 in the confidence table. Thus a confidence value can be calculated by summing the total number of ones and zeros and dividing them by the total size of the confidence table. A high confidence value shows a good behaviour, whereas a low confidence value means a faulty behaviour. However, due to memory limitations, this technique is not feasible to implement on an embedded system. The idea to calculate the level of degradation that is used for the life prediction of a gearbox in this project is basically adapted from the above method but the type of neural network and the technique used is totally different. However, Lee's technique is incomplete as it gives just a level of degradation or a confidence value. The technique proposed in this project is very simple and can be easily implemented on the embedded system. The author proposes back propagation neural networks as they are simple to program and need less memory as compared to the other neural network paradigms, such as CMAC neural networks that are totally dependent on pointer memory allocations to the weight table. Basically, in the proposed technique, a back propagation neural network is employed to perform the classification task.

The intelligent EID uses a vibration signal from the gearbox as a basic signature to monitor its degradation. As the gearbox starts to degrade, the vibration level begins to increase. There is a shift in the level of vibration as a whole with the increase in degradation because digital data in a digital signal oscillates around the signal's mean. If $x_1, x_2, \ldots\ldots\ldots\ldots, x_n$ are the observed values of the vibration signal at a particular stage of degradation, then there exists a probability of failure for that stage of degradation. If the RMS (Root Mean Square) value of a vibration signal or a range of data values in a vibration signal are assigned a class of failure probability then neural networks can be used to classify different levels of vibration under a particular class of probability of failure. If S_1, S_2, S_3 $S_4 \ldots\ldots\ldots\ldots$ S_n are different states of degradation containing different values of vibration data with assigned probabilities p_1, p_2, p_3, $p_4 \ldots\ldots\ldots\ldots$ p_n then it can be represented as shown in the figure below:

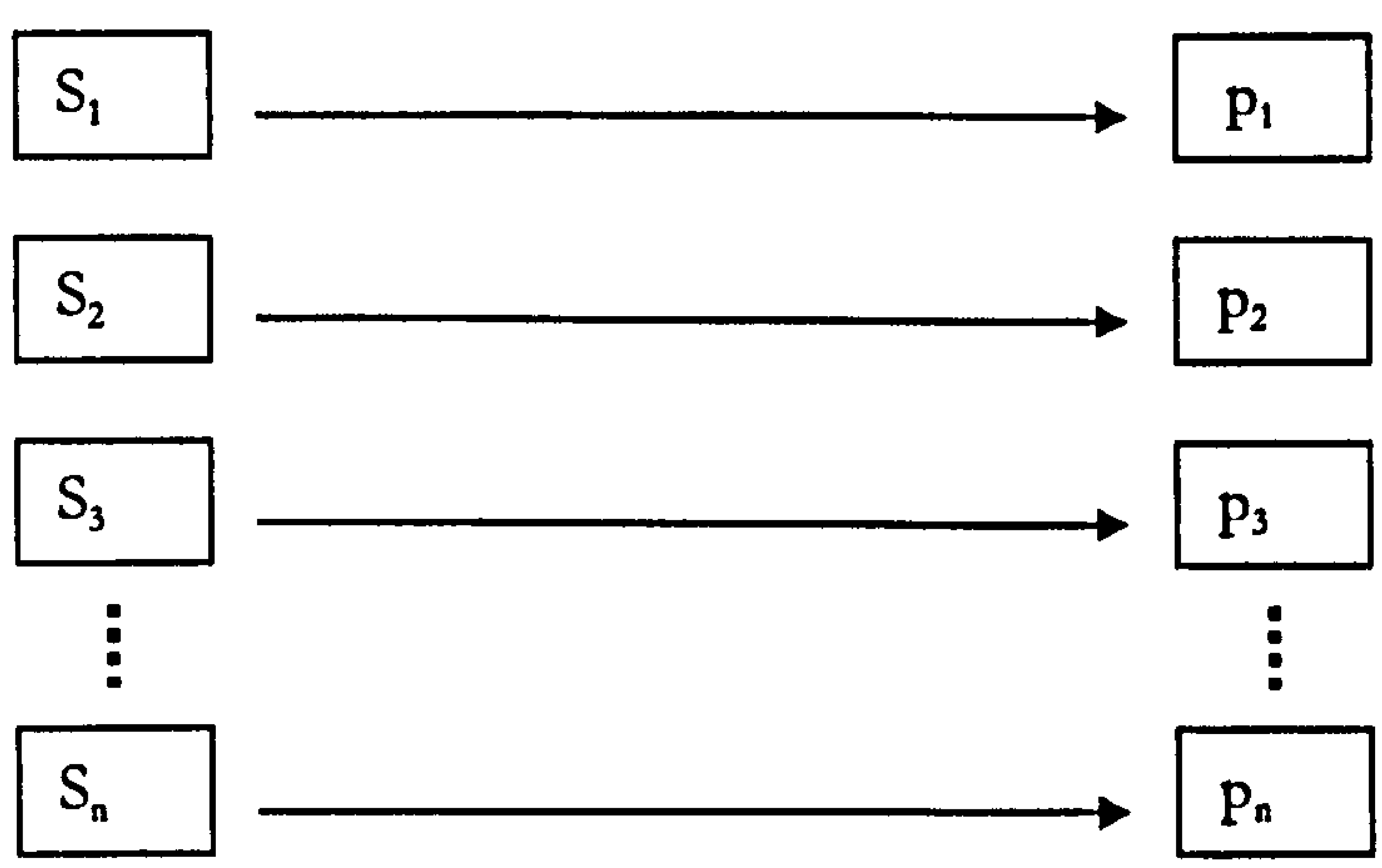


Fig.6.11. Probablity classes for different states of degradation

If the vibration levels of a new and a damaged gearbox are known, then the desired probabilities are assigned to these stages and the stages between these stages as well. For a new gearbox, the probability of failure is very low, whereas, for an old gearbox the probability of failure is high. However, these probabilities should be assigned on the basis of time to fail that must be determined experimentally via test. Most mechanical systems when they fail follow some probability distribution and their failure can be easily modelled based on this distribution. The candidate distributions to predict the life of a mechanical system are mainly exponential distribution, Weibull distribution and gamma distribution. However, normal distribution and its variant, logo-normal distribution, can also be used for this purpose. The exponential, Weibull and gamma distributions are variants of each other and their transformation into each other depends on the shape parameter. As described above, the shape factor is a parameter that is used to describe the shape of the curve of a particular distribution. Any of these distributions can be used to predict the life of a system. Now that the probability of degradation is known, if another parameter, like the failure rate, is determined experimentally then the possible time to fail depending upon the usage mode can calculated by using the probability density function of the appropriate distribution. This scheme is shown below.

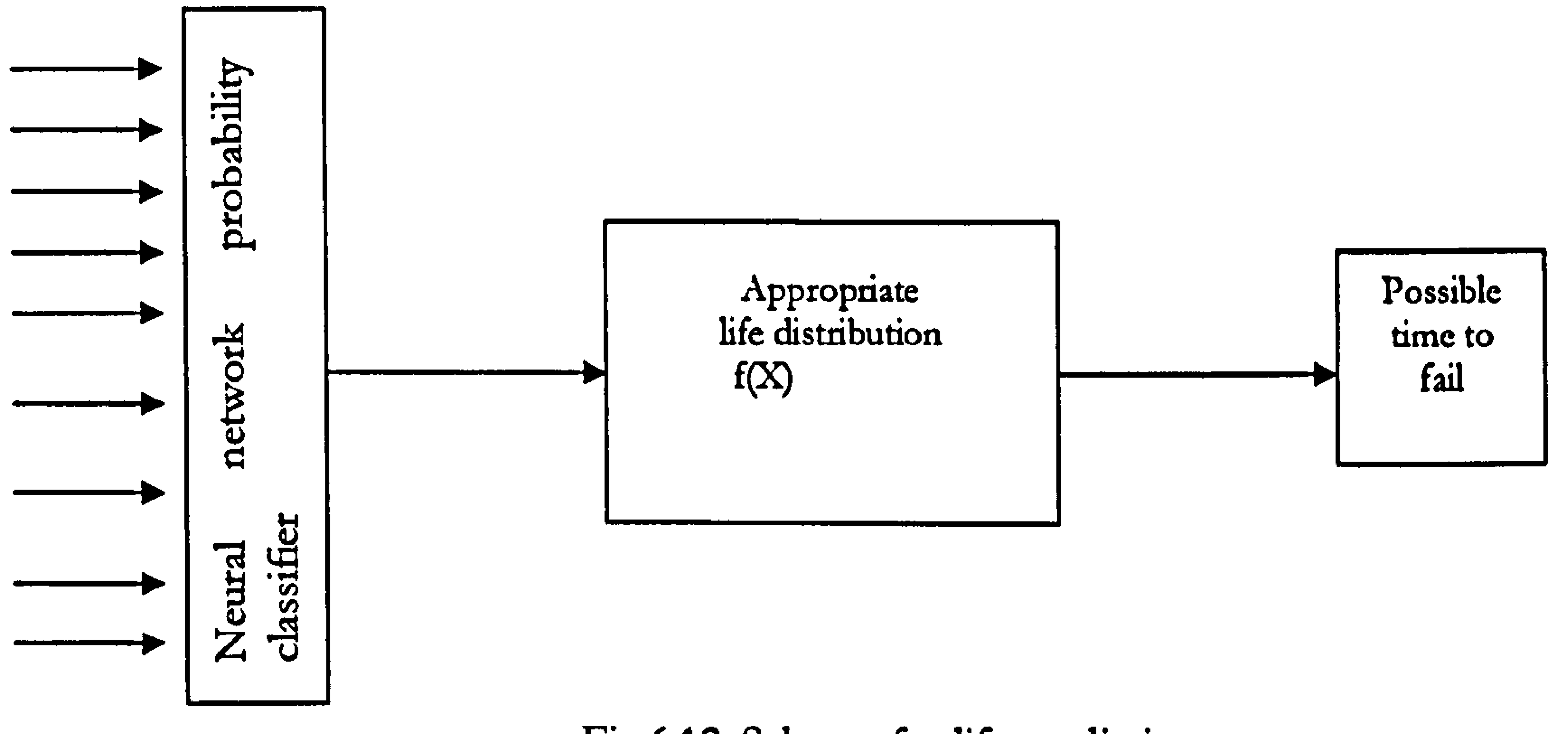


Fig.6.12. Scheme for life prediction

To understand the technique in more detail the reader should see the simulation that is performed for the choice of the proper reliability distribution in Chapter 7.

6.7 Summary of chapter 6

- This chapter provides a basic background to understand the tools and techniques that are employed in the life prediction algorithm.

- Neural networks are one the tools that are used in the field of artificial intelligence. Some common neural networks are back propagation neural networks, probablistic neural networks, Hopefiled networks, etc.

- The Weibull distribution, gamma distribution, and exponential distribution are some of the distributions that are used in reliability practice.

- A novel technique to predict a gearbox lifetime has been proposed that is a combination of neural networks and some appropriate reliability distribution.

Chapter 7

LIFE PREDICTION ALGORITHM

This chapter explains the results of the accelerated life test of a gearbox. It also explains the results for the statistical hypothesis testing for the choice of the appropriate reliability distribution for the life prediction algorithm. In addition, this chapter explains the results of the neural networks and the life prediction technique and covers the implementation of the life prediction algorithm. Finally, it explains the bidirectional communication interface for an intelligent EID.

7.1 Gearbox accelerated life test

As mentioned in Chapter 5, a test rig was designed to perform a gearbox accelerated life test and to create the scenario of a rough-usage mode. In this regard, two gearboxes were tested. The first gearbox was used to determine the failure rate and to collect the data for training the neural networks that are used in life prediction algorithm. The other gearbox was used to test the implemented life prediction algorithm. Using this rig, tests were conducted using a new gearbox running at 40 rpm. The gearbox was subjected to degradation by applying excessive load. The output torque of the gearbox at 40 rpm was about 2.2 Nm, whereas, the electrical powder brake used in the rig had an output torque of 5 Nm at an operating voltage of 24V. This means that the gearbox was subjected to a load twice that of the designed load, therefore, it was expected that the gearbox would tend to degrade quickly. As we all know that various defects are associated with an increase in the vibration level of a gearbox, therefore, a comparison of new and old vibration signals at two different states of a machine or piece of equipment can tell us whether the equipment is operating normally or showing some signs of failure or degradation. The gearbox was run in this state and the gearbox vibration data were recorded. It was observed that the vibration level of the gearbox tended to increase continuously, which was a clear indication of some sort of degradation. The vibration signal of the gearbox during the first hour of the test is shown in figure 7.1.

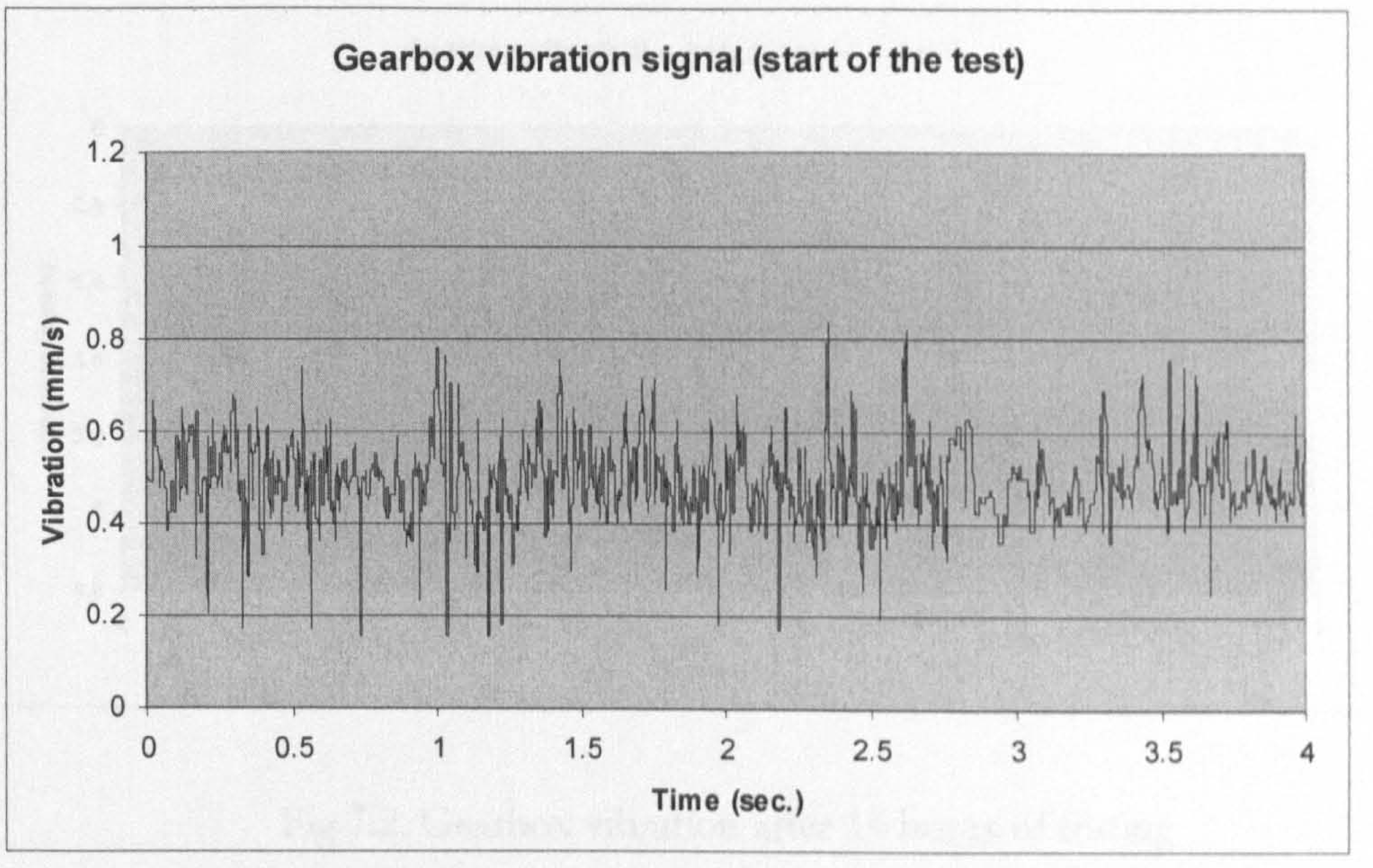


Fig.7.1. Gearbox vibration in the start of the test

The test was continued and an increase in the vibration level of the gearbox was observed until the 14th hour of the accelerated life test. However, after 14 hours, no considerable increase in the vibration of gearbox was observed, which might be due to complete localisation of some type of fault to all of the gear teeth. This was confirmed by the visual examination of the gears that is explained later in this section. In addition to this, during the 14th hour of the accelerated life test, a change in meshing sound was observed, which might be an indication of the degraded state of the gearbox **[115]**. However, the acoustic level of the gearbox was not measured. The level of gearbox vibration at the 14th hour is shown in Fig. 7.2.

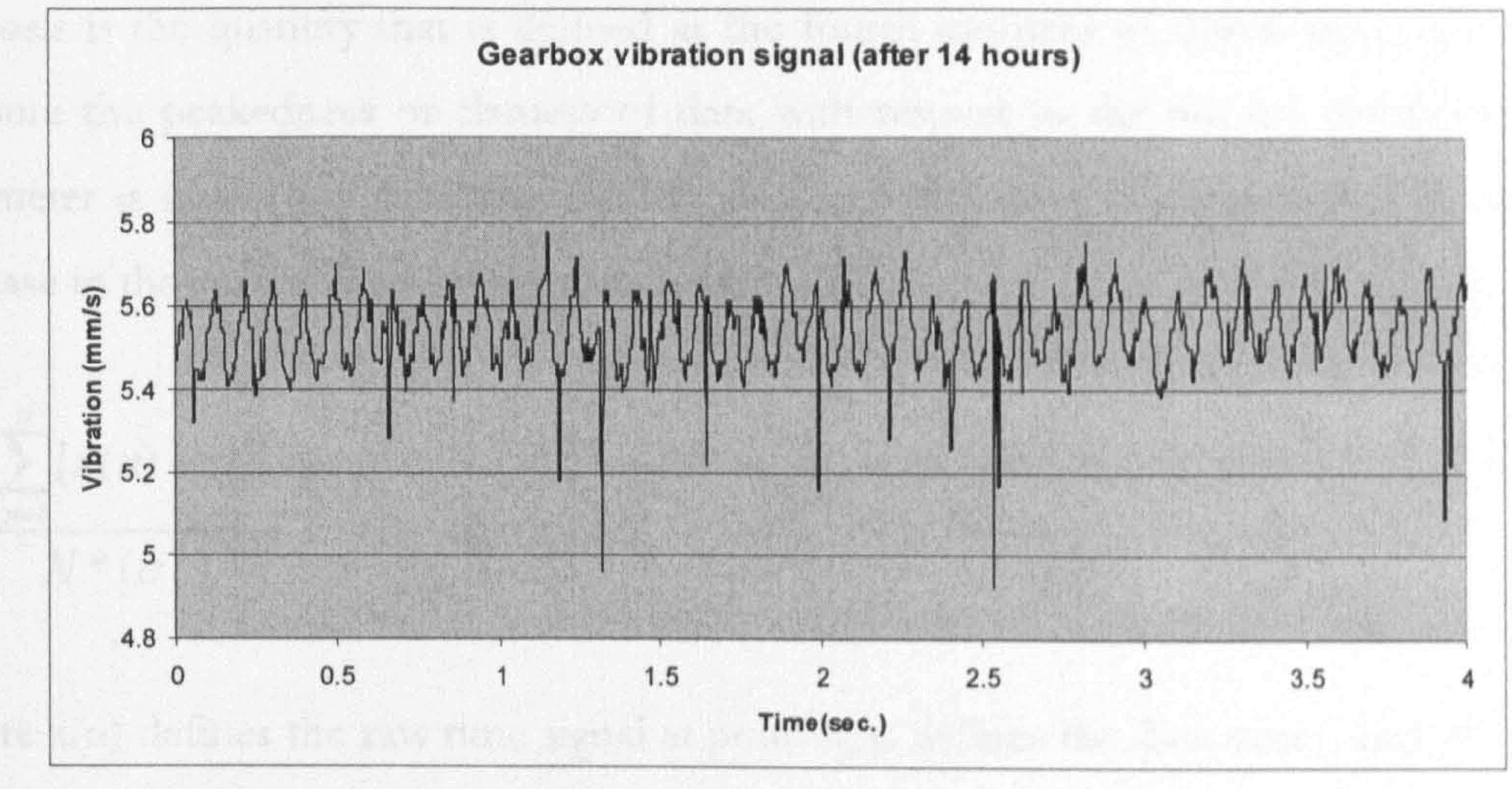


Fig.7.2. Gearbox vibration after 14 hours of testing

However, two features or condition indices, RMS (Root Mean Square) and Kurtosis, are in common use to determine the state of a gearbox **[116-121]**. They can be used to make an effective comparison between a new and degraded state. Various researchers have used and recommend these condition indices to monitor the health of a gearbox. In addition to these, Crest Factor, Delta RMS and FM4 are some other important metrics that are commonly used to indicate gear damage. Therefore, before making a clear decision to open the gearbox for a physical examination, these features were calculated from the gearbox vibration data. As explained earlier, the Root Mean Square value of a vibration signal is a time domain feature that gives us the measure of the power of the vibration signal. This measure is excellent in detecting an overall degradation in the gearbox performance. For a vibration signal that contains data values from x_1 to x_n, the RMS value over a sample of length N can be given as:

$$RMS = \sqrt{\frac{1}{N} * \sum_{n=1}^{N} x_n^2}$$

On the other hand, Delta RMS is the difference between the current and previous RMS values.

Kurtosis is the quantity that is defined as the fourth moment of distribution. It is used to measure the peakedness or flatness of data with respect to the normal distribution. This parameter is useful for detecting local faults like tooth wear or damage that results in an increase in the vibration level. Kurtosis is given by:

$$k = \frac{\sum_{n=1}^{N}[x(n) - \mu]^4}{N * (\sigma^2)^2}$$

Where x(n) defines the raw time signal at point n, μ defines the data mean, and σ^2 defines the variance of data that contains N number of points. Normal distribution has a Kurtosis value of 3, therefore, values of Kurtosis less than or equal to 3 show that the signal has less peaks and that the gearbox is in good condition of. On the other hand, a higher Kurtosis value means that the data or signal has more and sharper peaks. Hence, values greater than 3 show that the gearbox is faulty.

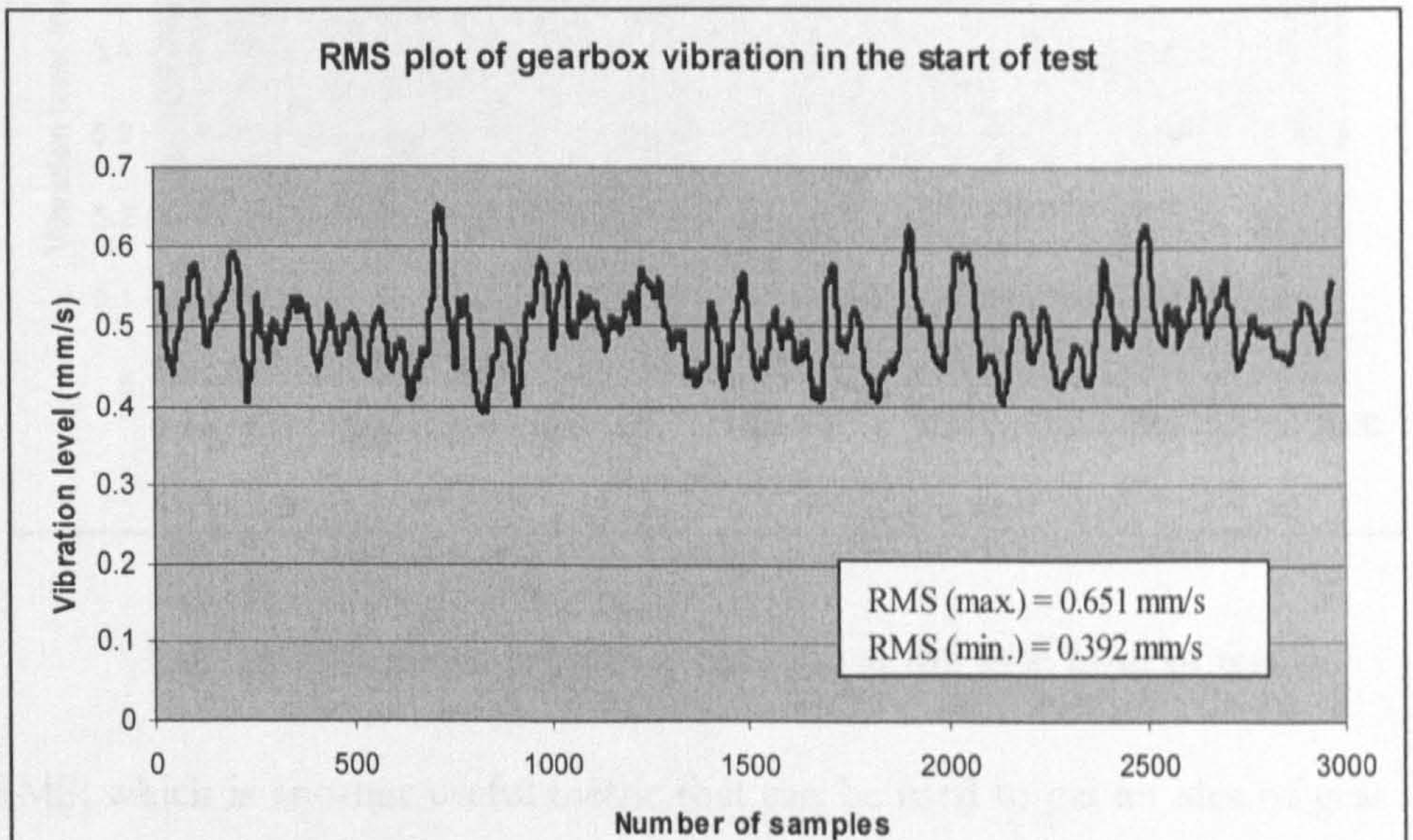


Fig.7.3. RMS plot of gearbox vibration in the start of test

As explained above, the RMS value is a very effective and sensitive method to judge the overall degradation in rotating systems, especially gearboxes. RMS values for a gearbox were calculated in Matlab using a window size of 30 samples. Figure 7.3 shows the RMS plot of gearbox vibration at the start of the accelerated life test. It is clear from the graph that at the start of the test the vibration level was very low with an RMS level measured as 0.651 mm/s (max) at the start of the test and a minimum level measured as 0.392 mm/s. However, this vibration level kept on increasing and in the 14th hour of the test the max level of RMS was observed to be 5.657 mm/s, whereas the minimum level at the 14th hour was 5.386 mm/s. This is shown in figure 7.4. This tremendous increase in the RMS level of vibration was a signature of possible gearbox damage.

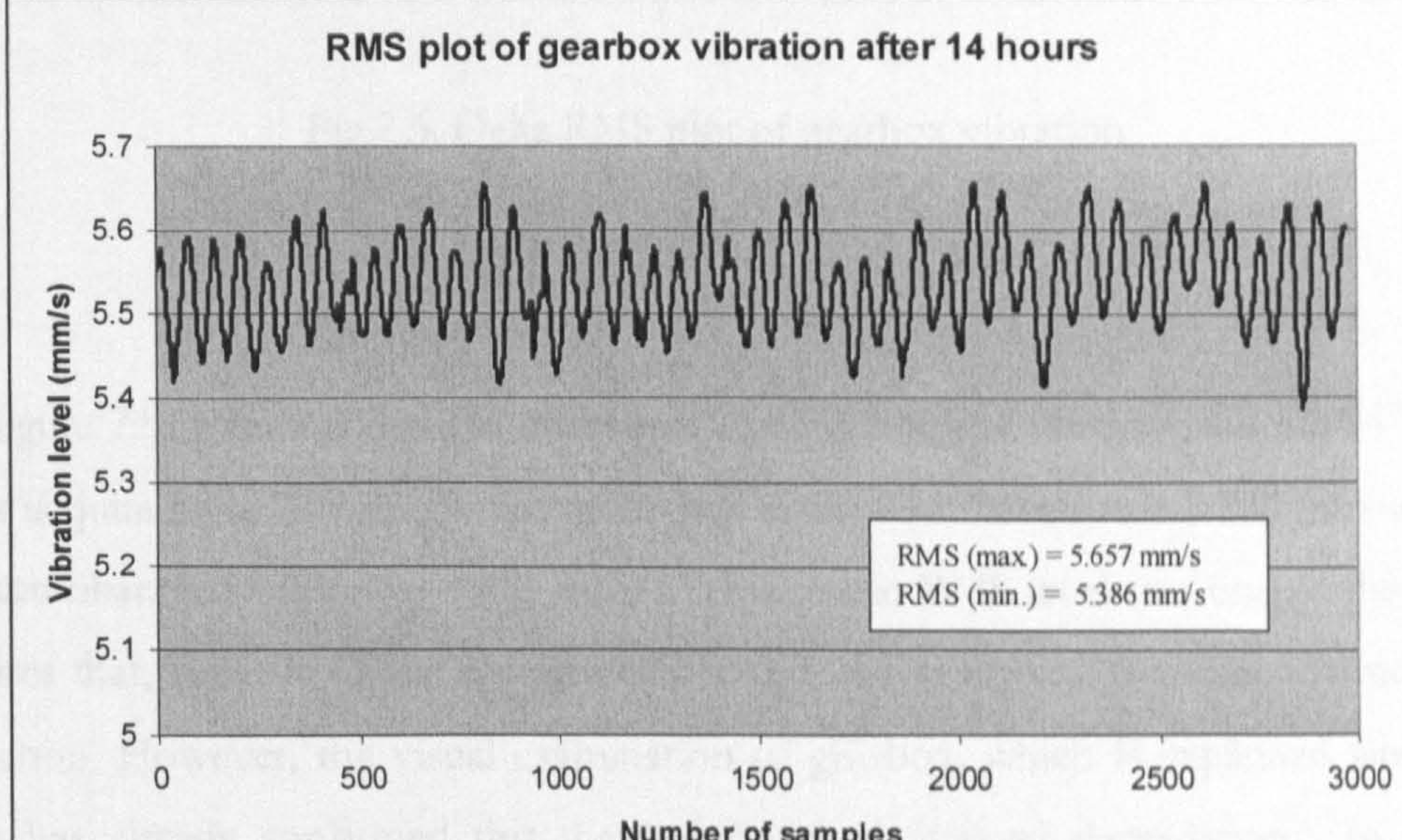


Fig.7.4. RMS plot of gearbox vibration at the 14th hour of test

Delta RMS, which is another useful metric that can be used to get an idea of gear damage, shows this difference. Figure 7.5 shows the plot of Delta RMS.

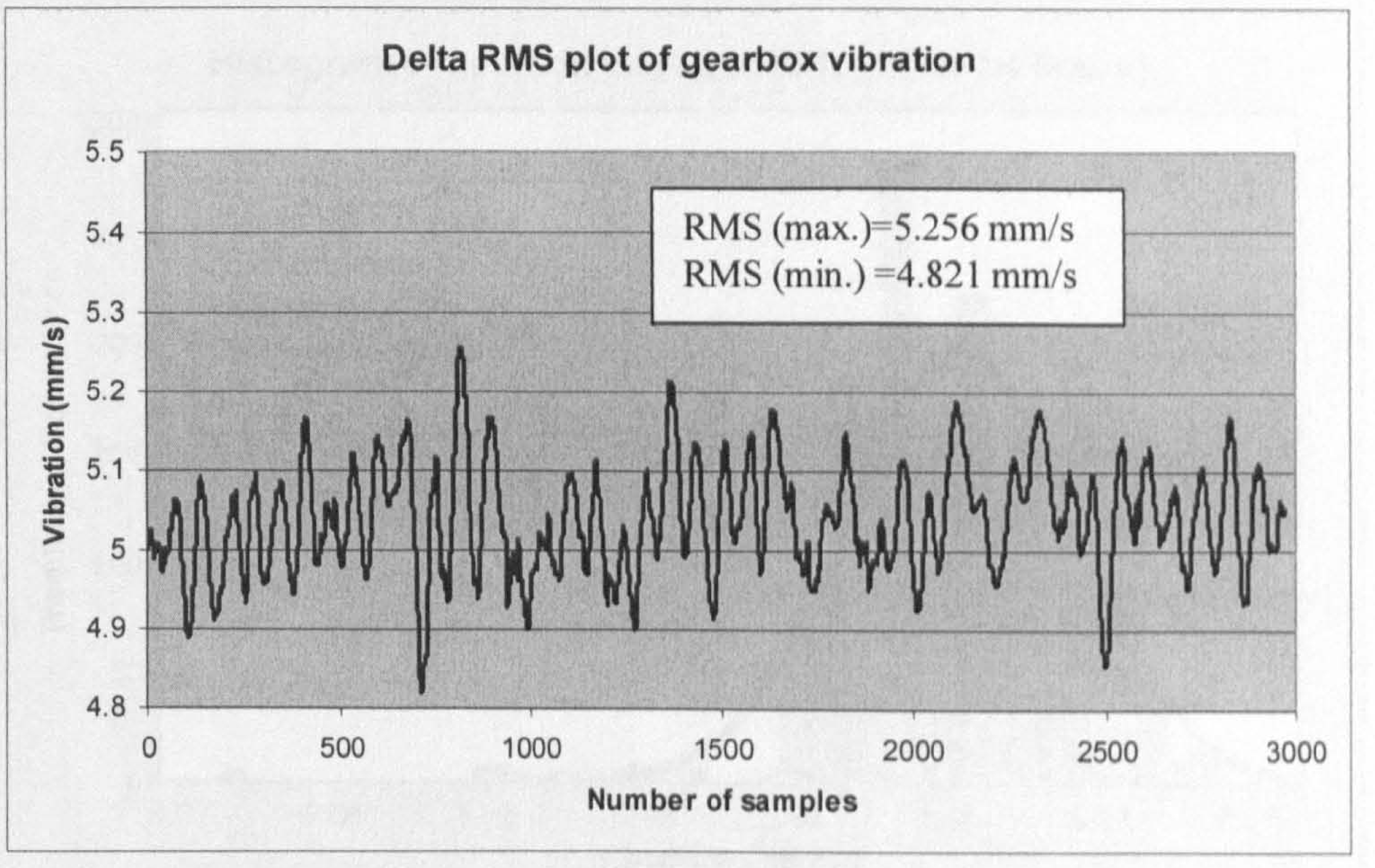


Fig.7.5. Delta RMS plot of gearbox vibration

From figure 7.5, it is clear that the difference in RMS levels at the start and the 14th hour of the test is quite high. The maximum difference in the RMS levels was 5.256 mm/s and the minimum observed value was 4.821 mm/s. This rise in RMS level was one of the possible signatures that, because of the accelerated life test, the gearbox has attained some state of degradation. However, the visual examination of gearbox, which is explained later in this section has already confirmed this that gearbox had attained degradation. In order to confirm this, Kurtosis, the other metric that is explained above, was calculated. A histogram is one of the best ways to describe the process data. Samples of data were drawn to check the Kurtosis values. Figure 7.6 shows the histogram of a sample of gearbox vibration data at the start of the 14th hour of the test with a distribution fit superimposed.

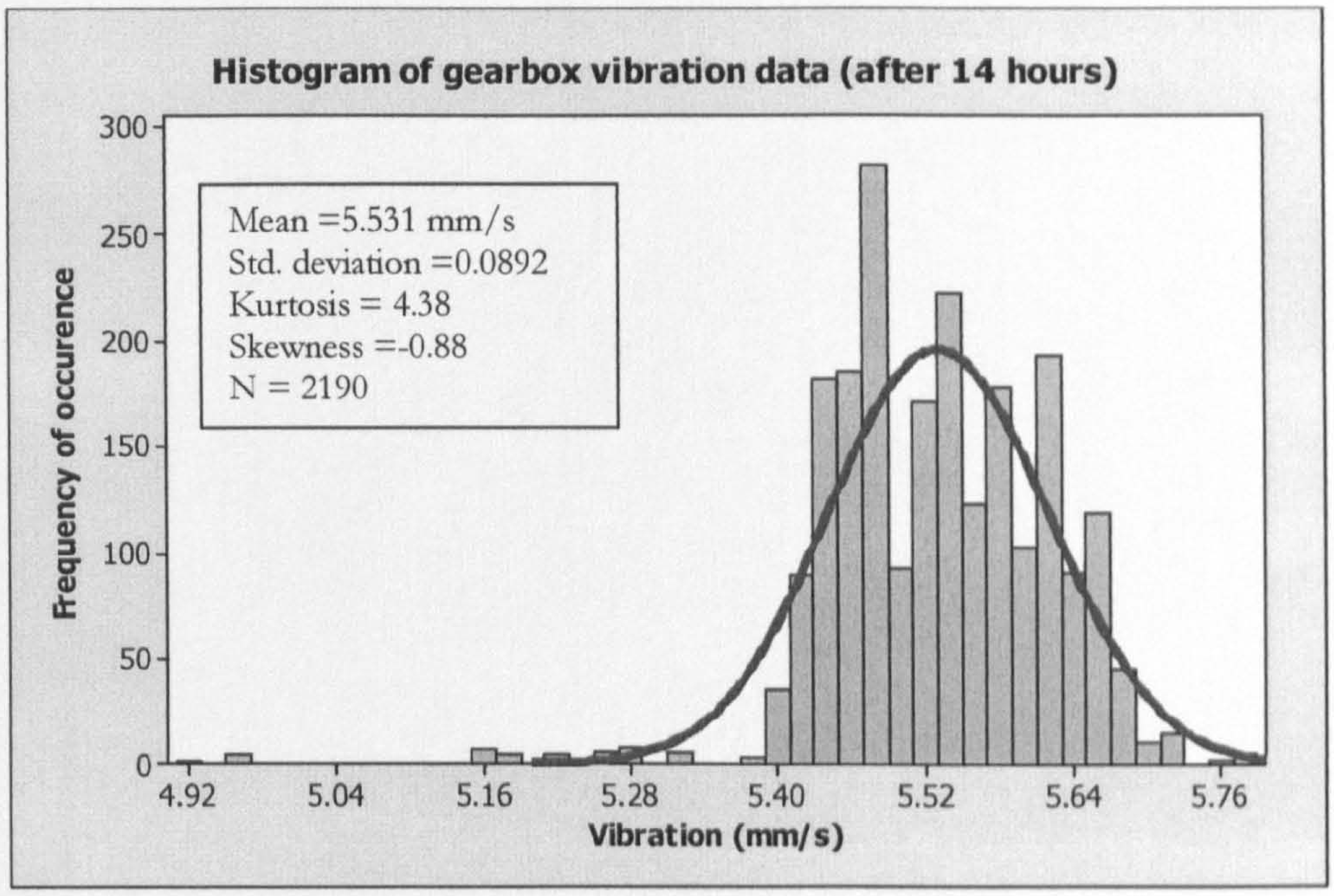


Fig.7.6. Histogram of gearbox vibration data (sample 1)

If we consider figure 7.6, then we can see that the calculated mean for this sample of data is 5.531 mm/s. The standard deviation is 0.0892 and the calculated Kurtosis is 4.38. This value of Kurtosis was quite high and it confirmed that the gearbox is no longer in good condition and has possibly developed some local fault such as tooth wear because a high value of Kurtosis is a clear indication of tooth wear **[122]**. A clearer picture of the signal can be presented with another type of histogram in figure 7.7. One can easily judge that the vibration signal is no longer normal. It is clear to see that the signal is not normally distributed. Skewness is another parameter that can be used. Another sample of data (see figure 7.8) was then drawn to confirm the higher value of Kurtosis after some time during the 14th hour of the test.

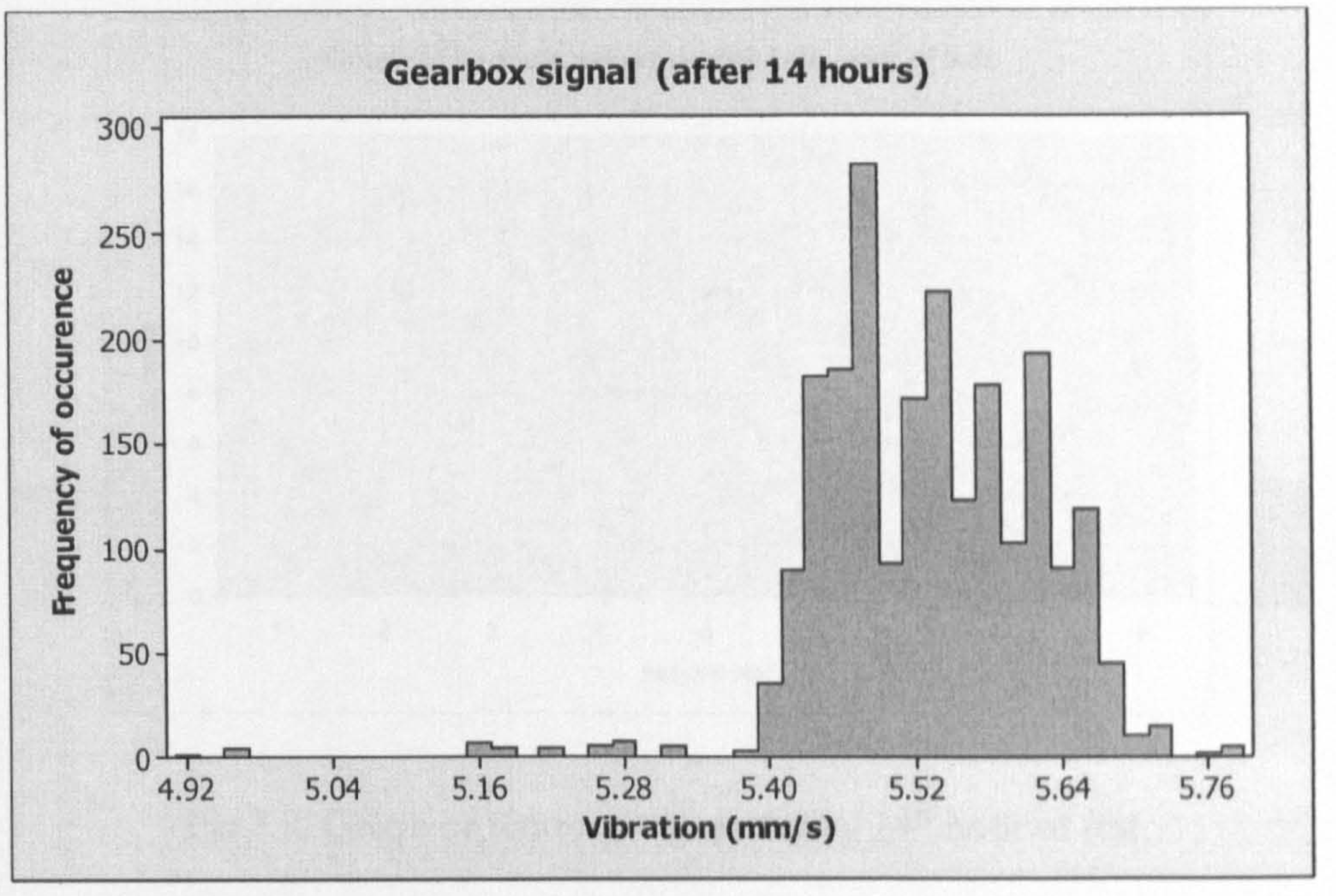


Fig.7.7. Histogram of gearbox vibration data (sample 1)

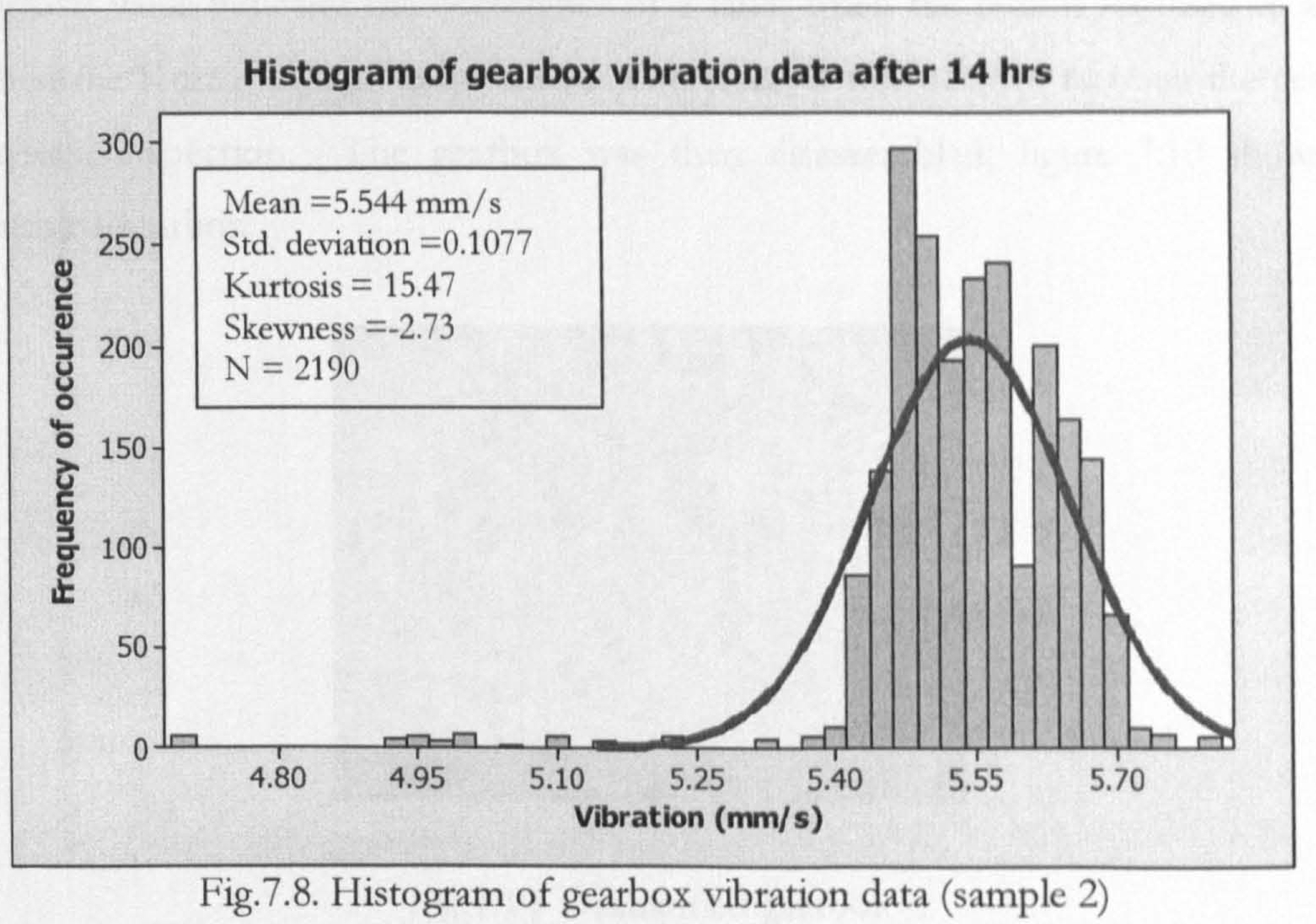


Fig.7.8. Histogram of gearbox vibration data (sample 2)

The value of Kurtosis from the 2nd sample is very high. According to Parey *et. al.* **[123]** this sudden rise of the Kurtosis value is a result of the occurrence of some fault.

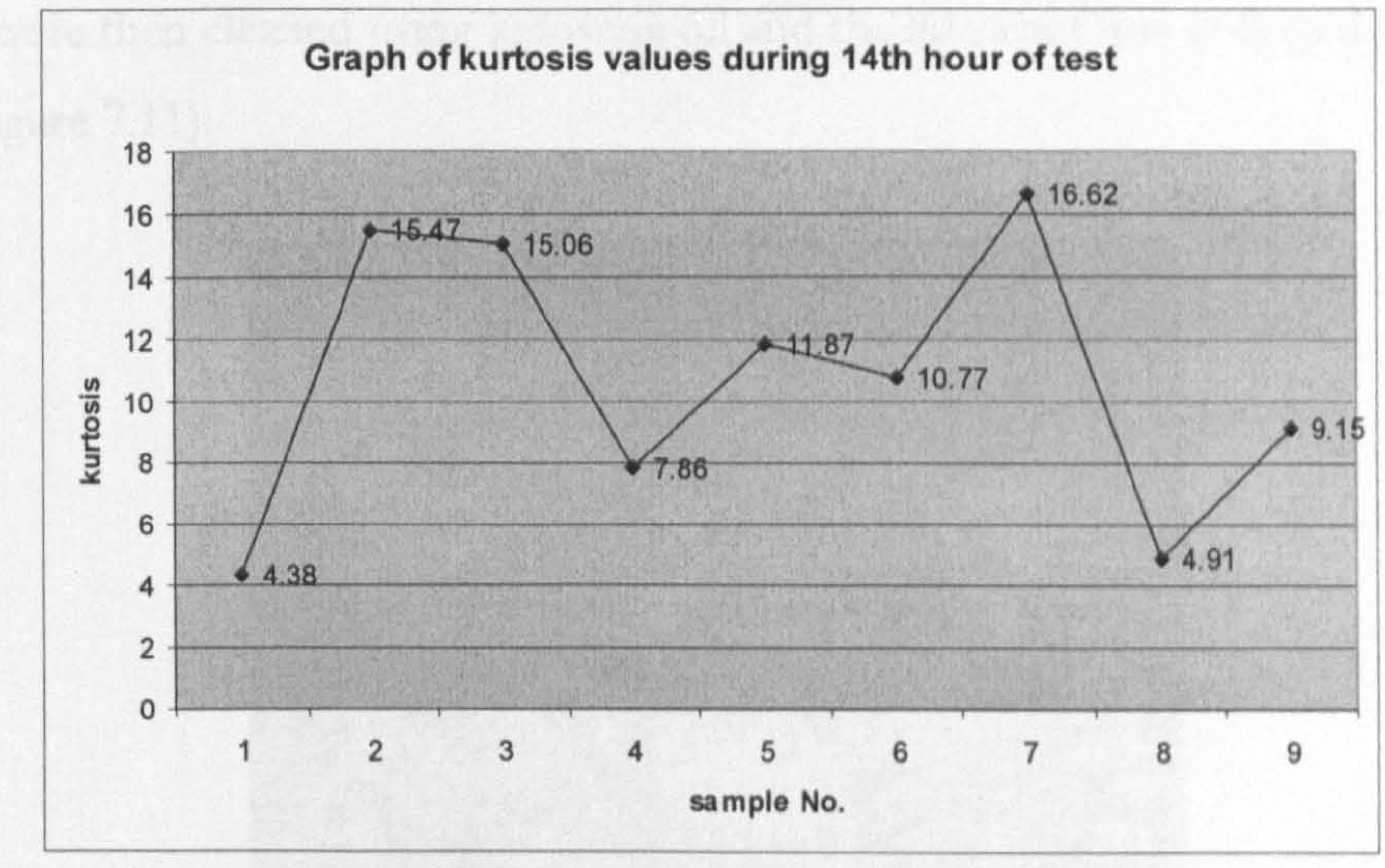


Fig.7.9. Graph of Kurtosis values during 14^{th} hour of test

Figure 7.9 shows different Kurtosis values during the 14^{th} hour of the test. A sudden rise in the Kurtosis value indicates the occurrence of a fault, when the fault is localised to all the teeth then the Kurtosis value drops down. Therefore, it was decided to open the gearbox for physical inspection. The gearbox was then disassembled; figure 7.10 shows the disassembled gearbox.

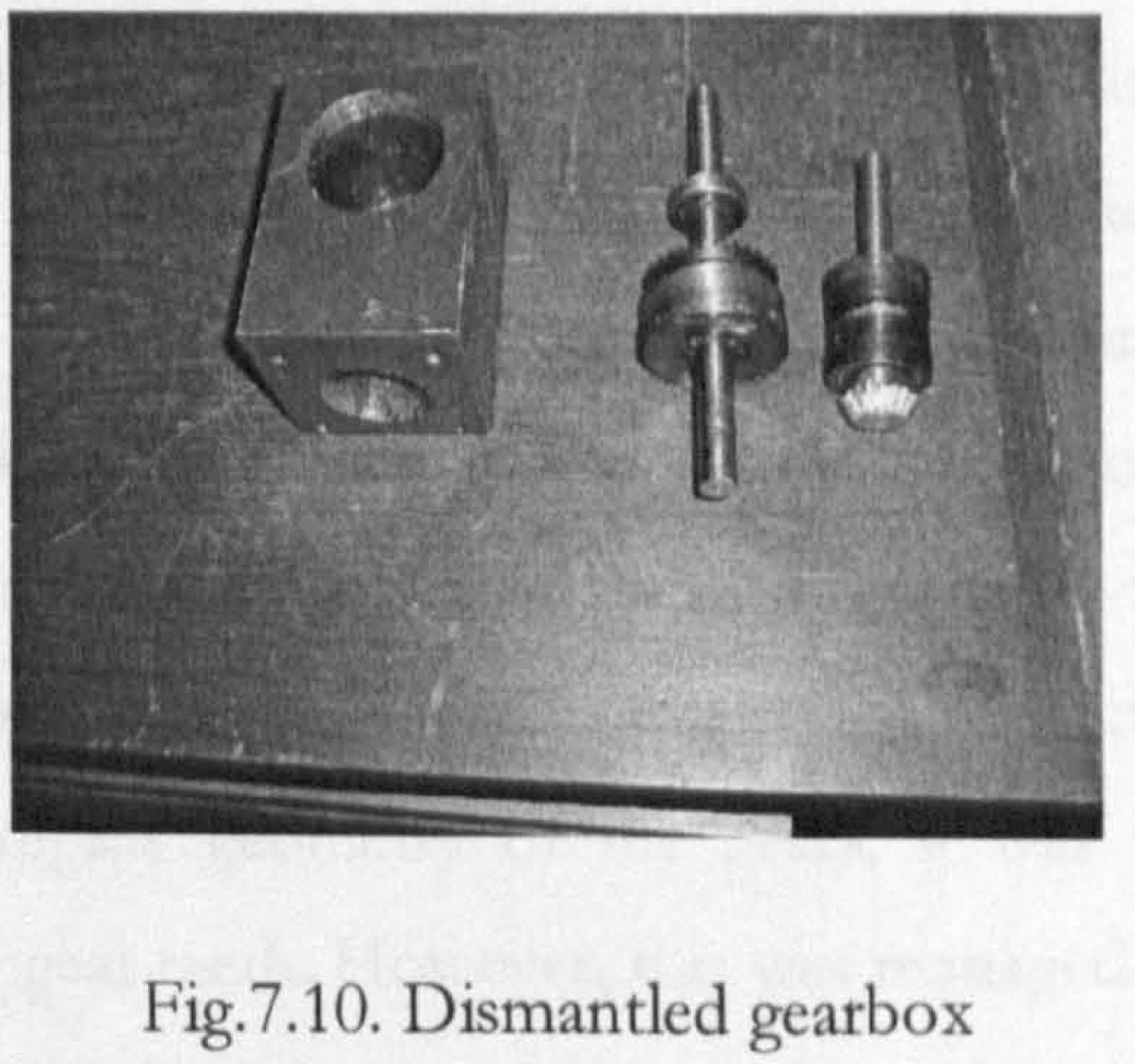


Fig.7.10. Dismantled gearbox

The gears were then cleaned using kerosene oil and the lubricant was collected in the sample pots (see figure 7.11).

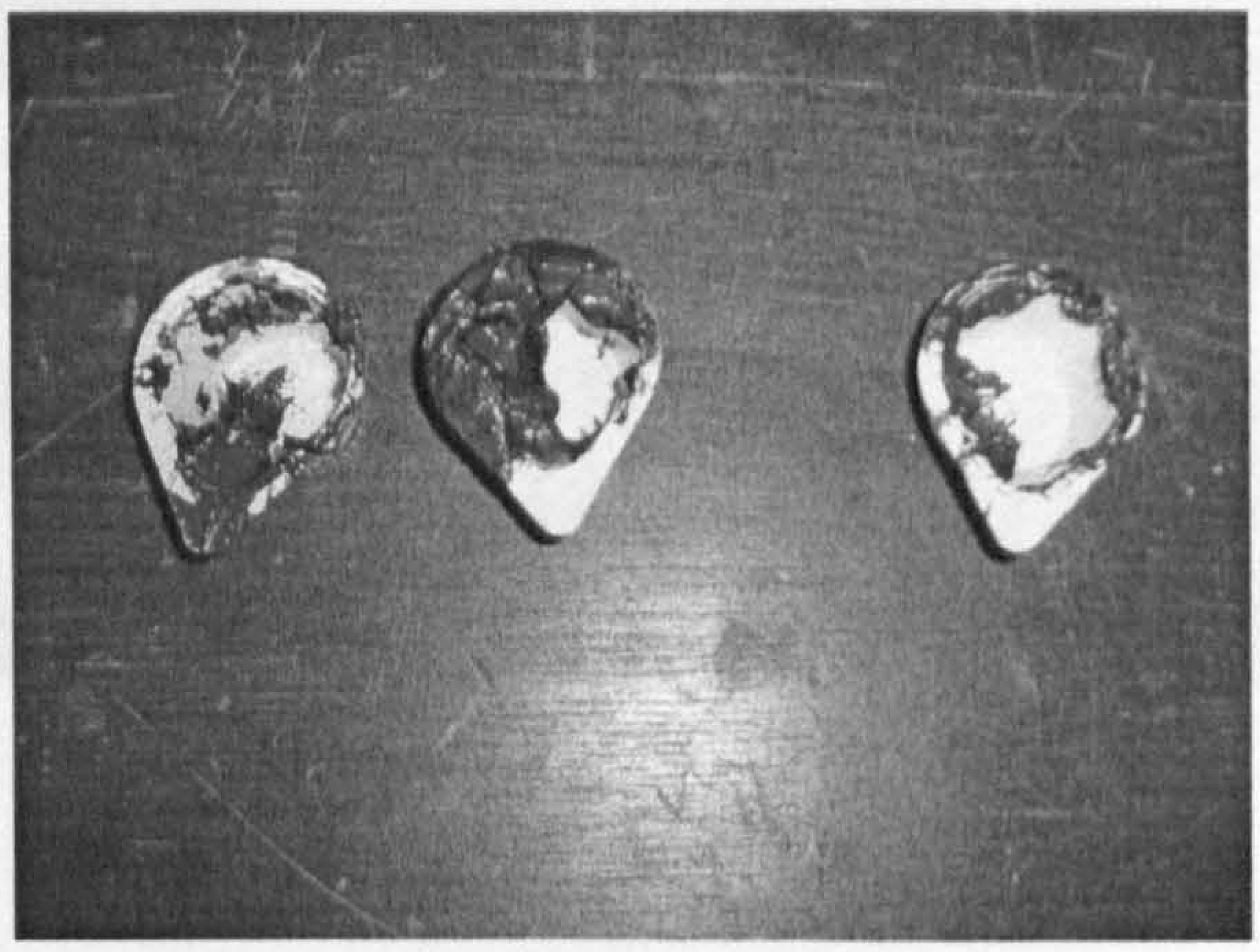


Fig.7.11. Collected lubricant

Both the pinion and the gear were found to be damaged and worn. Moreover, while washing the gears with the kerosene oil, heavy metal particles were seen. The presence of these metal particles was a clear indication that the gears had been subjected to heavy deterioration. Most of the modes of gear failure that are described in Chapter 5, like heavy metal pitting or erosion, tooth bending and wear were all observed and will be shown later in this chapter.

The damage appeared uniformly on all the teeth of the gear and the pinion. Marks of indentation due to heavy loading were found on the gear, which resulted in slight teeth bending and deformation. In addition to this, inspection of the gear revealed marks of slight welding indicating that that the gear had also been subject to thermal fatigue. That is obvious in a condition when gears are stressed under high loads and, due to excessive heat generation, the lubricant runs out, which results in a rough contact between mating surfaces. Due to the size and complex geometry of the gears, it was very difficult to take the photographs of individual gear teeth. However, this was managed by mounting the gear and the pinion on a special fixture in order to take the images of an individual tooth. Magnified images of both the pinion and the gear were taken with the help of industrial quality imaging equipment called Smartscope. Figure 7.12 shows a picture of the damaged pinion.

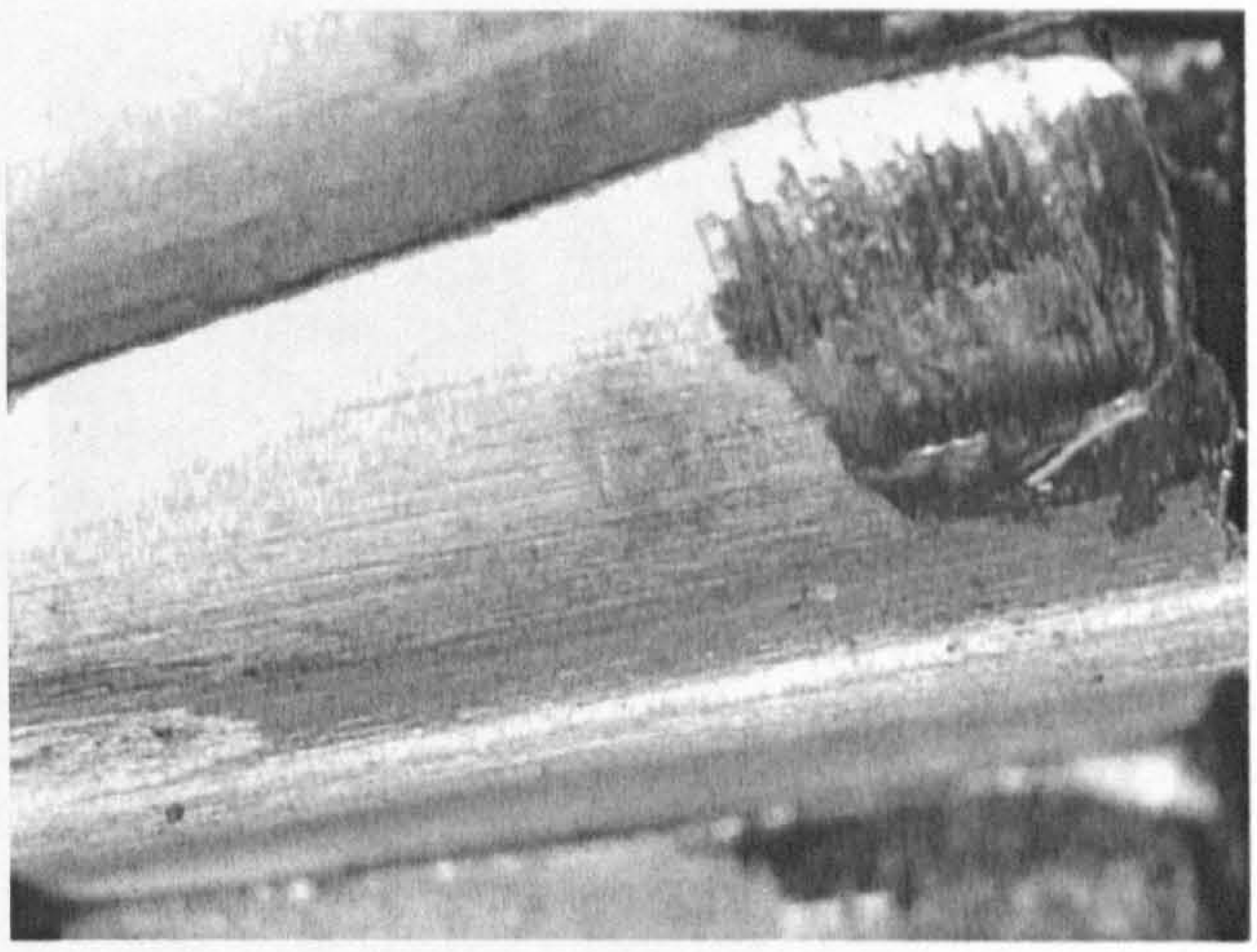


Fig.7.12. Damaged pinion (picture no. 1)

If we consider figure 7.12, we can see the heavy pitting and severe erosion on the tooth of the pinion. This pattern of damage was found on every tooth of the pinion. In addition to this, if we consider figure 7.13, we can see the damaged edge of the pinion tooth because of heavy pitting.

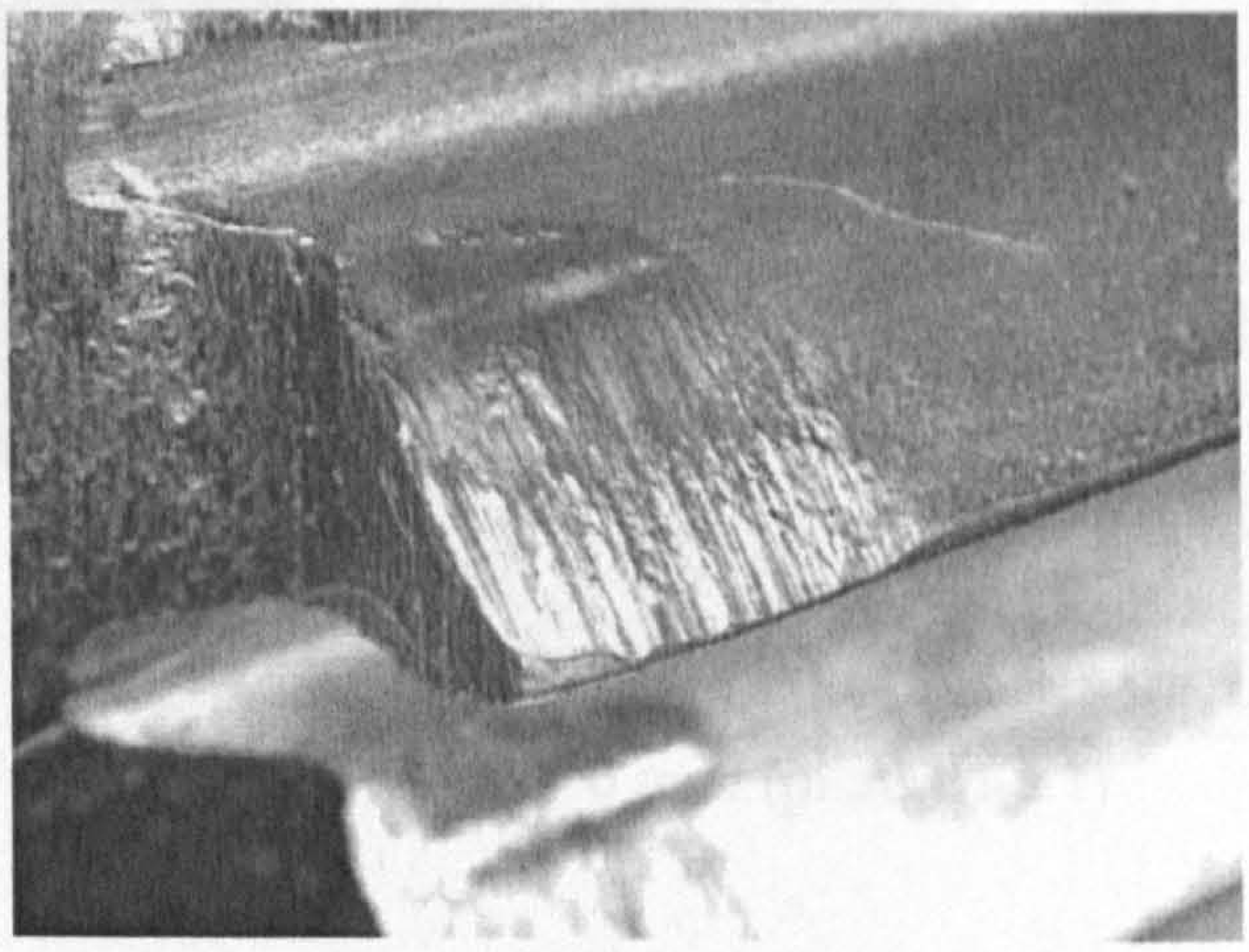


Fig.7.13. Damaged pinion (picture no.2)

Figure 7.14 presents another view of a damaged tooth of the pinion that shows slight tooth bending, whereas figures 7.15 and 7.16 show the pictures of the damaged gear.

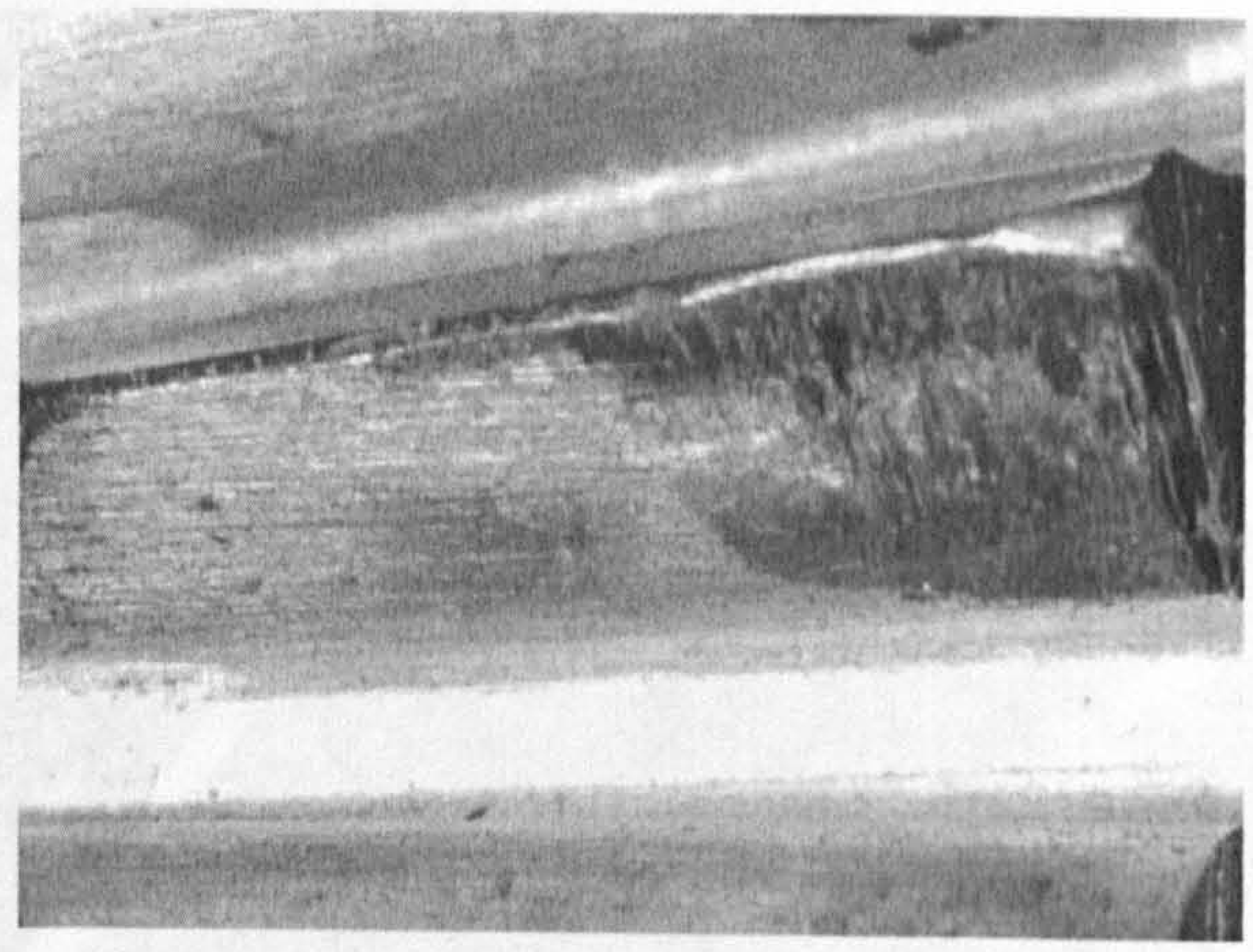


Fig.7.14. Damaged pinion (picture no.3)

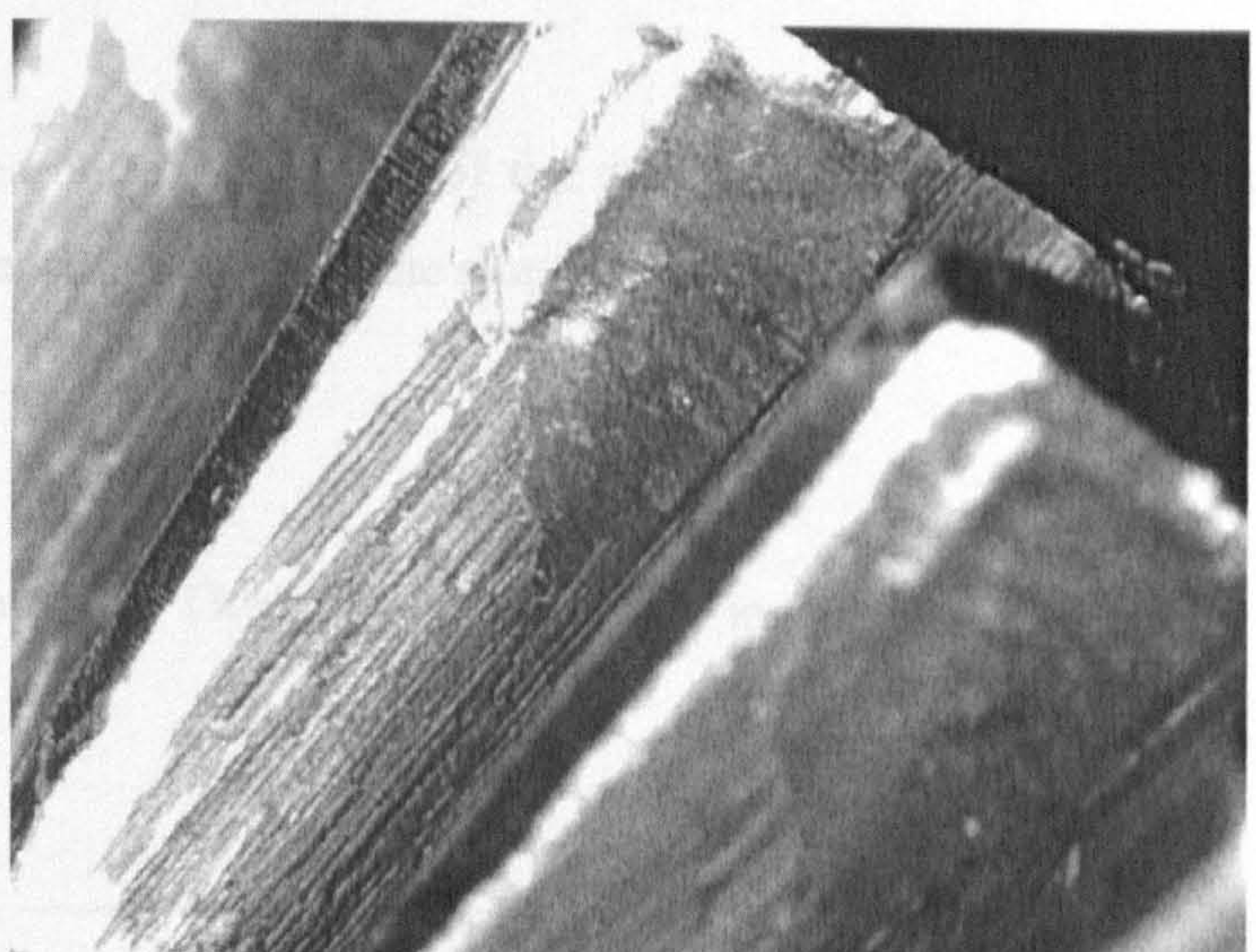


Fig.7.15. Damaged gear (picture no.1)

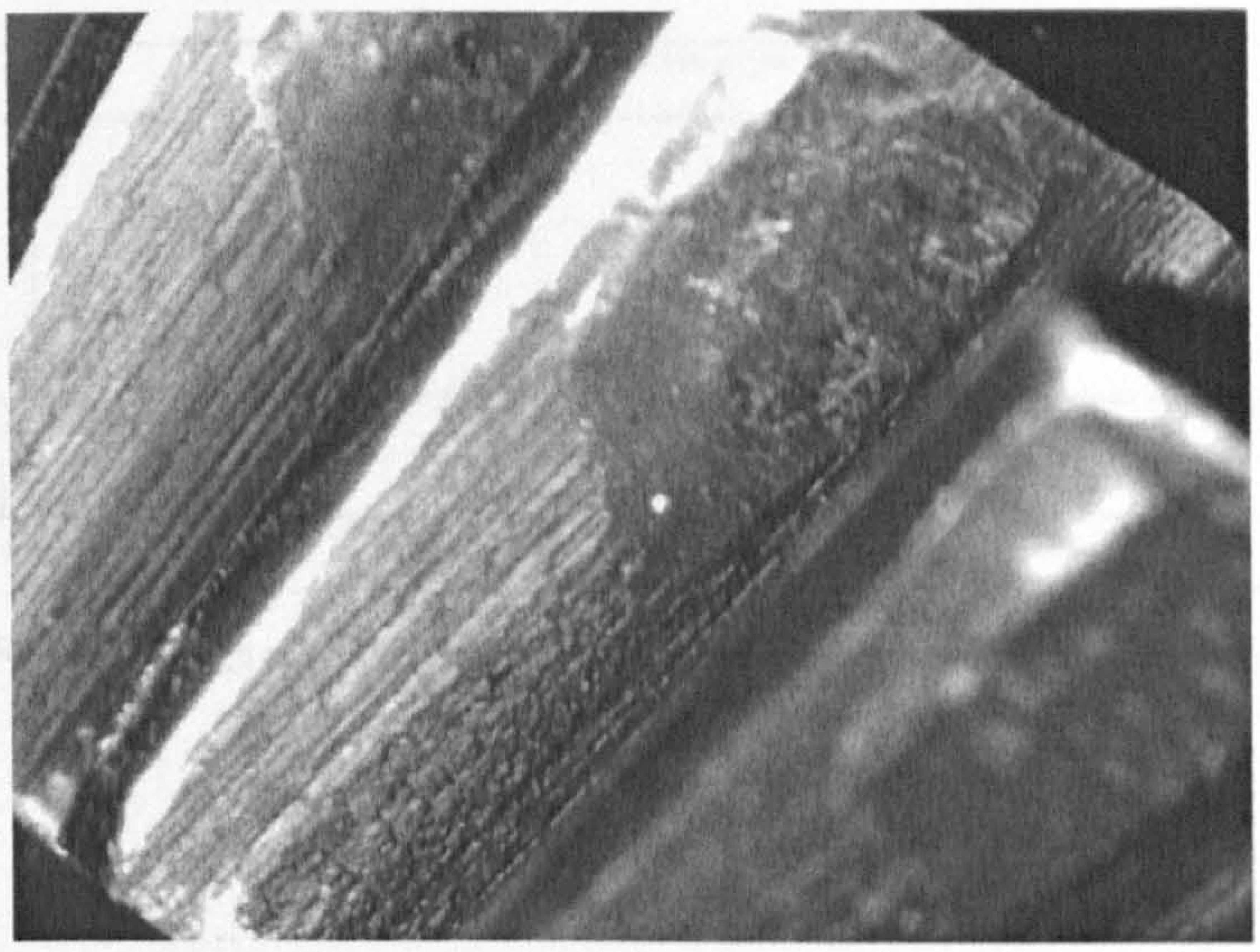


Fig.7.16. Damaged gear (picture no.2)

Some surface measurement profiles of the damaged pinion were taken with the help of a surface profile measurement machine along the surface length of

a damaged pinion tooth. These graphs are shown in figures 7.17 and 7.18 for the interest of the reader.

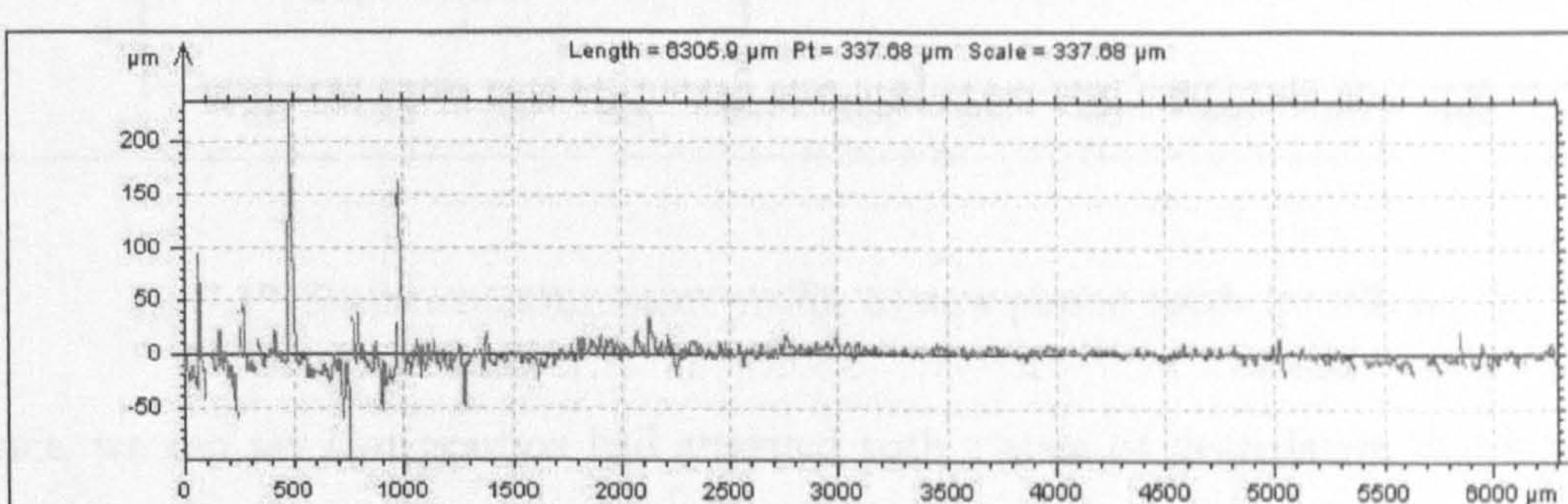


Fig.7.17. Surface measurement profile of damaged pinion tooth (profile no.1)

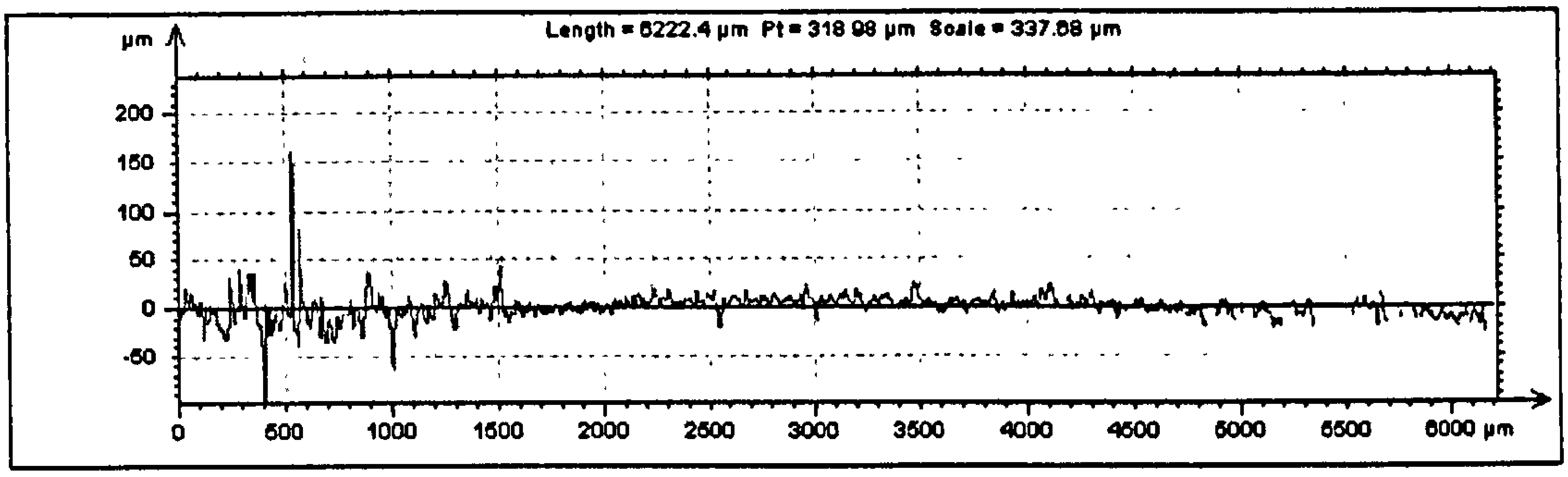


Fig.7.18. Surface measurement profile of damaged pinion tooth (profile no.2)

From figures 7.17 and 7.18, it is clear that higher peaks and valleys are present, mainly in the region where the pinion is subjected to deterioration. These peaks and valleys are obvious at a length of 0 to 1500 μm, which is the heavily affected area of the pinion's tooth. As compared to figures 7.17 and 7.18, figure 7.19 shows the surface measurement profile of a new pinion's tooth where no such peaks and valleys are present. This differentiates clearly a worn out gear from a healthy one.

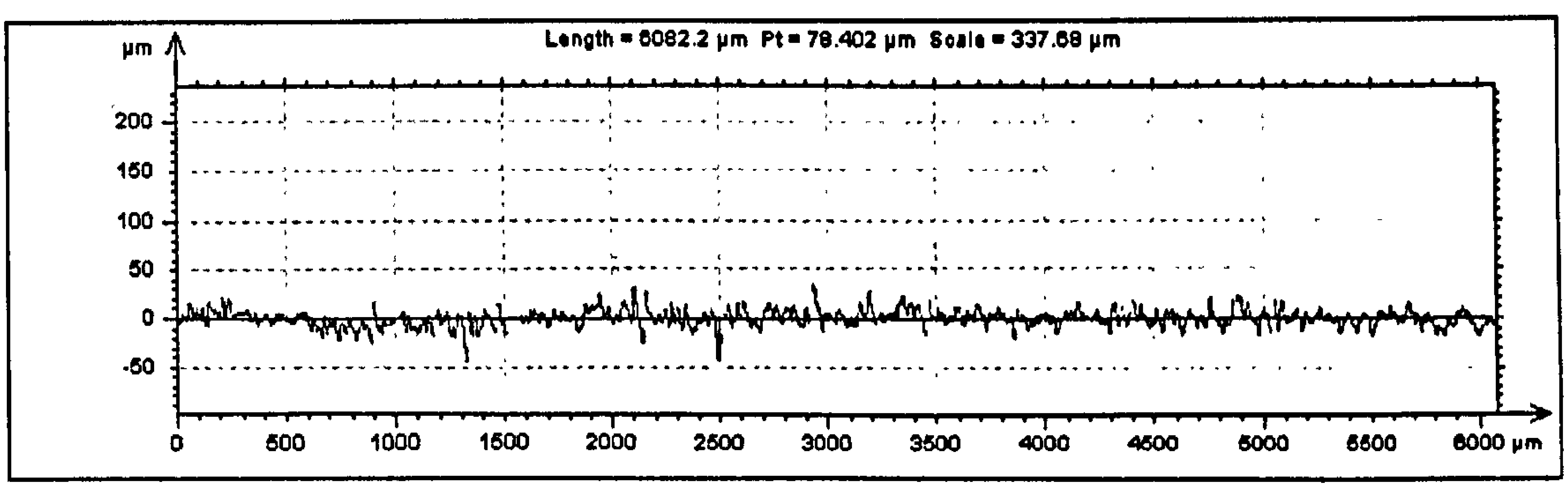


Fig.7.19. Surface measurement profile of new pinion tooth (profile no.2)

Hence, we can say that gearbox had attainted such a state of degradation that it was not possible to consider it for the purpose of reuse. The next section explains the hypothesis testing and simulation for the choice of a reliability distribution for use in the life prediction algorithm.

7.2 Hypothesis testing and simulation for the choice of reliability distribution

Before performing the simulation for the choice of proper reliability distribution, we will discuss the statistical hypothesis testing for the assumption of a particular reliability distribution for the life prediction algorithm.

7.2.1 Statistical hypothesis test

Statistical tests provide us with a quantitative way of examining data about a process and for making a useful decision regarding it. The statistical hypothesis test is dependent on the rejection of a supposition or hypothesis called a null hypothesis, denoted by H_0, to obtain support for an alternative hypothesis, denoted by H_A. In hypothesis testing, the null hypothesis is always taken as equality and is considered true throughout the test procedure. There are three ways to assume the alternative hypothesis:

a) An estimated parameter for the test is less than some particular value.

b) An estimated parameter for the test is greater than some particular value.

c) An estimated parameter is not equal to the particular value.

Here the estimated parameter refers to a numerical value that can be used, such as mean, standard deviation, etc. There are two types of hypothesis tests: one is called the one-sided or one-tailed test and the other is called the two-sided or two-tailed test.

A test is considered as one-sided or one-tailed if the assumption in the alternative hypothesis is set to be less or greater than a specified value, as in cases (a) and (b) mentioned above. On the other hand, a test is considered as two-sided or two-tailed if the assumption in the alternative hypothesis is set to be not equal to the specified value. Table 7.1 depicts different types of hypothesis tests.

	Condition	*Test type*
(a)	H_0: Estimated parameter = specified value H_A: Estimated parameter > specified value	*One-tailed test*
(b)	H_0: Estimated parameter = specified value H_A: Estimated parameter < specified value	*One-tailed test*
(c)	*H_0: Estimated parameter = specified value* *H_A: Estimated parameter $\neq$ specified value*	*Two-tailed test*

Table. 7.1. Types of hypothesis tests

To avoid any uncertainity associated with the process of hypothesis testing, a test is always performed at a specified level of significance. This level of significance is denoted by α. The purpose for performing the test at a particular level of significance is to avoid an incorrect decision to reject the null hypothesis when it is true. This error is called a type I error or an error of the first kind. This error can be avoided by performing the test at smaller values of significance levels like 0.01, 0.02, 0.005 or 0.025.

Another type of error that is associated with hypothesis testing is the incorrect decision to accept a null hypothesis when it is false. This error is called an error of type II or an error of the second kind. The probability of having an error of type II is denoted by β, with (1- β) being called the power of the test. The power of the test is basically the probability of rejecting a false null hypothesis, which in other words leads to a true decision. This is summarised in table 7.2.

	Case	Probability
A	Correct decision to accept null hypothesis when it is true.	Probability of correct decision = 1- α
B	Incorrect decision to accept null hypothesis when it is false.	Error of type II Probability (Type II error) = β
C	Incorrect decision to reject null hypothesis when it is true.	Error of type I Probability (Type I error) = α = significance level
D	Correct decision to reject null hypothesis when it is false.	Probability (correct decision) = 1 – β = power of the test

Table. 7.2. Different cases in hypothesis testing

In order to take a decision about a hypothesis, a quantity called the test statistic is calculated from a sample of data. Some of the common test statistics are z or t-tests. However, we will only define the Chi-square test statistic that is mentioned later in this section. Those values of the test statistic for which the null hypothesis is rejected are known as critical values and the critical region is defined as the region that consists of these critical values. This region is also known as the rejection region of the test. The basic rule for rejecting the null hypothesis is that if the calculated absolute value of the test statistic is greater than the critical value of the test then the null hypothesis is rejected. On the other hand, if the computed value of the test statistic is less than the crititcal value of the test then the null hypothesis is accepted. Actually, the greater the value of the computed test statistic than the critical value shows that there is no agreement between the assumed value of the test and the estimated value.

Steps for the statistical hypothesis test

Statistical hypothesis testing consists of the following procedure:

a) First step is to assume the null and alternative hypotheses.
b) The next step is to choose or fix the level of significance α.
c) After fixing the level of signiface for the test, the next step is to select a suitable test-statistic. Calculate the value of this test-statistic for the given sample of data for the assumption that the null hypothesis is true.
d) The next step is to find the critical values and critical region for the test from the chosen test statistic table.
e) After finding the critical values for the test, the next step is to mention the rejection rule for the null hypothesis.
f) The next step is to make a decision by comparing the calcutaed values with the critical or tabulated values. If the calculated value of the test-statistic is less than the critical value then accept the null hypothesis else reject the null hypothesis.
g) The last step is to conclude the test results.

Chi-square goodness-of-fit test

The goodness-of-fit test is a one-tailed hypothesis test that is used to determine whether a sample of data follows a specific distribution or not. The goodness-of-fit test uses the Chi-square distribution as the test-statistic, therefore, it is called the Chi-square goodness-of-fit test. In order to apply the Chi-square goodness-of-fit test, data should be arranged into bins i.e. divided into classes. The classes are defined as non-overlapping intervals of data showing the frequency of occurrence of each value in the group. The Chi-square test-statistic for the goodness-of-fit test is given by:

$$\aleph^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$$

Where,

$\aleph^2$ = Chi-square distribution

n = Number of classes or bins

O_i = Observed frequency

E_i = Expected frequency

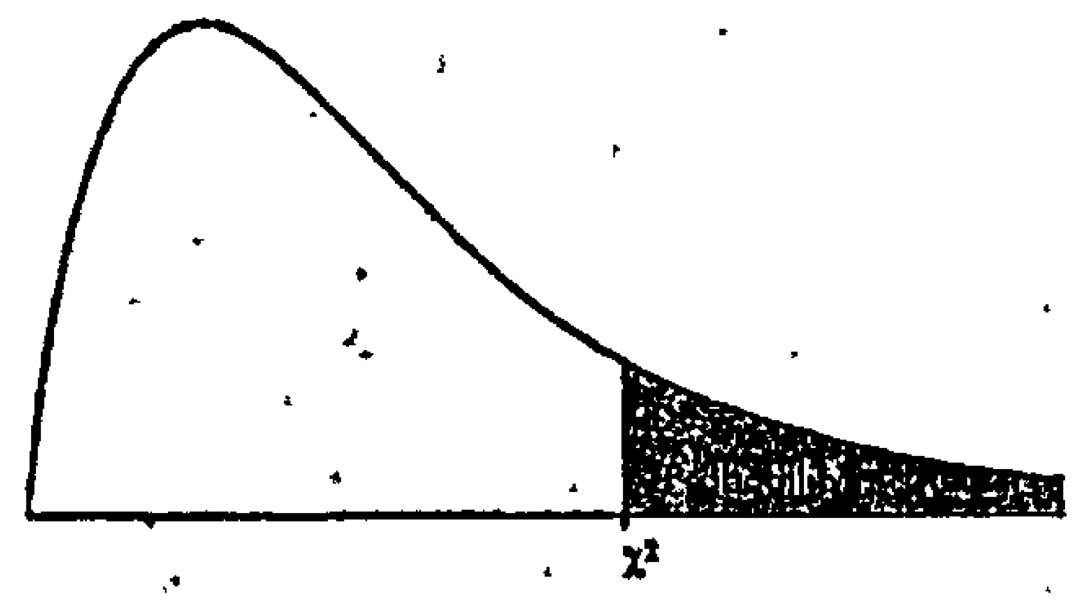
The expected frequency can be calculated using the following formula:

$E_i = N \times (F(L_u) - F(L_l))$

Degrees of freedom (d.f) = n-1

Where F is the cumulative distribution function of the Chi-square distribution and L_u and L_l are the upper and lower limits of the class intervals. N defines the size of the sample in the formula.

As mentioned above, goodness-of-fit is applied to the binned data but there is no restriction on the bin length for the test, however, for more accurate results it is better that the expected frequency E_i should be greater than, or equal to, 10 for each class if there are only two classes of data. In cases where there are more than two classes, the expected frequency should be greater than 5 for each class in order to ensure more accurate results. The Chi-square statistic is calculated from the above-mentioned formula and is compared with the tabulated value. The tabulated value of the test can be checked in table 7.3 against particular degrees of freedom and the defined level of significance. If the calculated value is less than the tabulated value then the hypothesis is accepted and if the calculated value is greater than the tabulated value then the hypothesis is rejected.



χ^2 CRITICAL VALUES

	Tail probability p										
df	.25	.20	.15	.10	.05	.025	.02	.01	.005	.0025	.001
1	1.32	1.64	2.07	2.71	3.84	5.02	5.41	6.63	7.88	9.14	10.83
2	2.77	3.22	3.79	4.61	5.99	7.38	7.82	9.21	10.60	11.98	13.82
3	4.11	4.64	5.32	6.25	7.81	9.35	9.84	11.34	12.84	14.32	16.27
4	5.39	5.99	6.74	7.78	9.49	11.14	11.67	13.28	14.86	16.42	18.47
5	6.63	7.29	8.12	9.24	11.07	12.83	13.39	15.09	16.75	18.39	20.51
6	7.84	8.56	9.45	10.64	12.59	14.45	15.03	16.81	18.55	20.25	22.46
7	9.04	9.80	10.75	12.02	14.07	16.01	16.62	18.48	20.28	22.04	24.32
8	10.22	11.03	12.03	13.36	15.51	17.53	18.17	20.09	21.95	23.77	26.12
9	11.39	12.24	13.29	14.68	16.92	19.02	19.68	21.67	23.59	25.46	27.88
10	12.55	13.44	14.53	15.99	18.31	20.48	21.16	23.21	25.19	27.11	29.59
11	13.70	14.63	15.77	17.28	19.68	21.92	22.62	24.72	26.76	28.73	31.26
12	14.85	15.81	16.99	18.55	21.03	23.34	24.05	26.22	28.30	30.32	32.91
13	15.98	16.98	18.20	19.81	22.36	24.74	25.47	27.69	29.82	31.88	34.53
14	17.12	18.15	19.41	21.06	23.68	26.12	26.87	29.14	31.32	33.43	36.12
15	18.25	19.31	20.60	22.31	25.00	27.49	28.26	30.58	32.80	34.95	37.70
16	19.37	20.47	21.79	23.54	26.30	28.85	29.63	32.00	34.27	36.46	39.25
17	20.49	21.61	22.98	24.77	27.59	30.19	31.00	33.41	35.72	37.95	40.79
18	21.60	22.76	24.16	25.99	28.87	31.53	32.35	34.81	37.16	39.42	42.31
19	22.72	23.90	25.33	27.20	30.14	32.85	33.69	36.19	38.58	40.88	43.82
20	23.83	25.04	26.50	28.41	31.41	34.17	35.02	37.57	40.00	42.34	45.31
21	24.93	26.17	27.66	29.62	32.67	35.48	36.34	38.93	41.40	43.78	46.80
22	26.04	27.30	28.82	30.81	33.92	36.78	37.66	40.29	42.80	45.20	48.27
23	27.14	28.43	29.98	32.01	35.17	38.08	38.97	41.64	44.18	46.62	49.73
24	28.24	29.55	31.13	33.20	36.42	39.36	40.27	42.98	45.56	48.03	51.18
25	29.34	30.68	32.28	34.38	37.65	40.65	41.57	44.31	46.93	49.44	52.62
26	30.43	31.79	33.43	35.56	38.89	41.92	42.86	45.64	48.29	50.83	54.05
27	31.53	32.91	34.57	36.74	40.11	43.19	44.14	46.96	49.64	52.22	55.48
28	32.62	34.03	35.71	37.92	41.34	44.46	45.42	48.28	50.99	53.59	56.89
29	33.71	35.14	36.85	39.09	42.56	45.72	46.69	49.59	52.34	54.97	58.30
30	34.80	36.25	37.99	40.26	43.77	46.98	47.96	50.89	53.67	56.33	59.70
40	45.62	47.27	49.24	51.81	55.76	59.34	60.44	63.69	66.77	69.70	73.40
50	56.33	58.16	60.35	63.17	67.50	71.42	72.61	76.15	79.49	82.66	86.66
60	66.98	68.97	71.34	74.40	79.08	83.30	84.58	88.38	91.95	95.34	99.61
80	88.13	90.41	93.11	96.58	101.9	106.6	108.1	112.3	116.3	120.1	124.8
100	109.1	111.7	114.7	118.5	124.3	129.6	131.1	135.8	140.2	144.3	149.4

Table. 7.3. Table of Chi-square critical values

Simulation and results

The Monte Carlo method is one of the popular simulation techniques that employ random numbers and probability to solve different problems. Monte Carlo is better than other simulation techniques because it behaves in a stochastic manner. It is useful in cases where modelling a system involves real-life predictions. The Monte Carlo simulation is widely used in a number of fields such as reliability engineering, finance, computer graphics and for modelling biological phenomena.

The candidate distributions for the life prediction algorithm have already been described in Chapter 6. Any of these distributions can be used for the process of life prediction; however, due to ease of programming, simplicity and from the perspective of implementation, an exponential distribution was preferred. Therefore, the goodness of fit test was conducted to check whether an exponential distribution is a satisfactory choice for the life prediction algorithm or not. In addition to this, an exponential distribution is a good choice to model processes with a constant failure rate.

As from the gearbox accelerated life test we know that the gearbox took 14 hours to reach this stage or mode of failure, therefore it was assumed that there are 14 stages of degradation, one for each of the 14 hrs. Three sets of random probabilities having ranges between 0 and 1 were generated. The transformation that is described below was then applied to the generated probabilities, and time values were calculated. Each set consisted of 5,000 data points. The trial version of Minitab 15 software was used for hypothesis testing and this statistical analysis.

From Chapter 6 we know that for exponential distribution, the probability density function is given by:

$$f(x) = \frac{1}{\beta} e^{-\frac{x}{\beta}} \text{ for x } > 0$$

Where f(x) is the probability density function and β is the time to fail. We also know that the failure rate λ and the time to fail β are related as:

$$\lambda = 1/\beta$$

Therefore, the above equation can also be written as:

$$f(x) = \lambda e^{-\lambda x} \text{ for } x>0$$

If p(x) is the probability of failure at time t, then the probability density of the function of exponential distribution can be written as :

$$p(x=t) = \frac{1}{\beta} e^{-\frac{t}{\beta}} \text{ for } t \geq 0, \beta>0$$

$$\text{or } \beta p(x=t) = e^{\frac{-t}{\beta}}$$

$$\text{or } \ln(\beta p(x=t)) = -\frac{t}{\beta}$$

$$\text{or } \ln(\beta) + \ln(p(x=t)) = -\frac{t}{\beta}$$

$$\text{or } t = -\beta[\ln(\beta) + \ln(p(x=t))]$$

Now the last equation can be used to calculate the failure time if the probability of failure and time to fail are known.

From the gearbox test, we know that it took approximately 14 hrs to reach this mode of failure; therefore we can say that:

TTF(time to fail) = 14 hours

Or β = 14 hrs

Therefore, using the derived equation and the simulated probabilities, time values for simulated probability values were calculated. As from the pdf plot of the exponential distribution we know that exponential distribution does not operate on negative values, the negative values were discarded. A range of probabilities and time values between 0 and 14 were selected to simulate the exact scenario of gearbox failure and the rest of the data values were censored. Calculated time values were classified into 14 different classes from class N to class A. After data classification, the goodness of fit test was applied on each of the five datasets. Tests and their results are presented below:

Test for dataset No. 1

1. Null Hypothesis: H_0: Data follows exponential distribution

2. Level of significance: $\alpha = 0.005$

3. Test-statistic: $\aleph^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)}{E_i}$

4. Rejection rule: Reject H_0 if $\chi^2_{calculated} > \chi^2_{tabulated}$

5. Result: Calculated value = 21.458

Tabulated value = 29.82

$\chi^2_{calculated} < \chi^2_{tabulated}$

Therefore, accept H_0 (Data follows exponential distribution).

All the test statistics and calculations for dataset no.1 are shown in table 7.4. Figure 7.20 shows the chart of the Chi-square contribution for each class. Figure 7.21 shows the chart of observed and expected frequencies for dataset No. 1.

Class Interval (time hrs)	Class Name	O_i=Observed Frequency	E=Expected Frequency	$(O_i-E_i)^2$	$\aleph^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$
0.00 – 0.99	N	15	16.8751	3.516	0.20460
1.00 – 1.99	M	20	16.8751	9.765	0.58596
2.00 – 2.99	L	24	16.8751	50.7642	3.02663
3.00 – 3.99	K	21	16.8751	17.0148	1.01816
4.00 – 4.99	J	21	16.8751	17.0148	1.01816
5.00 – 5.99	I	17	16.8751	0.0156	0.00121
6.00 – 6.99	H	21	16.8751	17.0148	1.01816
7.00 – 7.99	G	19	16.8751	4.5152	0.27240
8.00 – 8.99	F	17	16.8751	0.0156	0.00121
9.00 – 9.99	E	21	16.8751	17.0148	1.01816
10.00– 10.99	D	9	16.8751	62.0172	3.66223
11.00– 11.99	C	9	16.8751	62.0172	3.66223
12.00– 12.99	B	15	16.8751	3.516	0.20460
13.00 -13.99	A	7	16.8751	97.5176	5.76392
Total		N=236			21.458

Table 7.4. Test statistics for dataset No.1

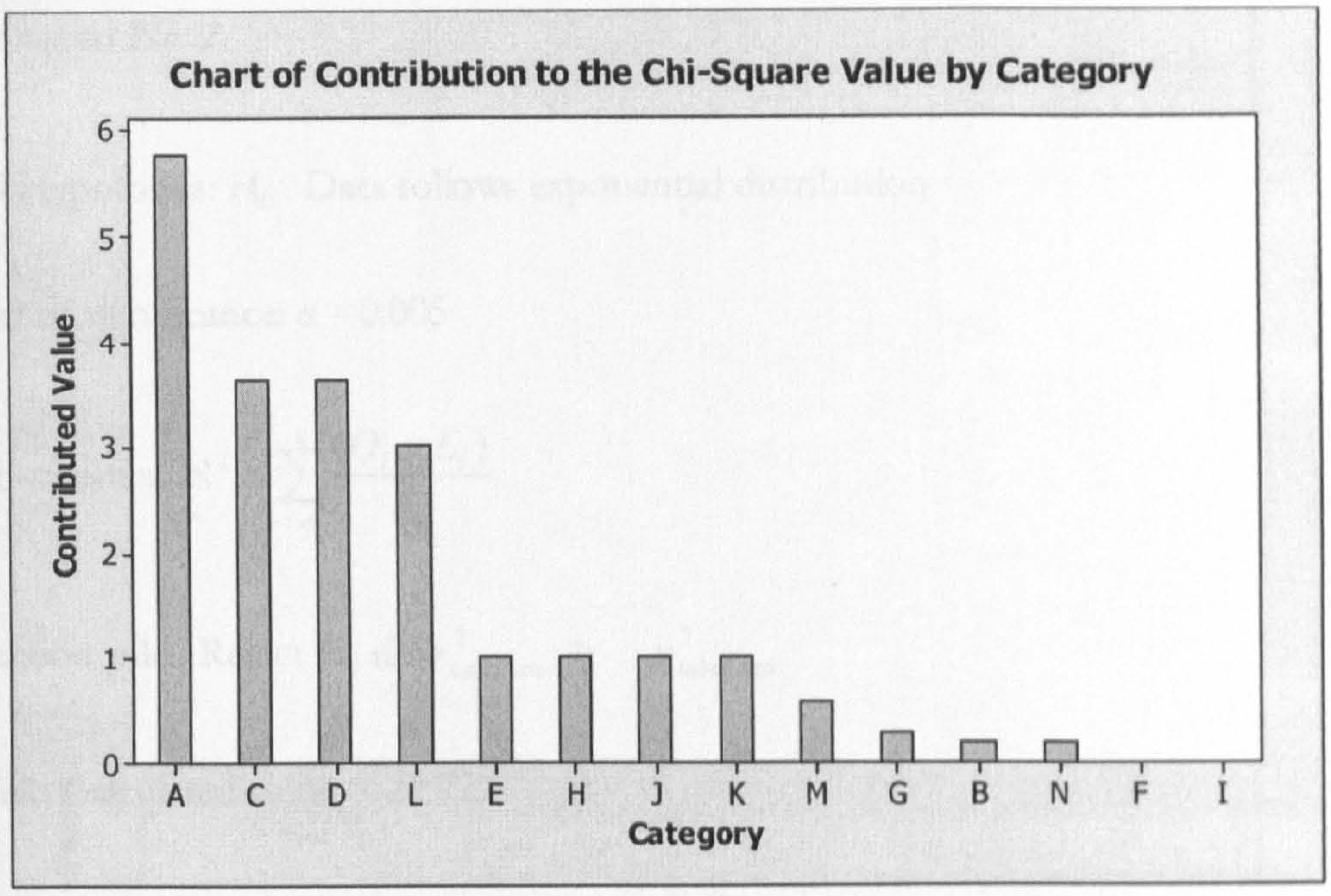


Fig.7.20. Chart of contribution to Chi-square value (dataset No.1)

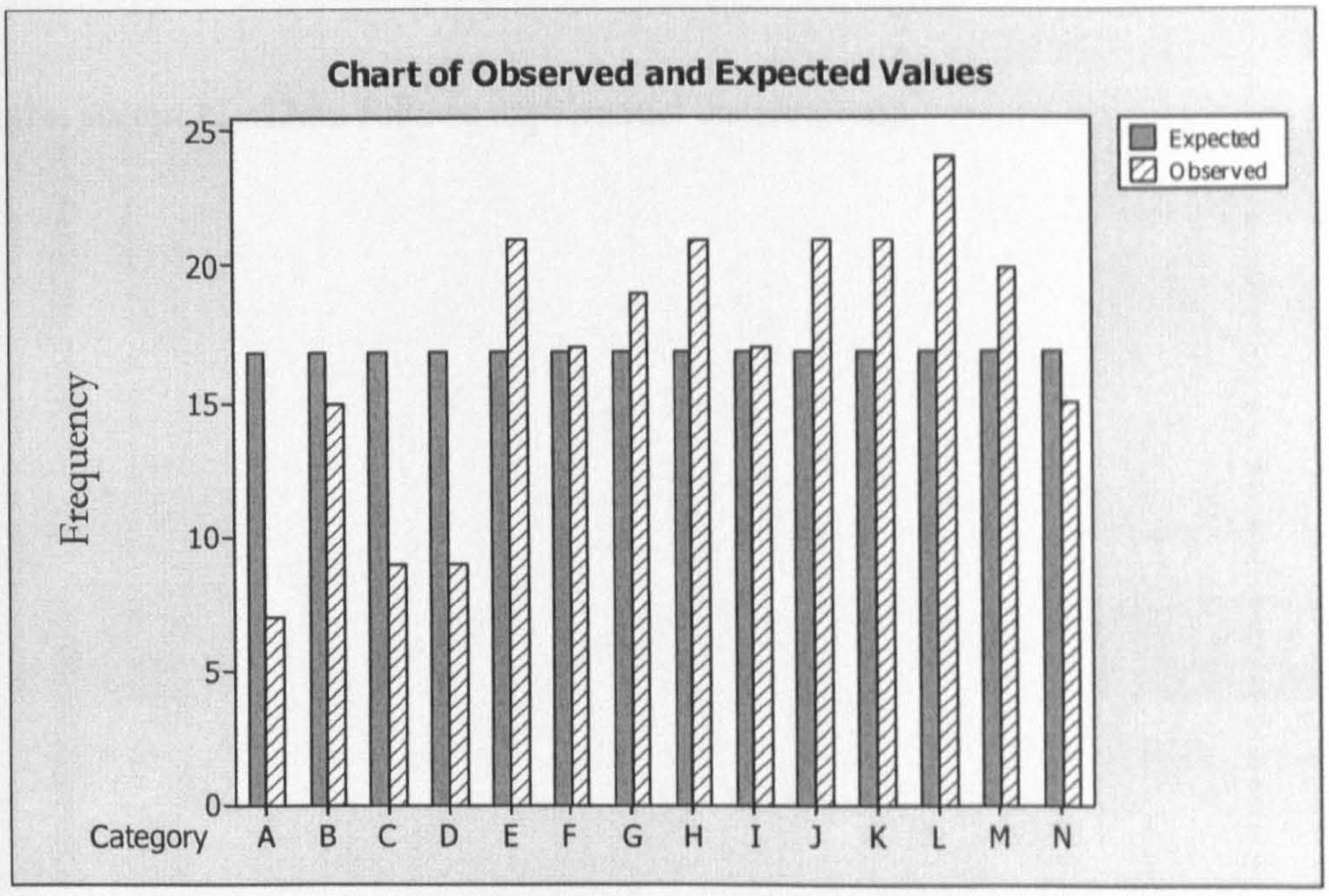


Fig.7.21. Chart of observed and expected frequencies (dataset No.1)

Test for dataset No. 2

1. Null Hypothesis: H_0 : Data follows exponential distribution

2. Level of significance: α =0.005

3. Test-statistic: $\aleph^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)}{E_i}$

4. Rejection rule: Reject H_0 if $\chi^2_{calculated} > \chi^2_{tabulated}$

5. Result: Calculated value = 27.929

Tabulated value = 29.82

$\chi^2_{calculated} < \chi^2_{tabulated}$

Therefore, accept H_0 (Data follows exponential distribution).

Class Interval (time hrs)	Class Name	O_i=Observed Frequency	E=Expected Frequency	$(O_i-E_i)^2$	$\aleph^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$
0.00 – 0.99	N	29	16.2857	161.653	9.92607
1.00 – 1.99	M	21	16.2857	22.2246	1.36466
2.00 – 2.99	L	18	16.2857	2.9388	0.18045
3.00 – 3.99	K	19	16.2857	7.3674	0.45238
4.00 – 4.99	J	19	16.2857	7.3674	0.45238
5.00 – 5.99	I	9	16.2857	53.0814	3.2594
6.00 – 6.99	H	19	16.2857	7.3674	0.45238
7.00 – 7.99	G	16	16.2857	0.0816	0.00501
8.00 – 8.99	F	20	16.2857	13.7960	0.84712
9.00 – 9.99	E	17	16.2857	0.5102	0.03133
10.00– 10.99	D	15	16.2857	1.6530	0.1015
11.00– 11.99	C	8	16.2857	68.6528	4.21554
12.00– 12.99	B	10	16.2857	39.5100	2.42607
13.00 -13.99	A	8	16.2857	68.6528	4.21554
Total		N = 228			27.9298

Table 7.5. Test statistics for dataset No.2

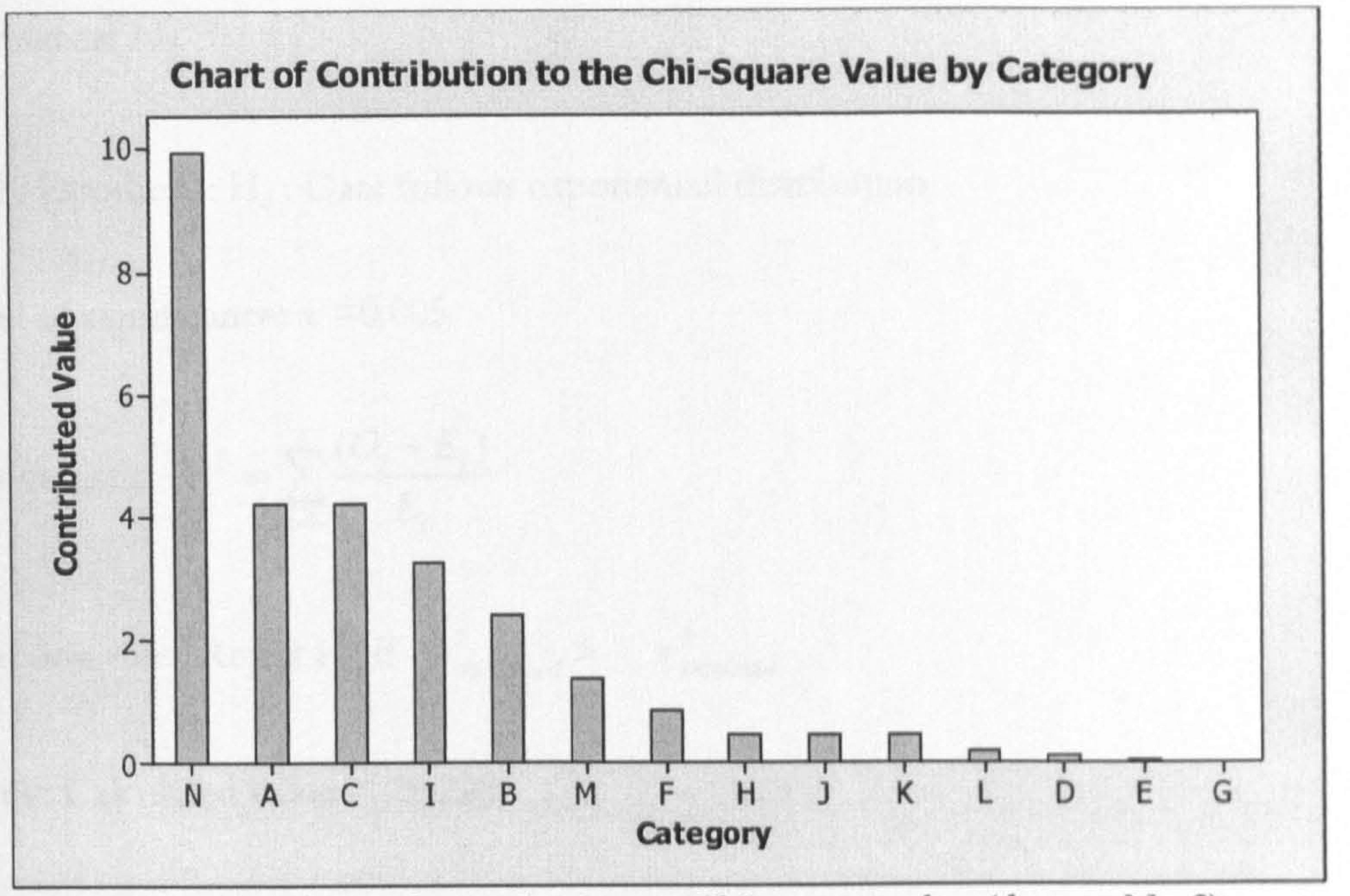


Fig.7.22. Chart of contribution to Chi-square value (dataset No.2)

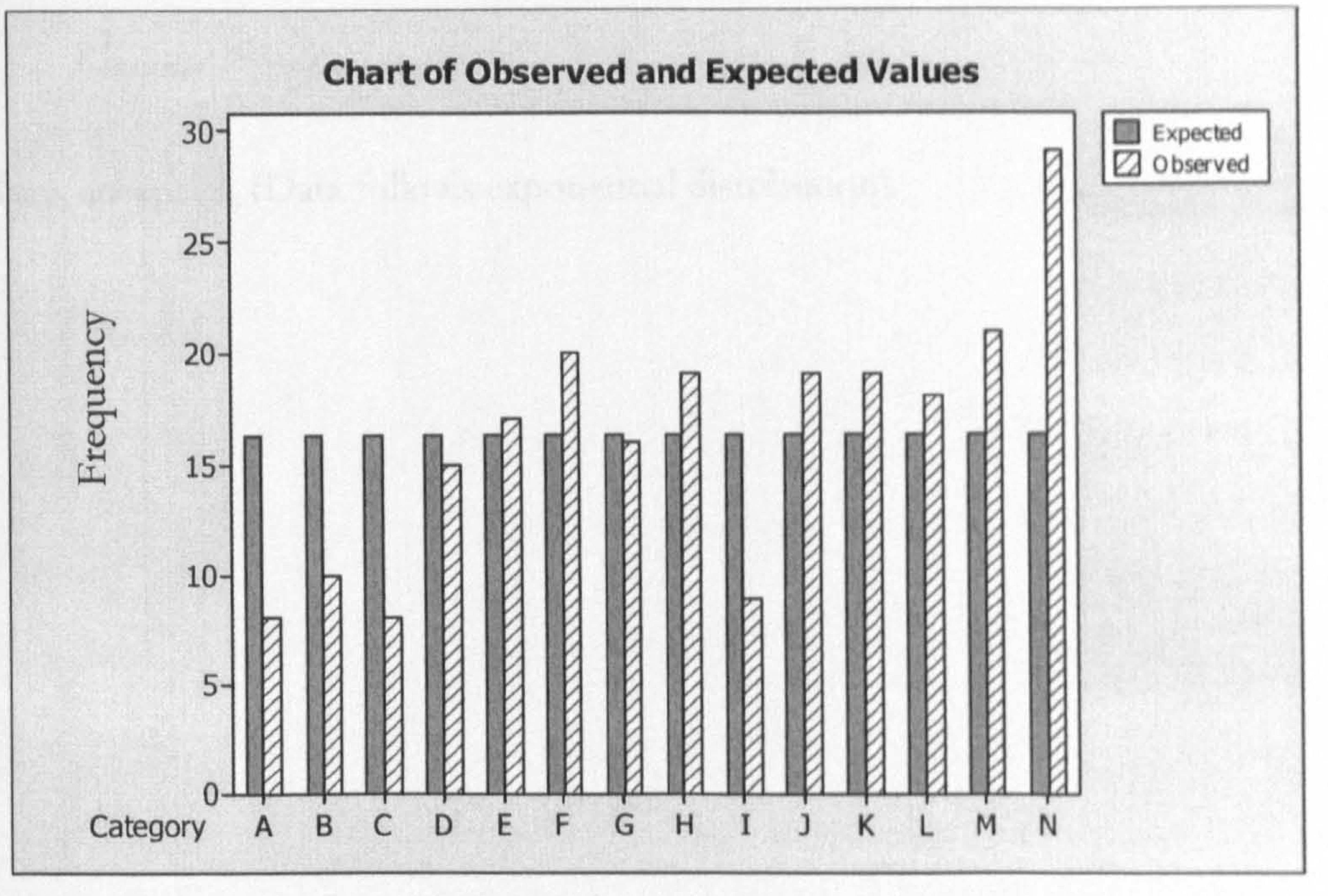


Fig.7.23. Chart of observed and expected frequencies (dataset No.2)

Test for dataset No. 3

1. Null Hypothesis: H_0 : Data follows exponential distribution

2. Level of significance: α =0.005

3. Test-statistic: $\aleph^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)}{E_i}$

4. Rejection rule: Reject H_0 if $\chi^2_{calculated} > \chi^2_{tabulated}$

5. Result: Calculated value = 29.228

Tabulated value = 29.82

$\chi^2_{calculated} < \chi^2_{tabulated}$

Therefore, accept H_0 (Data follows exponential distribution).

Class Interval (time hrs)	Class Name	O_i=Observed Frequency	E=Expected Frequency	$(O_i-E_i)^2$	$\aleph^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$
0.00 – 0.99	N	18	15.6429	5.5559	0.35519
1.00 – 1.99	M	26	15.6429	107.269	6.8574
2.00 – 2.99	L	24	15.6429	69.8411	4.4648
3.00 – 3.99	K	18	15.6429	5.5559	0.3552
4.00 – 4.99	J	16	15.6429	0.12752	0.0082
5.00 – 5.99	I	10	15.6429	31.8423	2.0356
6.00 – 6.99	H	23	15.6429	54.1269	3.4602
7.00 – 7.99	G	20	15.6429	18.9843	1.2136
8.00 – 8.99	F	12	15.6429	13.2707	0.8483
9.00 – 9.99	E	10	15.6429	31.8423	2.0356
10.00– 10.99	D	11	15.6429	21.5565	1.3780
11.00– 11.99	C	13	15.6429	6.9849	0.4465
12.00– 12.99	B	8	15.6429	58.4139	3.7341
13.00 -13.99	A	10	15.6429	31.8423	2.0356
Total		N =219			29.2283

Table 7.6. Test statistics for dataset No.3

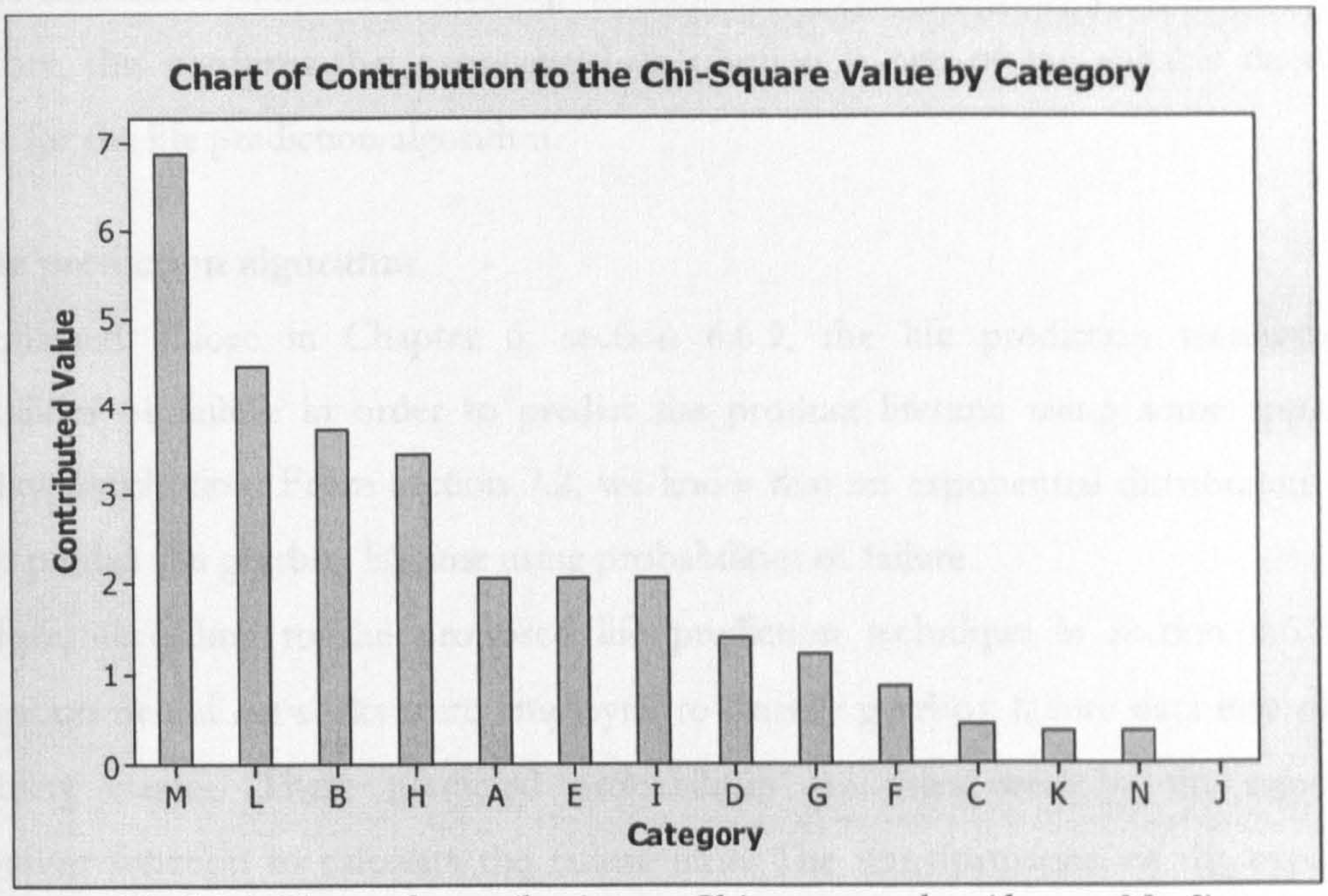


Fig.7.24. Chart of contribution to Chi-square value (dataset No.3)

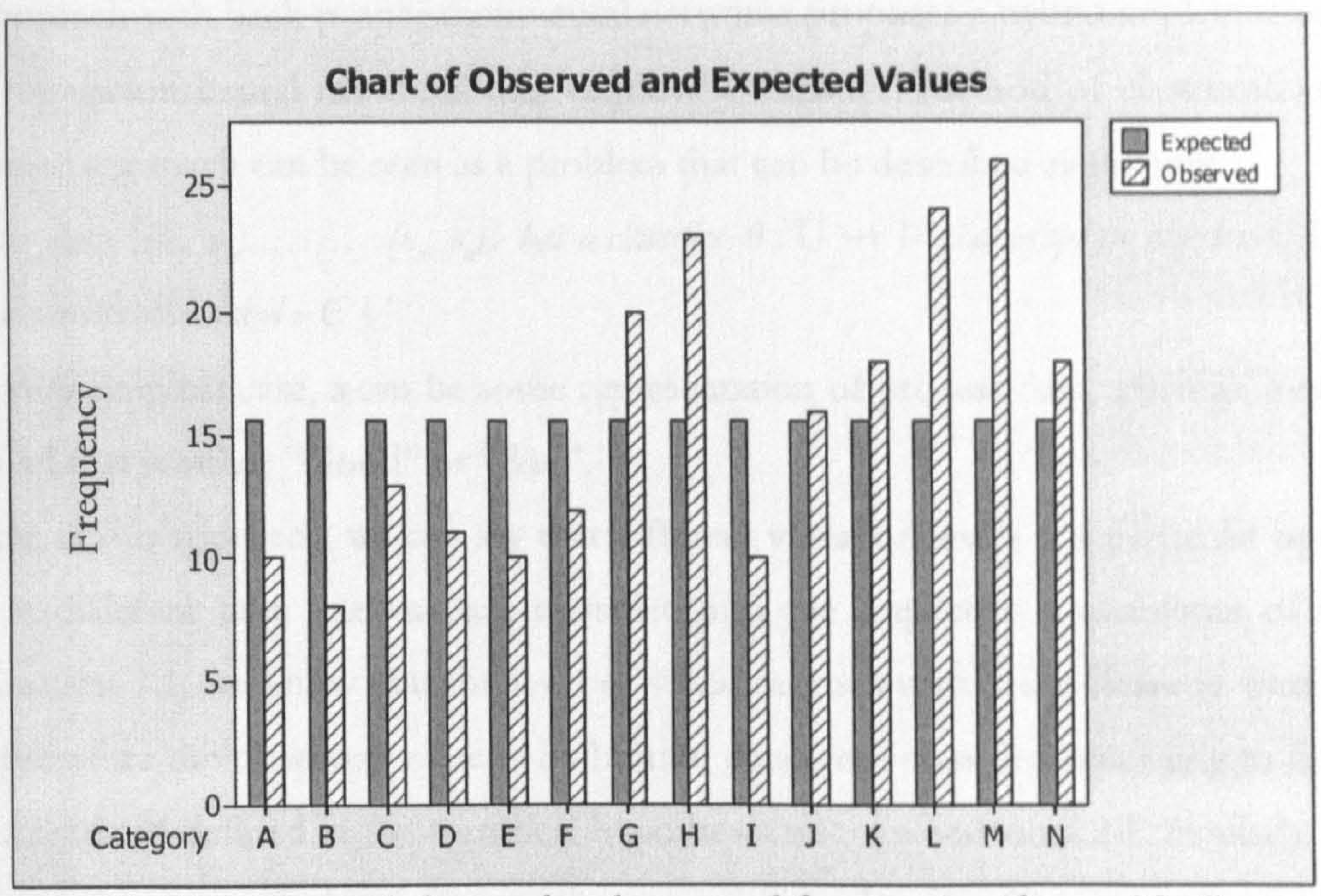


Fig.7.25. Chart of observed and expected frequencies (dataset No.3)

From the test results of dataset No.1, dataset No.2 and dataset No.3, it is found that the calculated value of the Chi-square statistic is less than the tabulated value. Hence, we can say that the simulation data follows an exponential distribution with the β value equal to 14. Therefore, this confirms that exponential distribution is one of the suitable distribution models for the life prediction algorithm.

7.3 Life prediction algorithm

As explained before in Chapter 6, section 6.6.9, the life prediction technique uses probabilities of failure in order to predict the product lifetime using some appropriate reliability distribution. From section 7.2, we know that an exponential distribution can be used to predict the gearbox lifetime using probabilities of failure.

Therefore, according to the proposed life prediction technique in section 6.6.9, back propagation neural networks were employed to classify gearbox failure data into different probability classes. These predicted probabilities are then used by the exponential distribution function to calculate the failure time. The transformation of the exponential distribution function to calculate time has already been explained in the previous section. This approach with back-propagation neural networks proposes a hybrid implementation of back-propagation neural networks that employs a statistical method of classification. This class-based approach can be seen as a problem that can be described as follows:

If training data $\{(u_1, v_1), \ldots\ldots\ldots (u_n, v_n)\}$ *has a classifier* $0 : U \rightarrow V$ *that maps an object* $u \in U$ *to the respective classification label* $v \in V$

In the very simplest case, u can be some representation of process data, whereas, v can be a class label that is either "Good" or "Bad".

Similarly, in our approach, we can say that different vibration levels at a particular operating speed at different time intervals are classified into the respective probabilities of failure. From section 7.1, we know that the level of vibration rises with the increase in wear of the gears, therefore the observed values of vibration data were classified according to different time intervals as defined in the statistical hypothesis test, see section 7.2.1. Similarly, failure probabilities were calculated using the probability density function of exponential distribution.

S No.	Time to fail (hours)	Class	Assigned probability of failure
1	0.00 – 0.99	N	0.071
2	1.00 – 1.99	M	0.067
3	2.00 – 2.99	L	0.062
4	3.00 – 3.99	K	0.058
5	4.00 – 4.99	J	0.054
6	5.00 – 5.99	I	0.050
7	6.00 – 6.99	H	0.047
8	7.00 – 7.99	G	0.043
9	8.00 – 8.99	F	0.040
10	9.00 – 9.99	E	0.038
11	10.00– 10.99	D	0.035
12	11.00– 11.99	C	0.033
13	12.00– 12.99	B	0.030
14	13.00 -13.99	A	0.028

Table 7.7. Classes and assigned target probabilities

These calculated failure probabilities were assigned as a classification label for each class of observed values during a particular time interval of the test. Table 7.7 shows classes and the assigned probability values at an operating speed of 40 RPM.

The life prediction algorithm is stored in the program memory of the Axis device server. Initially, it was programmed in GNU C and later compiled under the Criss cross-compiler in order to execute in the Axis device server embedded environment. The code is stored in the form of an executable binary file. It consists of a back propagation neural network that consists of three layers. The first layer is the input layer followed by a middle layer and an output layer. It takes two inputs, the vibration and the operational speed, which is kept constant at 40 RPM as the test was conducted at this speed.

The vibration data that is coming from the RS232 port of the Axis device server is first normalised and then fed to the life prediction algorithm. One of the reasons for using this class-based approach is its easy implementation in the embedded and real time system. The life prediction software also uses a text file. This text file contains a trained neural network, basically the adjusted weights that are required to classify different levels of degradation of the gearbox into respective probabilities of failure. A program is written to train the neural network externally. The program takes the sets of inputs and the desired outputs that are the probabilities of failure in the form of training sets. The training sets are stored in the form of a text file and then fed to the training software. The training software then initially creates a neural network with random weights and then trains the network according to the sets of inputs and the desired outputs that are fed to the training software in the form of a text file. The training software then generates another text file that is a trained neural network. This file of the trained neural network is sent or transferred to the program memory of the Axis device server in the ASCII format. The life prediction software then uses this trained neural network to classify the degradation behaviour of the gearbox. The programmed neural networks were trained until the output error was minimised to zero up to four places of decimals. The reason for doing this was to ensure the classification performance of neural networks into exact probabilities of failure that are actually floating point decimal and in the form of three places after the decimal point such as 0.028, 0.030, 0.071, etc. The probability of failure that neural networks fire is then used by the probability density function of the exponential distribution to predict the lifetime of the gearbox. Neural networks were tested with different classes of data values. The next section explains the results of the response of the programmed neural networks.

7.3.1 Results and discussion

The performance of programmed neural networks was evaluated for different data classes; Figure 7.26 shows the response for data class A. The solid line in the graph shows the response of the neural network, which is the probability of failure, whereas the dotted line represents the desired output or desired probability of failure. Despite of the fact that the programmed neural networks were trained until the training error had been reduced to zero up to four places of decimals (0.0000) but this type of behaviour can be expected from neural networks if the classification is required with the precision to classify probability classes that are in the range of 0.028 to 0.071. Classifying the outputs to such a level of precision is indeed a difficult task. Fluctuations in the solid line graph show the actual behaviour of the neural networks that ideally should follow the straight dotted line as shown in the figure 7.26. Graphs of neural network response for classes A to N are presented in the following pages.

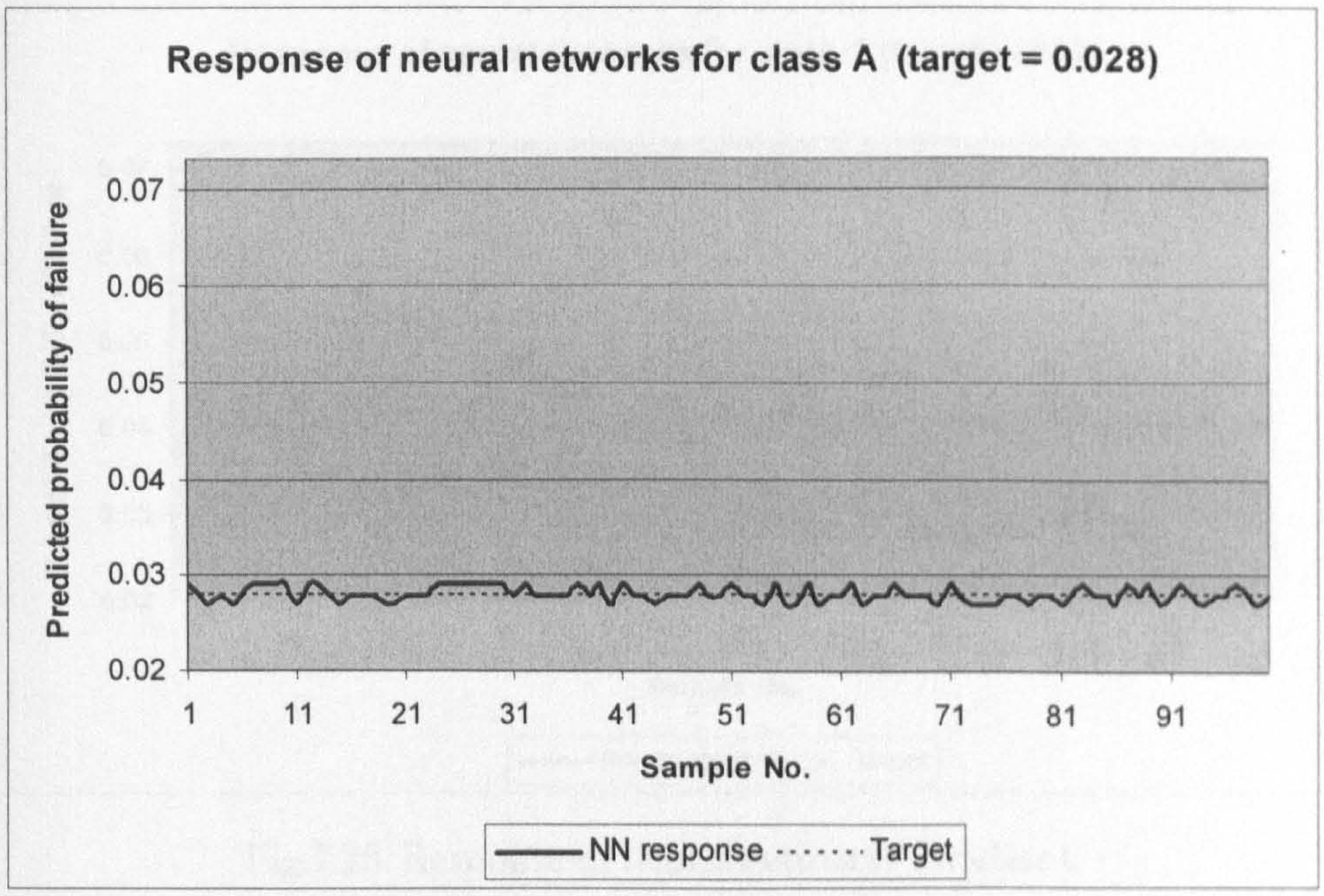


Fig.7.26. Response of neural networks for class A

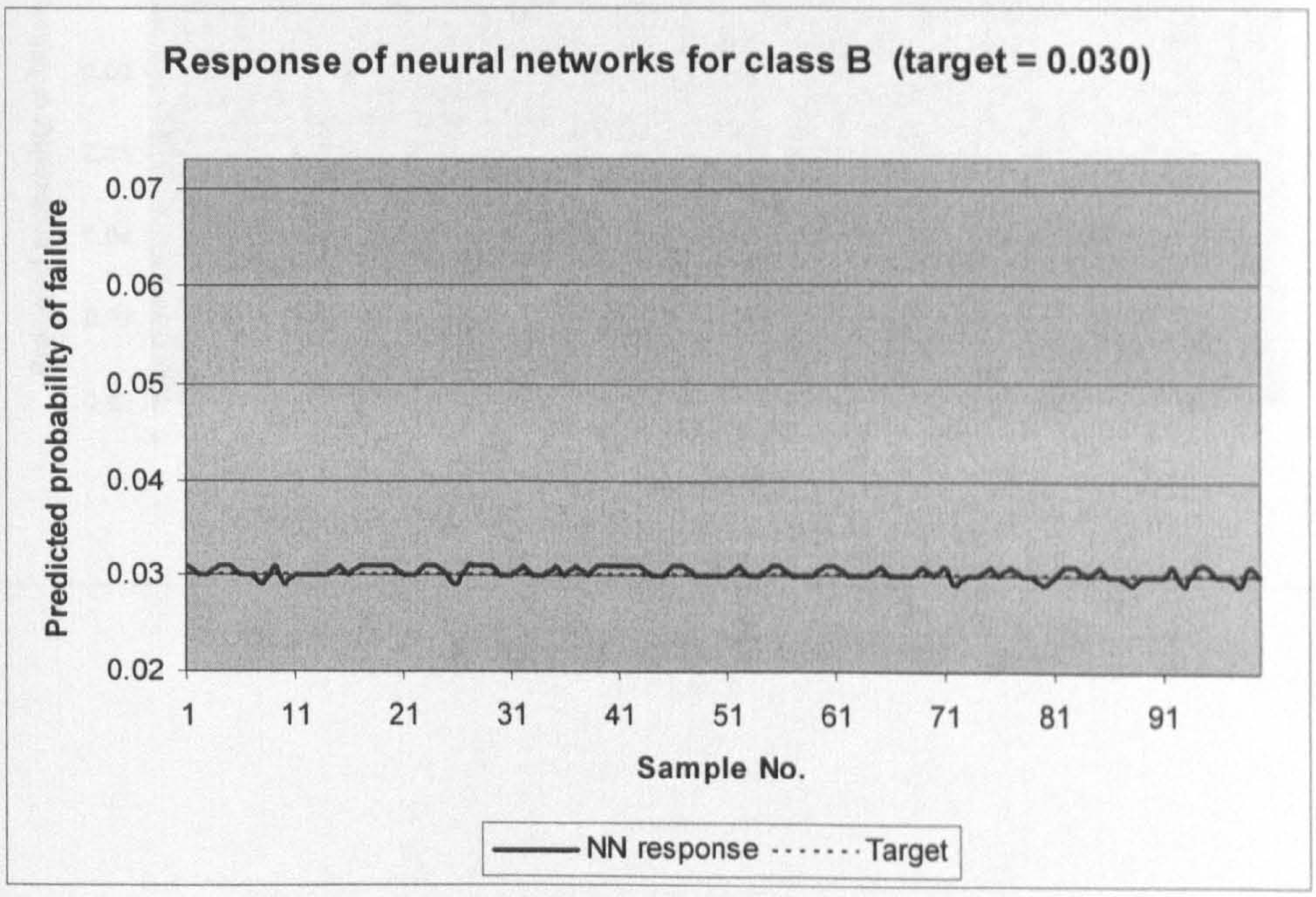


Fig.7.27. Response of neural networks for class B

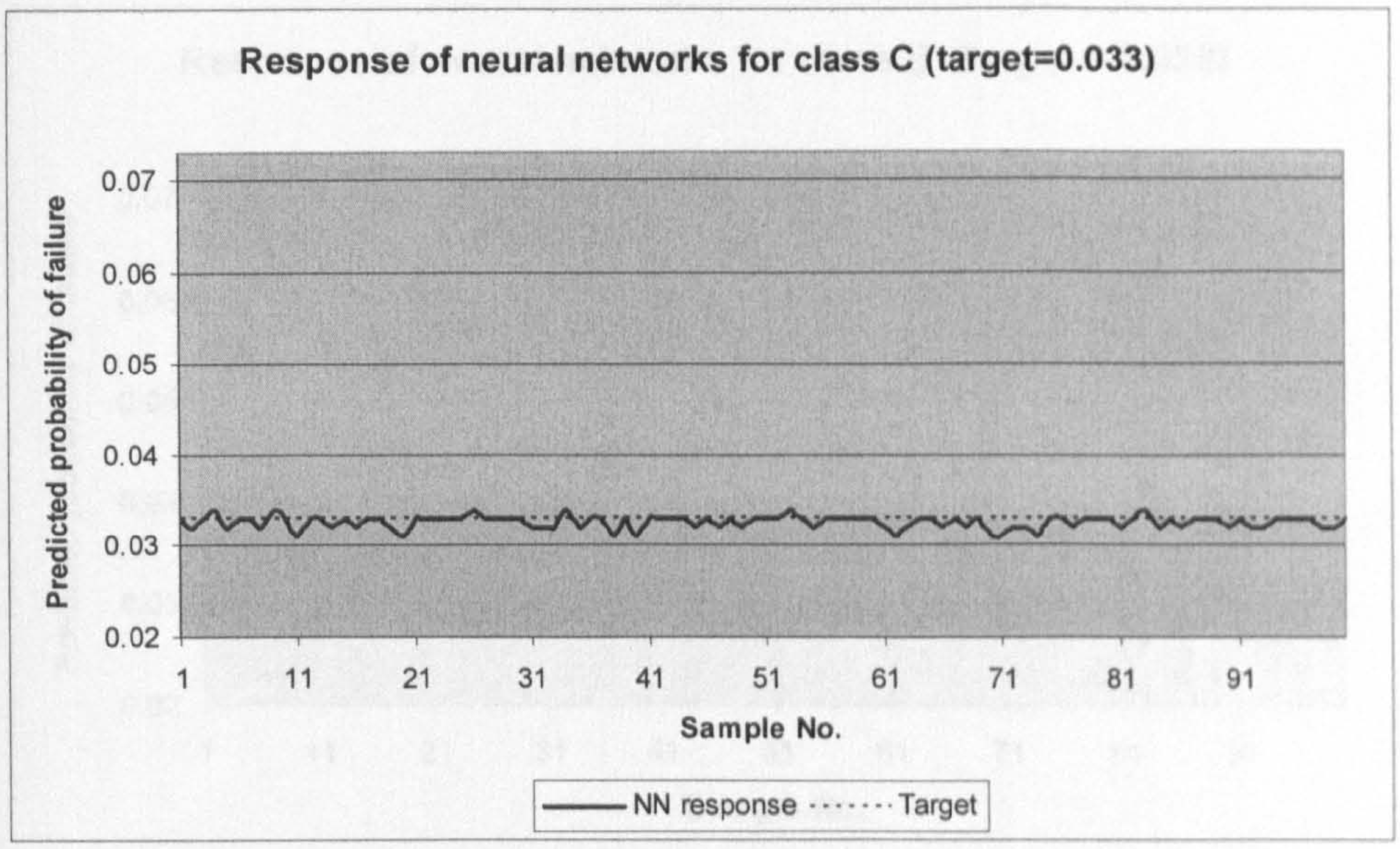


Fig.7.28. Response of neural networks for class C

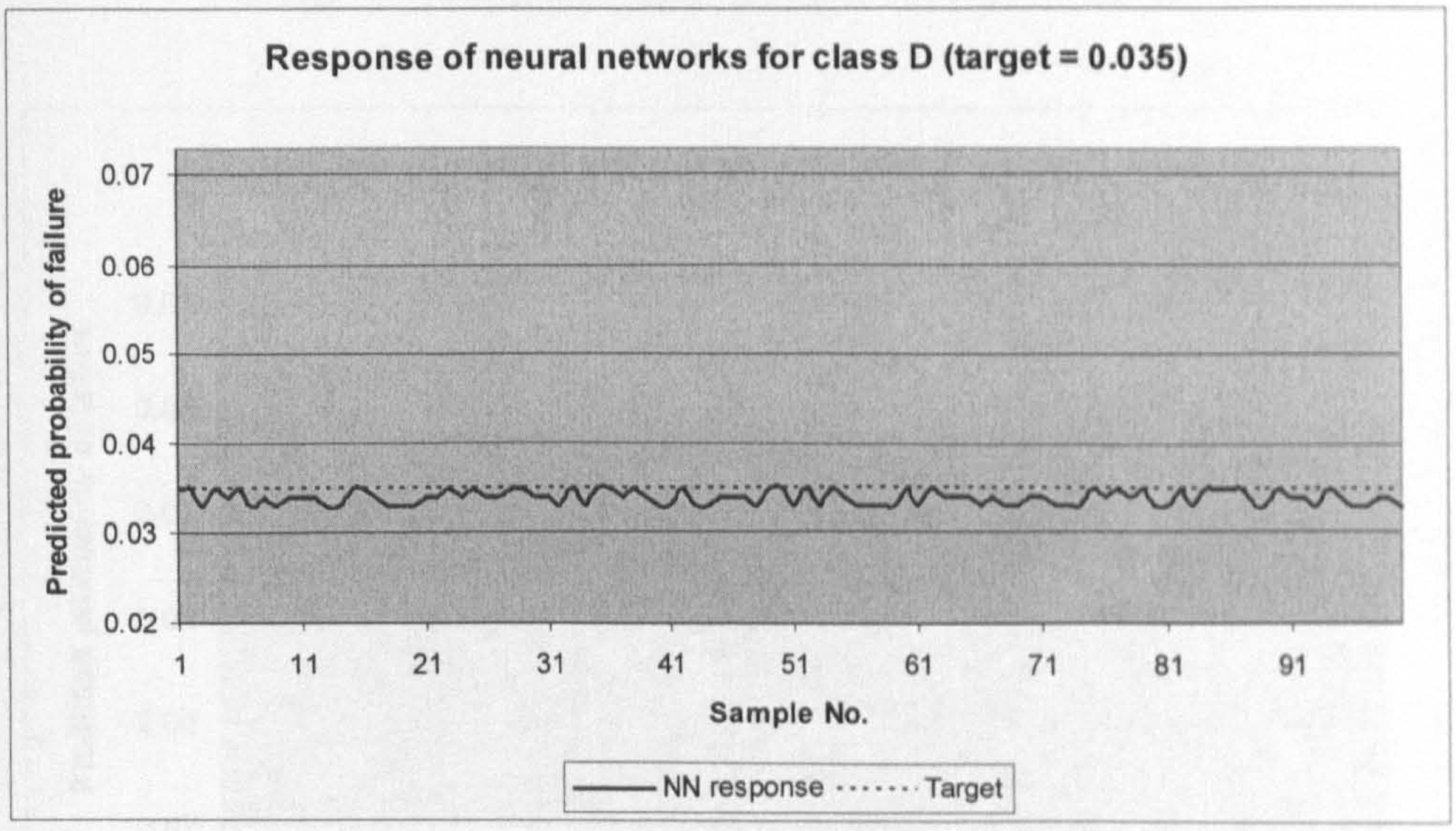


Fig.7.29. Response of neural networks for class D

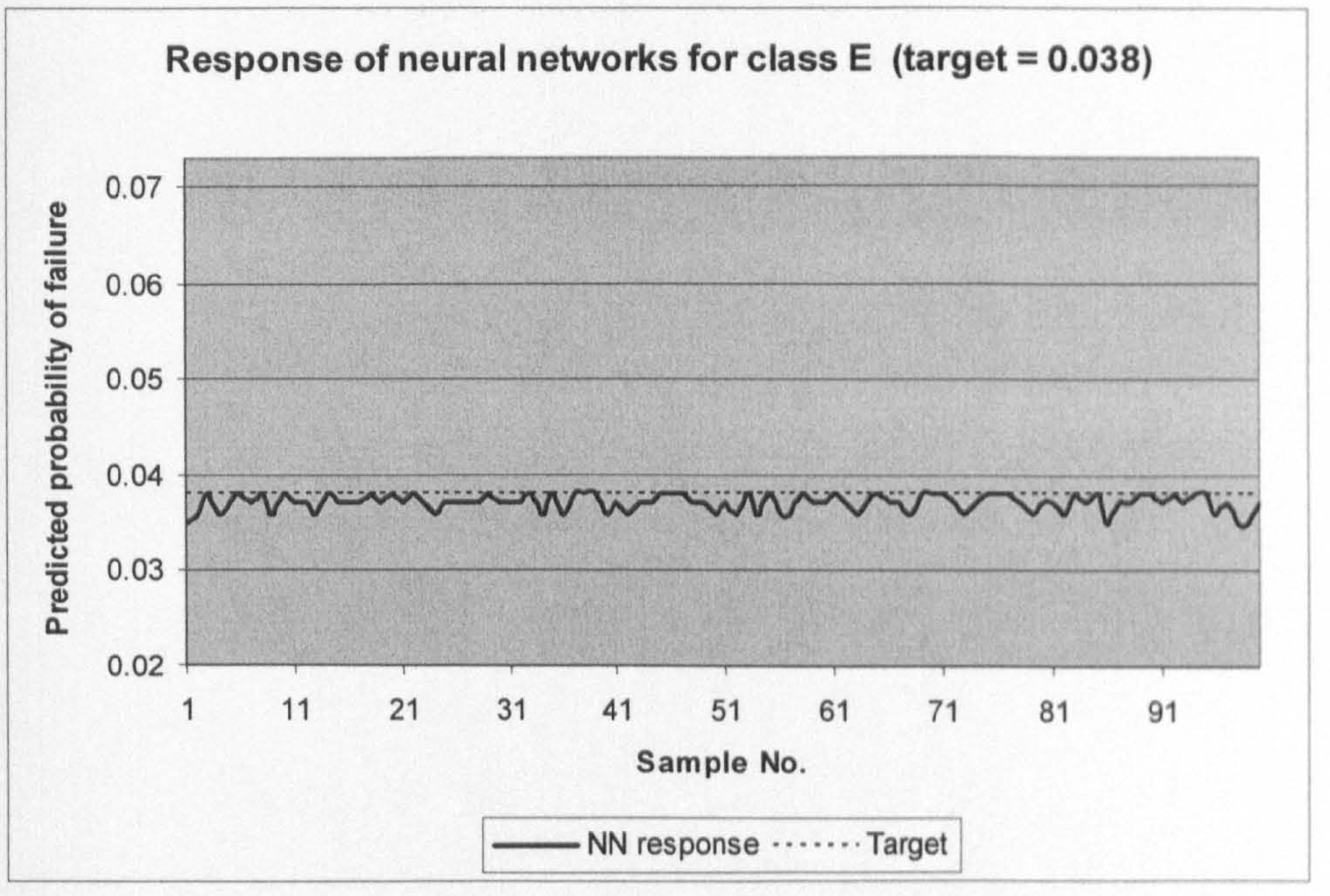


Fig.7.30. Response of neural networks for class E

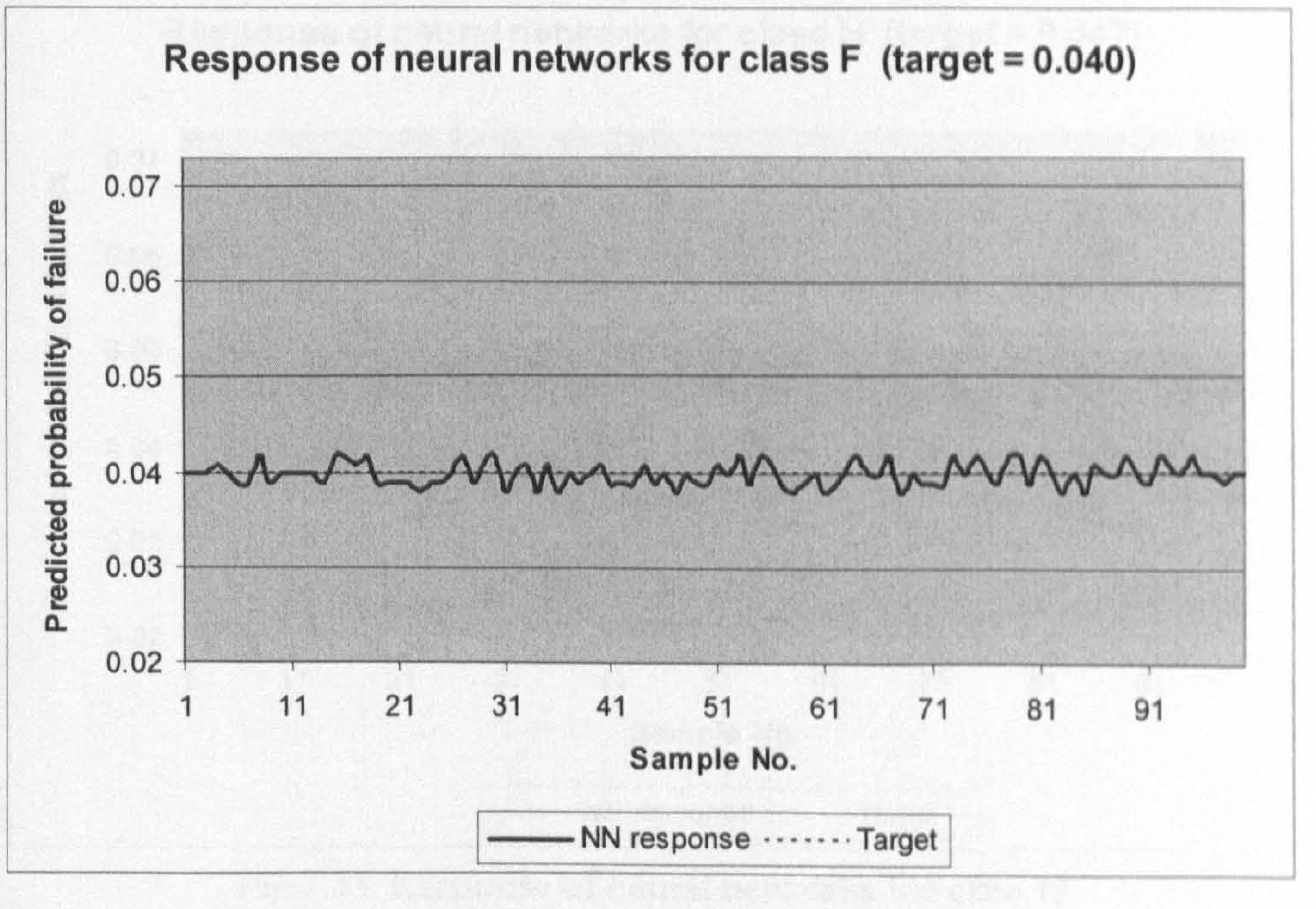


Fig.7.31. Response of neural networks for class F

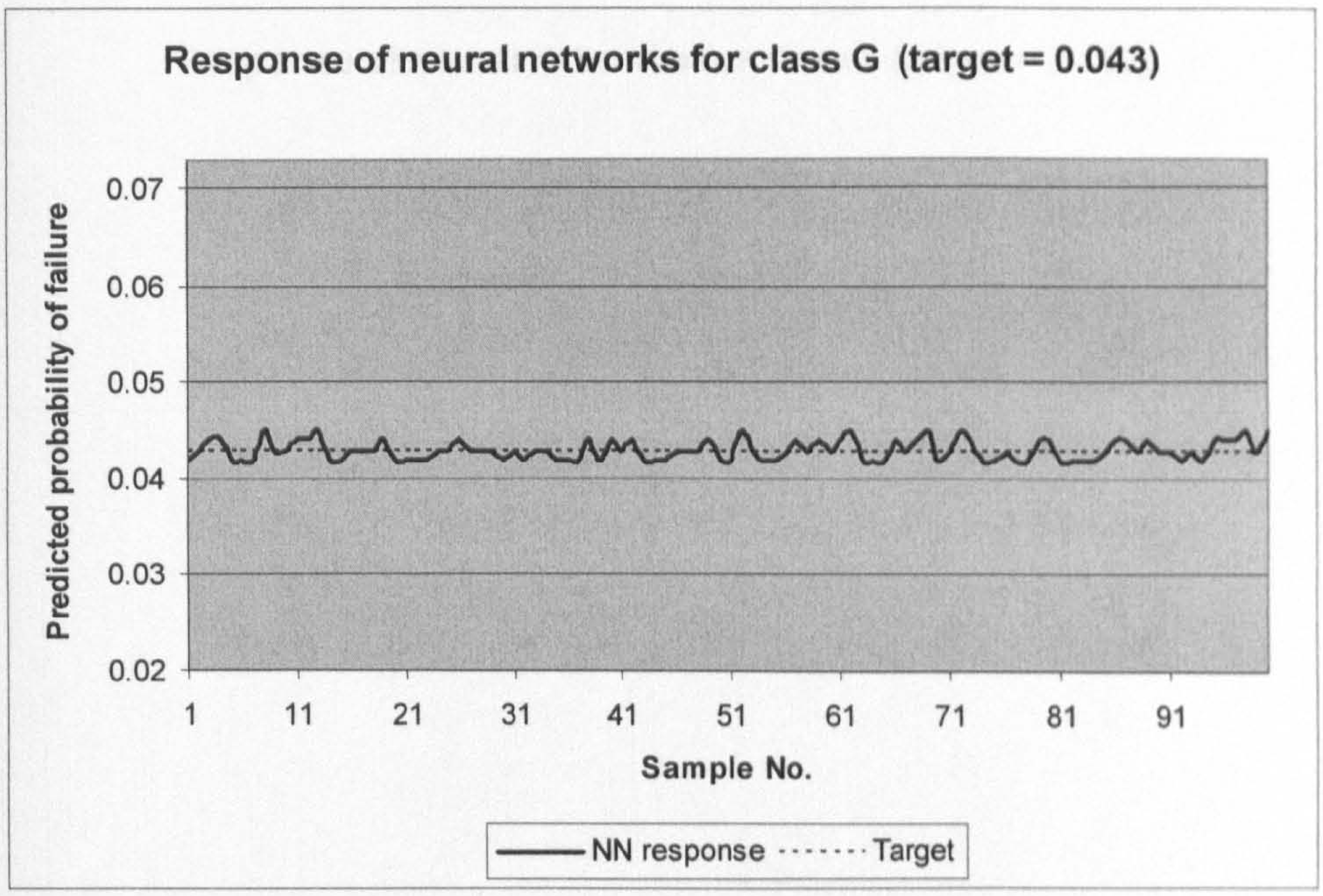


Fig.7.32. Response of neural networks for class G

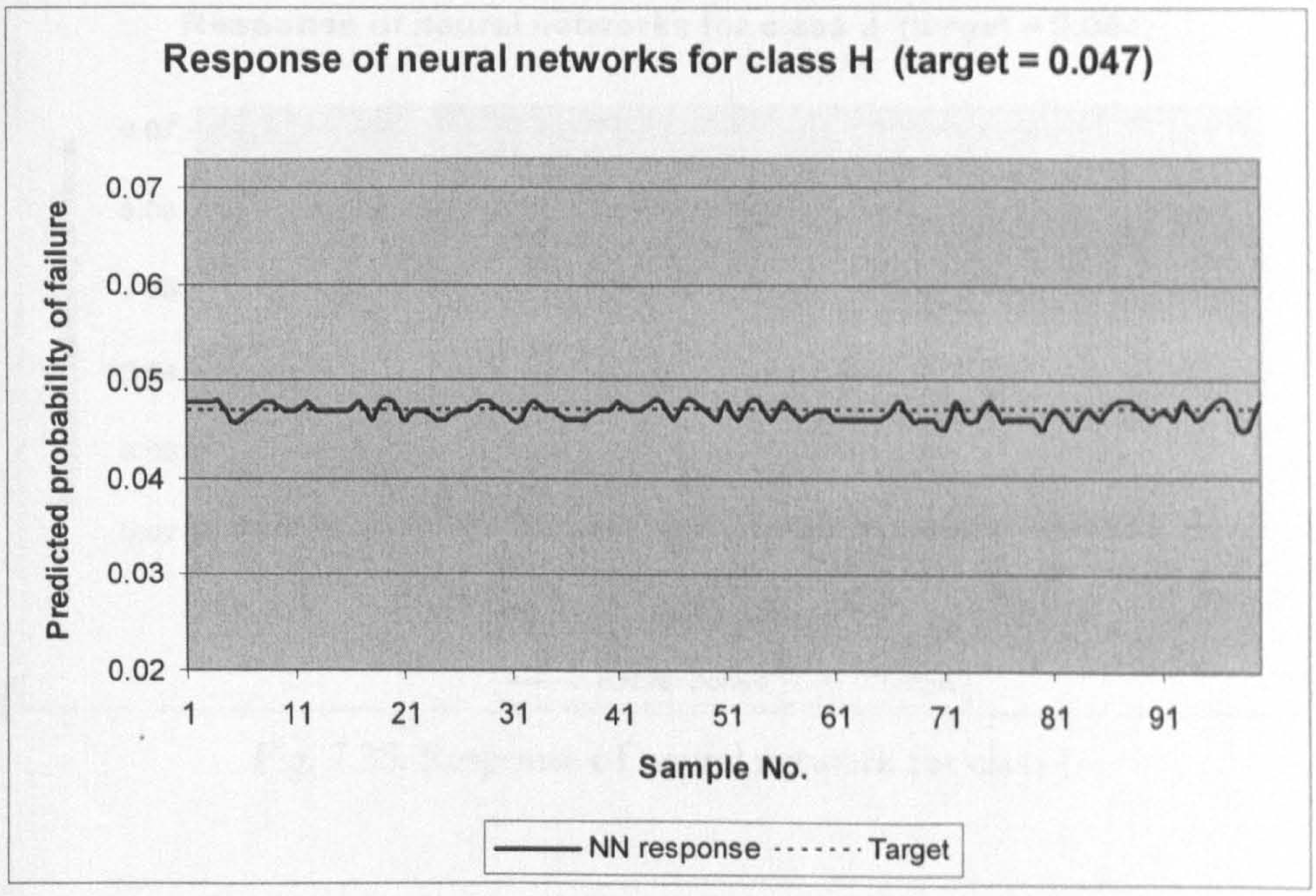


Fig.7.33. Response of neural networks for class H

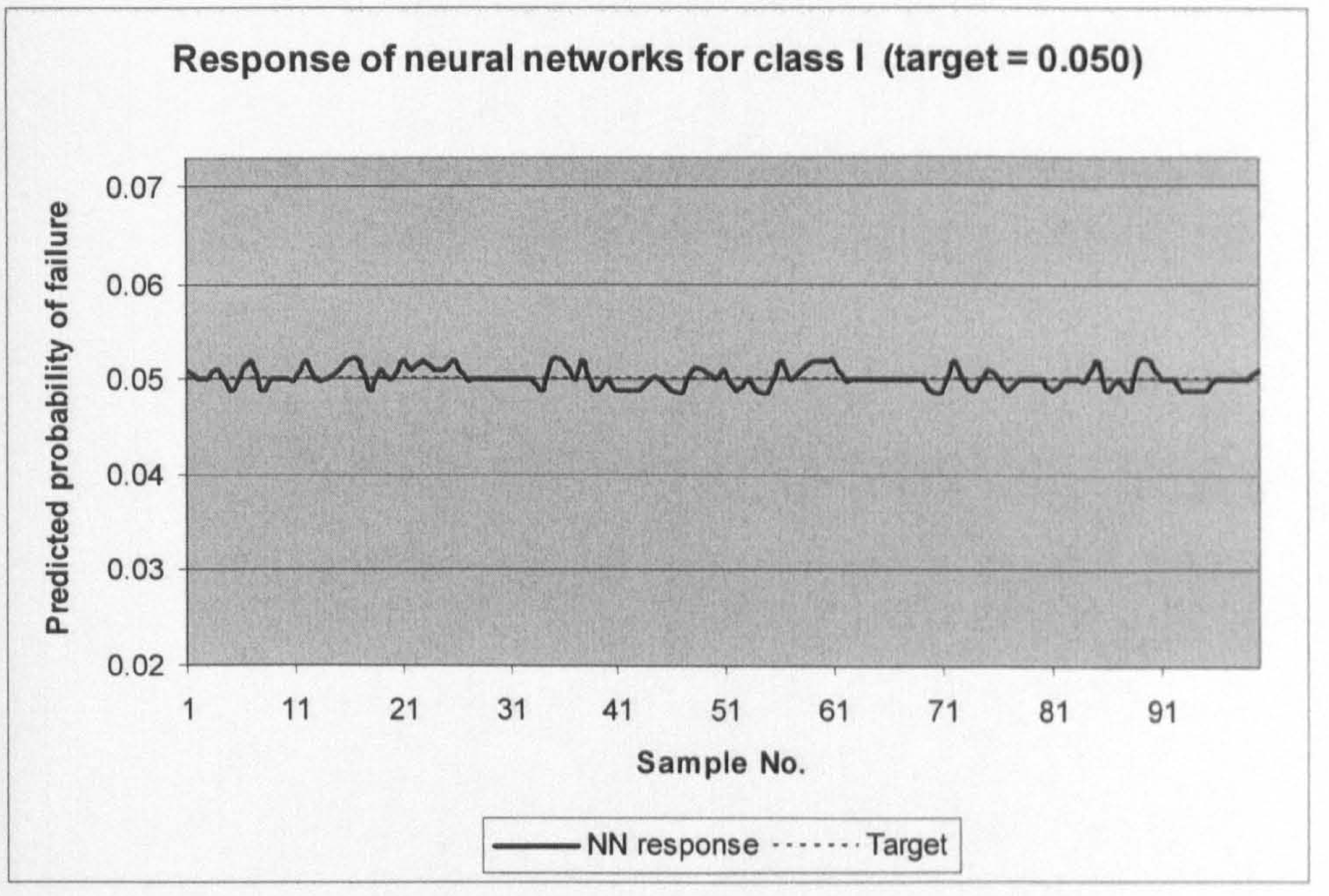


Fig.7.34. Response of neural networks for class I

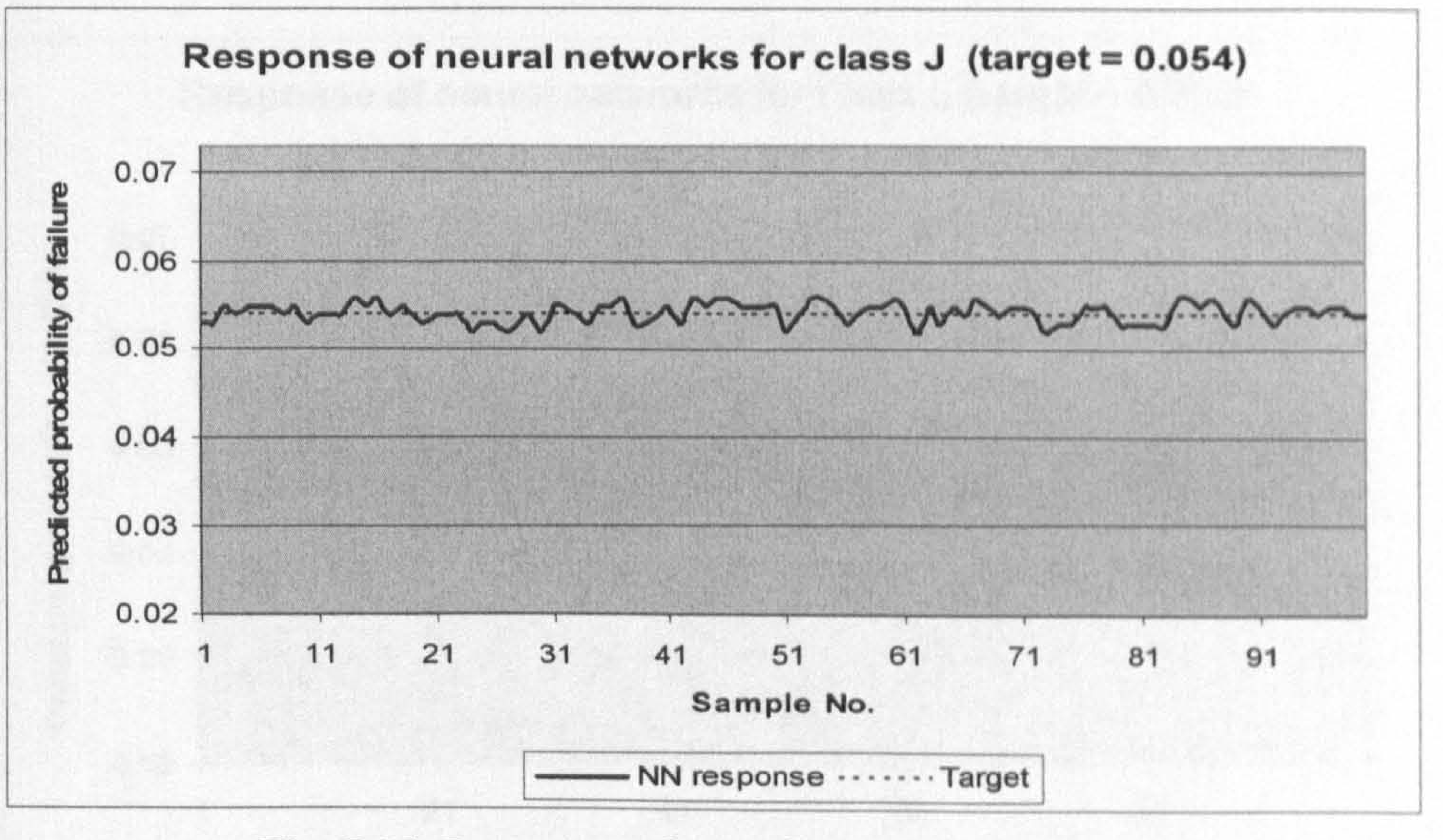


Fig. 7.35. Response of neural network for class J

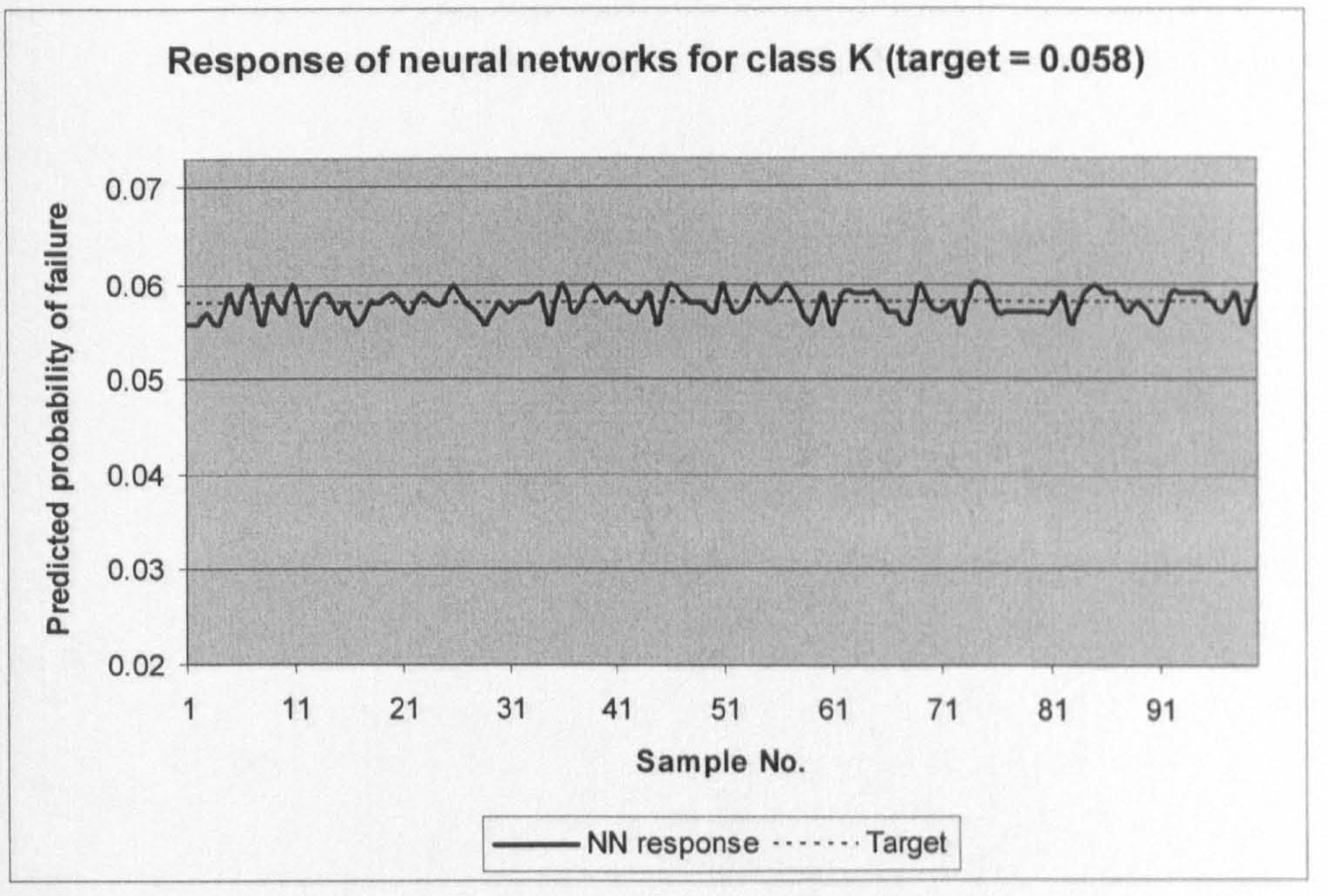


Fig.7.36. Response of neural networks for class K

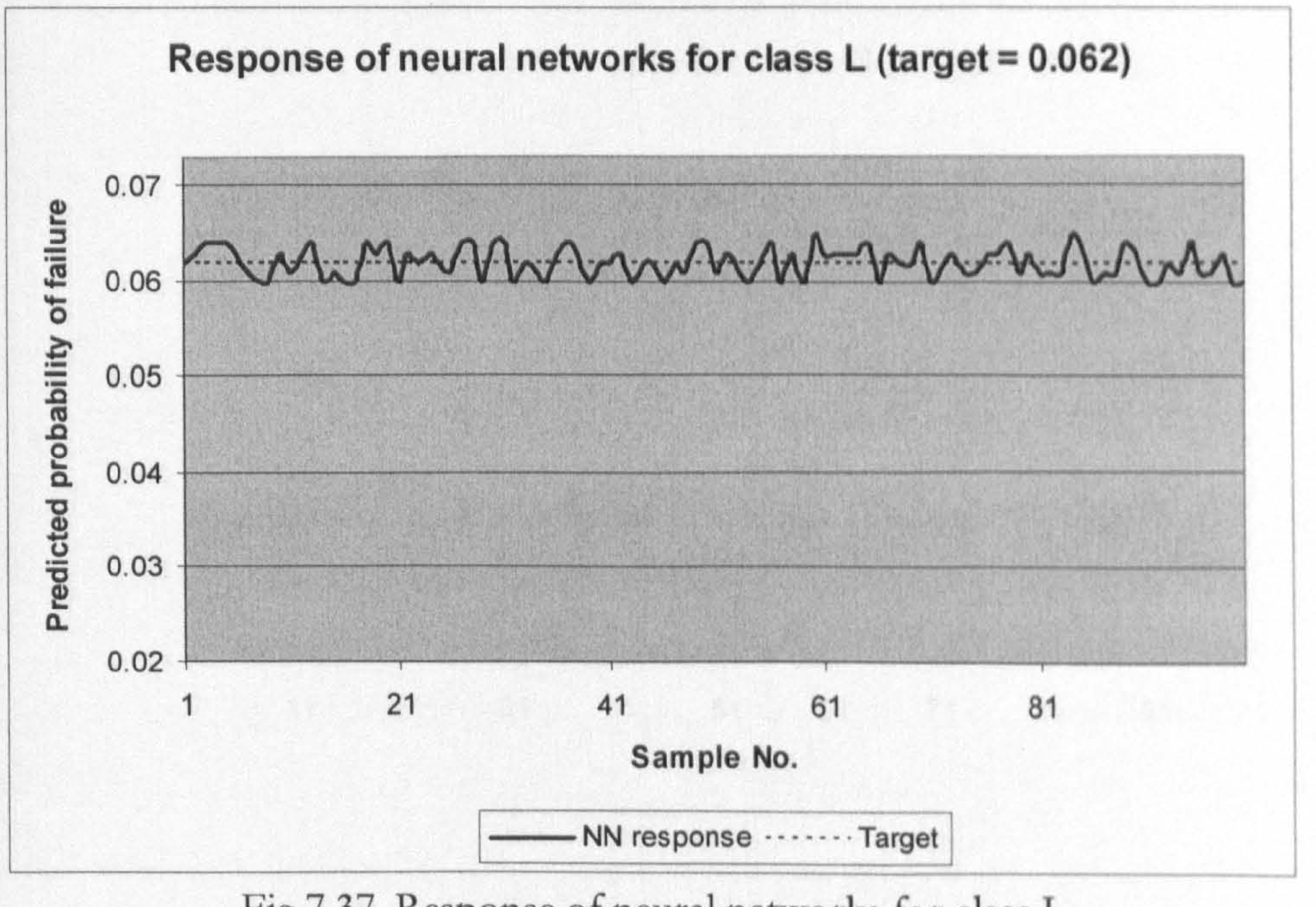


Fig.7.37. Response of neural networks for class L

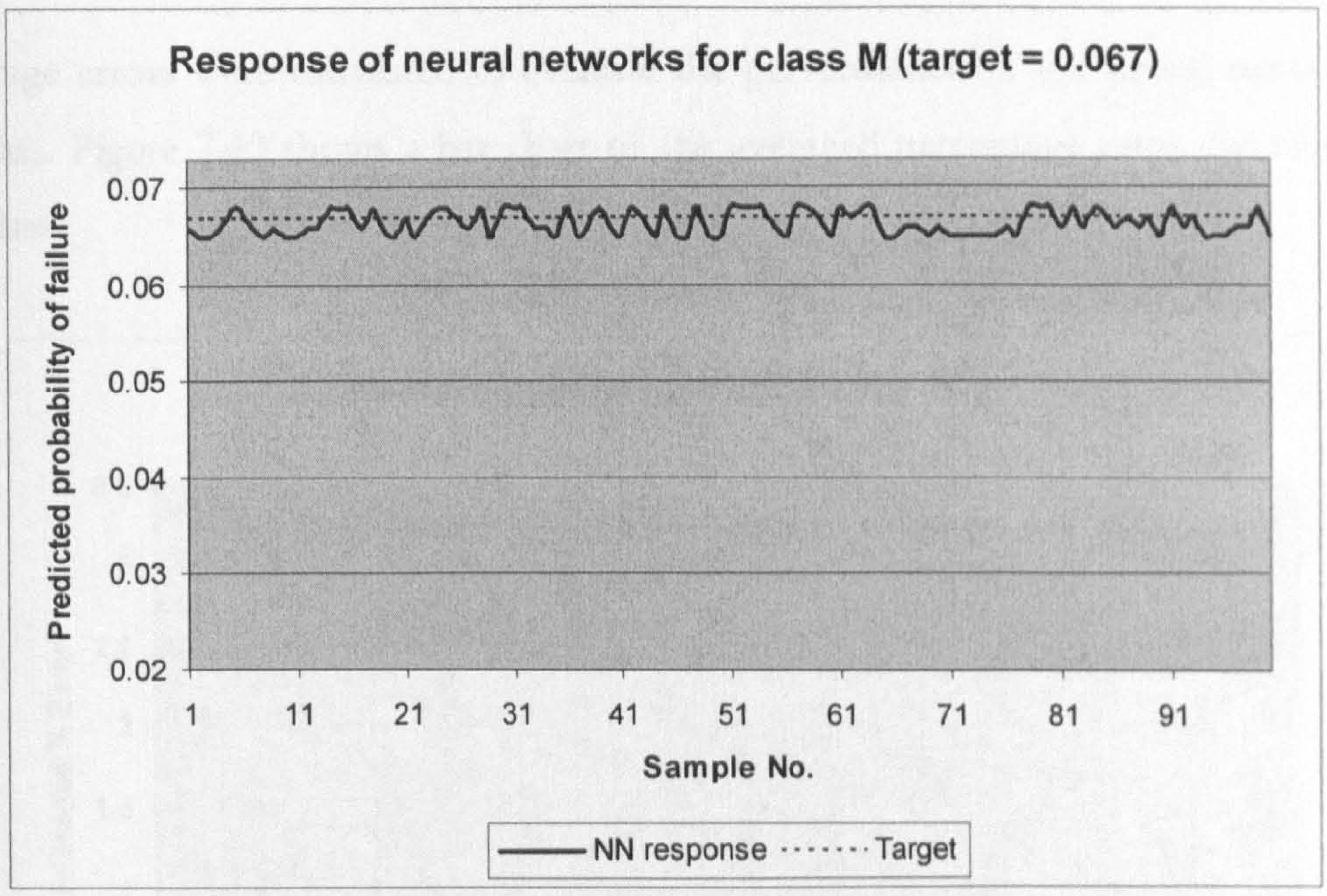


Fig.7.38. Response of neural networks for class M

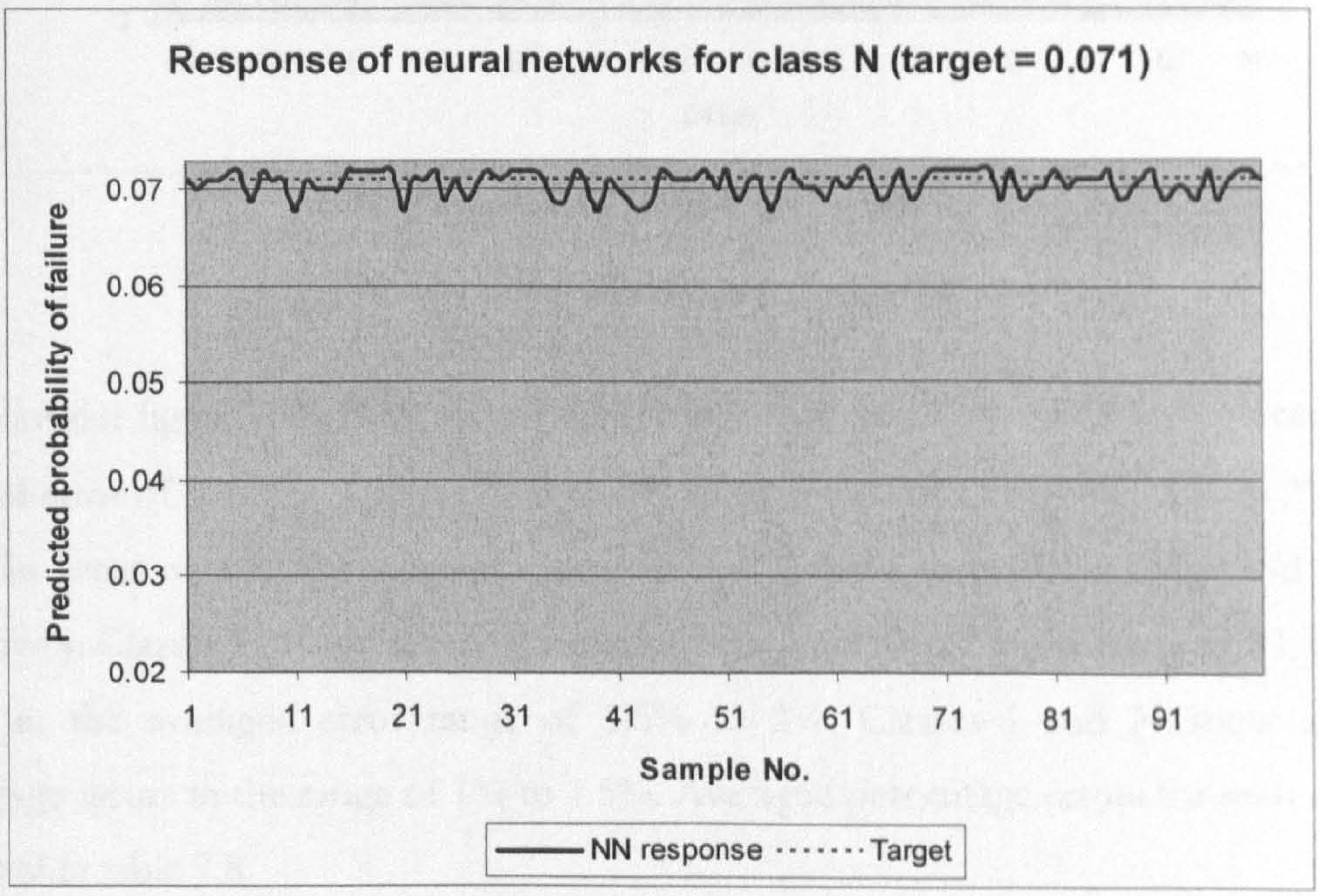


Fig.7.39. Response of neural networks for class N

Percentage errors were calculated to evaluate the performance of the neural networks for each class. Figure 7.40 shows a bar chart of the averaged percentage error contributed by every class.

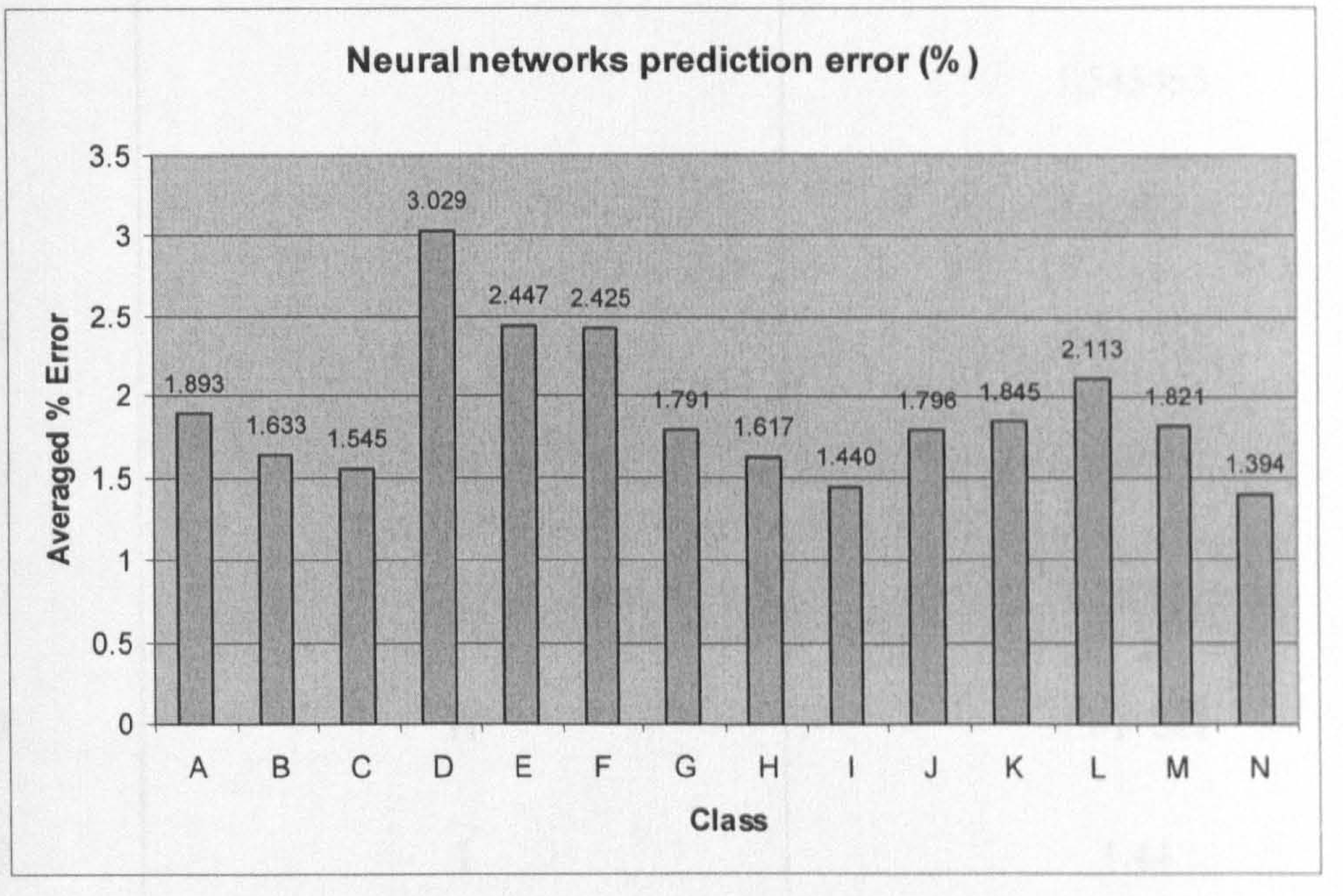


Fig.7.40. Bar chart of averaged percentage error

If we consider figure 7.40, then we can easily judge that class D shows a high percentage of averaged error of 3.029%. Classes A, B and C fall into the error range of 1.5% to 2%. Class A has an error of 1.893%, whereas classes B and C have errors of 1.633% and 1.545% respectively. Classes E, F and L fall in the error range of 2% to 2.5%. Classes G, H, J, K and M fall in the averaged error range of 1.5% to 2%. Classes I and N show averaged percentage errors in the range of 1% to 1.5%. Averaged percentage errors for each class are presented in table 7.8.

S No.	Class	Average % Error
1	A	1.892857
2	B	1.633333
3	C	1.545455
4	D	3.028571
5	E	2.447368
6	F	2.425
7	G	1.790698
8	H	1.617021
9	I	1.44
10	J	1.796296
11	K	1.844828
12	L	2.112903
13	M	1.820896
14	N	1.394366
Average		1.913543

Table 7.8. Values of averaged % Error

Figure 7.41 shows the scatter plot of failure time calculated by the life prediction algorithm using these probabilities of failure.

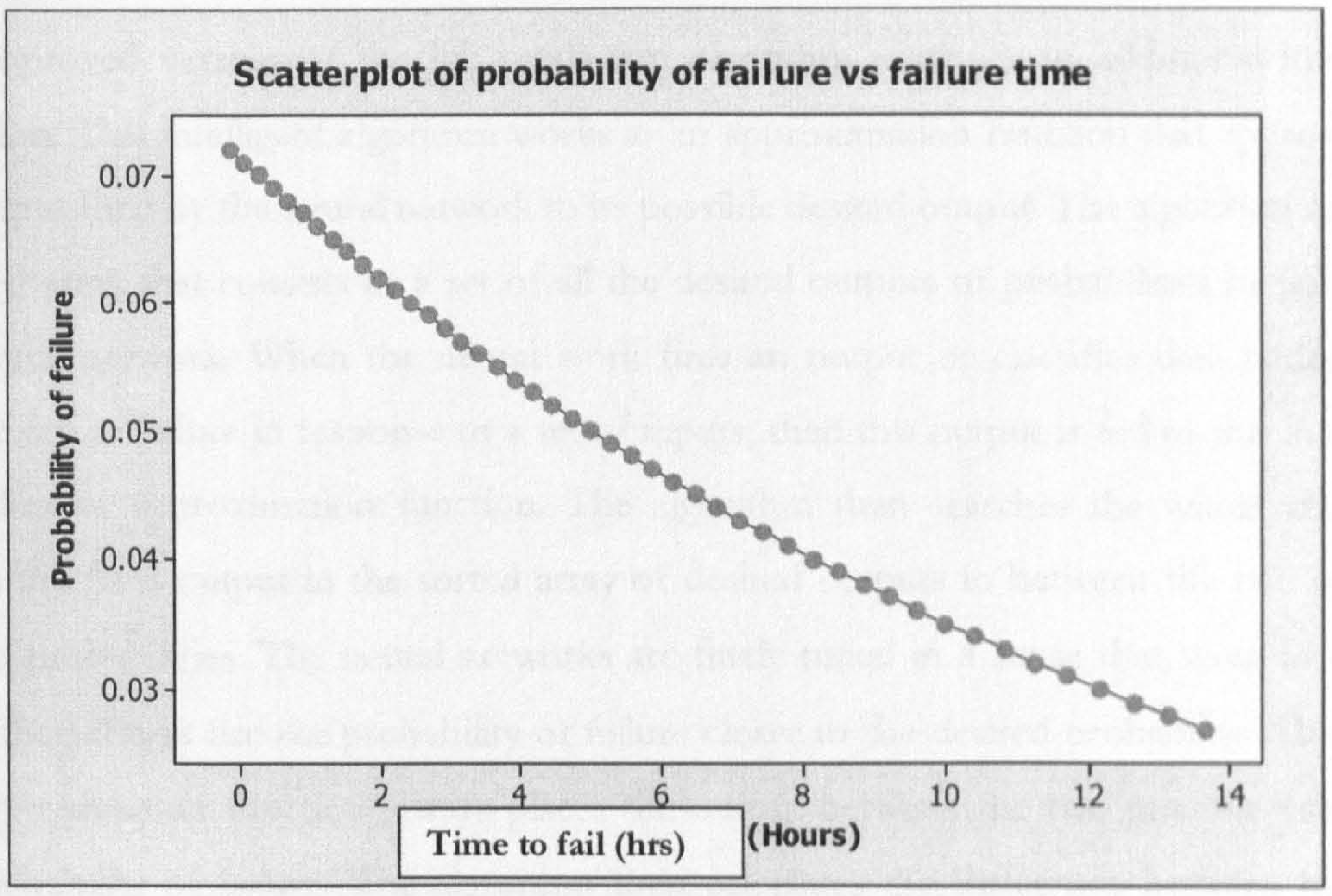


Fig.7.41. Scatter plot of failure probability Vs failure time

If we consider the graph presented in figure 7.41, then from the shape of the plot we can see that the scatter plot is the probability density function plot of the exponential distribution. However, if we consider the graph in detail, then we can see that some of the calculated time values are negative. These values can be seen crossing zero on the time scale. This is because of errors in the probability prediction by neural networks that result in negative values for time. Therefore, this plot shows a negative exponential distribution that contradicts the assumption made in section 7.2. This suggests an improvement in the life prediction algorithm to make more accurate predictions. The next section explains the improvements made to the life prediction algorithm.

7.3.2 Improvement in the life prediction algorithm

The improved version of the life prediction algorithm contains an additional intelligent algorithm. This intelligent algorithm works as an approximation function that approximates the output fired by the neural network to its possible desired output. The algorithm contains a sorted array that consists of a set of all the desired outputs or probabilities of failure for the neural network. When the neural work fires an output or classifies data under some probability of failure in response to a set of inputs, then this output is fed to this intelligent algorithm or approximation function. The algorithm then searches the whole array and inserts the fired output in the sorted array of desired outputs in between the two possible desired probabilities. The neural networks are finely tuned in a sense that, even in case of error, they always fire the probability of failure closer to the desired probability. Therefore, the approximation function always places the output between the two possible values for the probability of failure. The algorithm then calculates the difference between the fired probability and the possible desired outputs. Finally, it approximates the fired probability to the possible desired probability that has less difference with the fired output. The next section explains the results after improvement in the life prediction algorithm.

Results after improvement

Figure 7.42 shows the response of the neural networks for class A after improvement in the life prediction algorithm. If we compare this response with the response for data class A before improvement (see figure 7.26) then we will see that the fluctuation in the graph has reduced to the extent that the trend of response is linear. Graphs of neural network responses after improvement in the life prediction algorithm are presented in the next pages (see figures No. 7.43 to 7.54). If we compare all these graphs with the graphs of neural network response before improvement in the life prediction algorithm (consider figures No. 7.26 to 7.39) then a great improvement is observed in the response of the neural networks, which proves the efficiency of the improved algorithm.

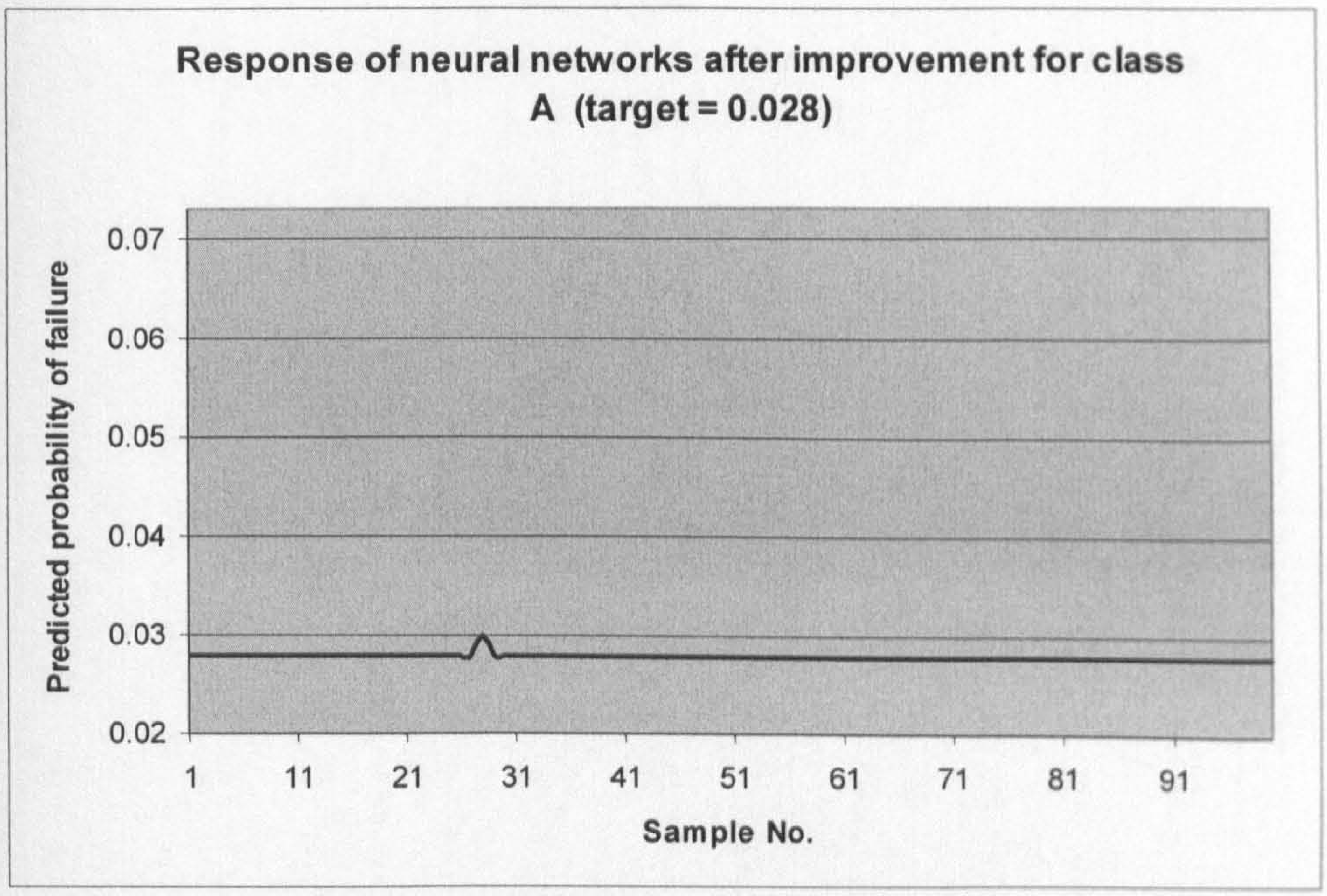


Fig.7.42. Response of neural networks for class A (after improvement)

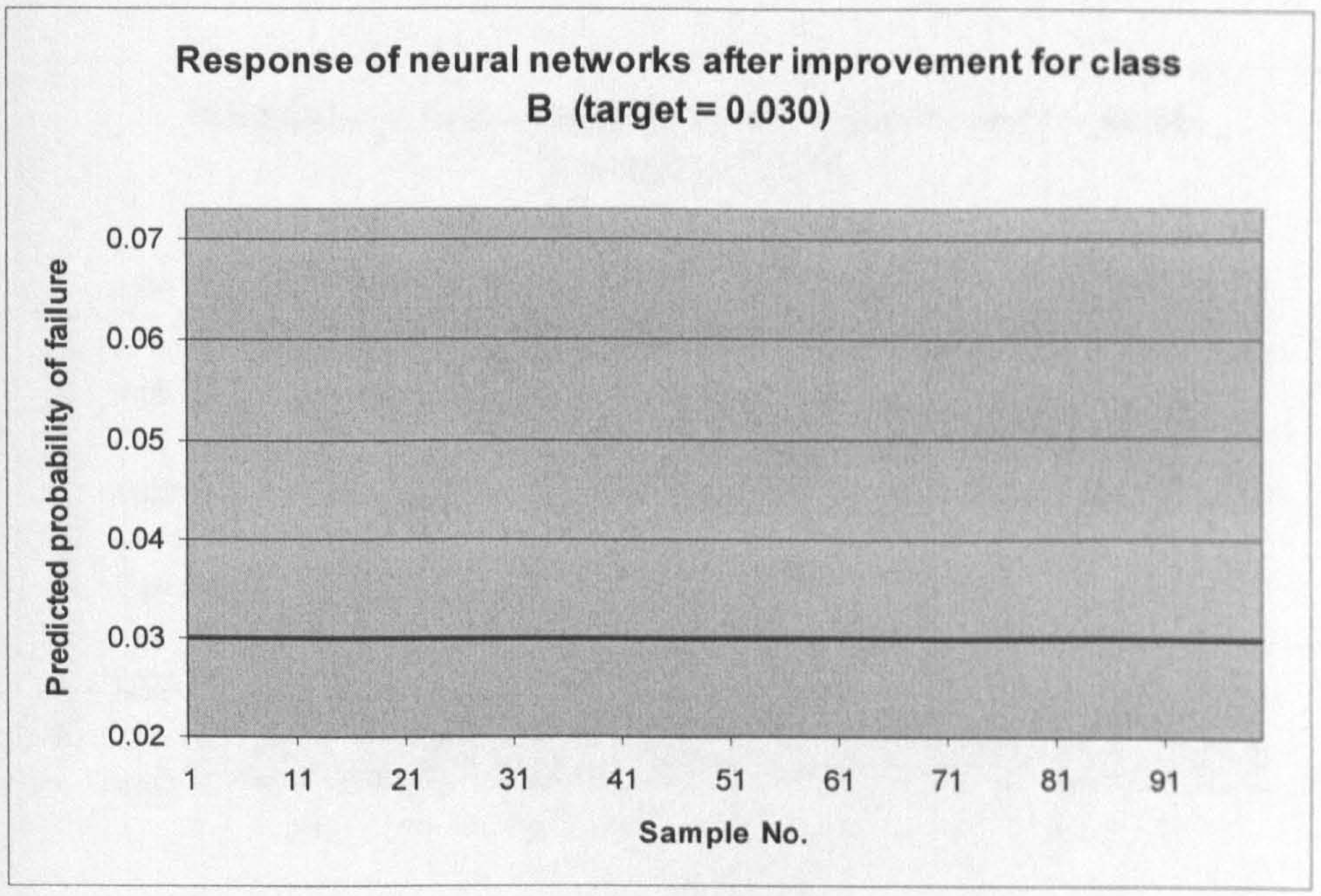


Fig.7.43. Response of neural networks for class B (after improvement)

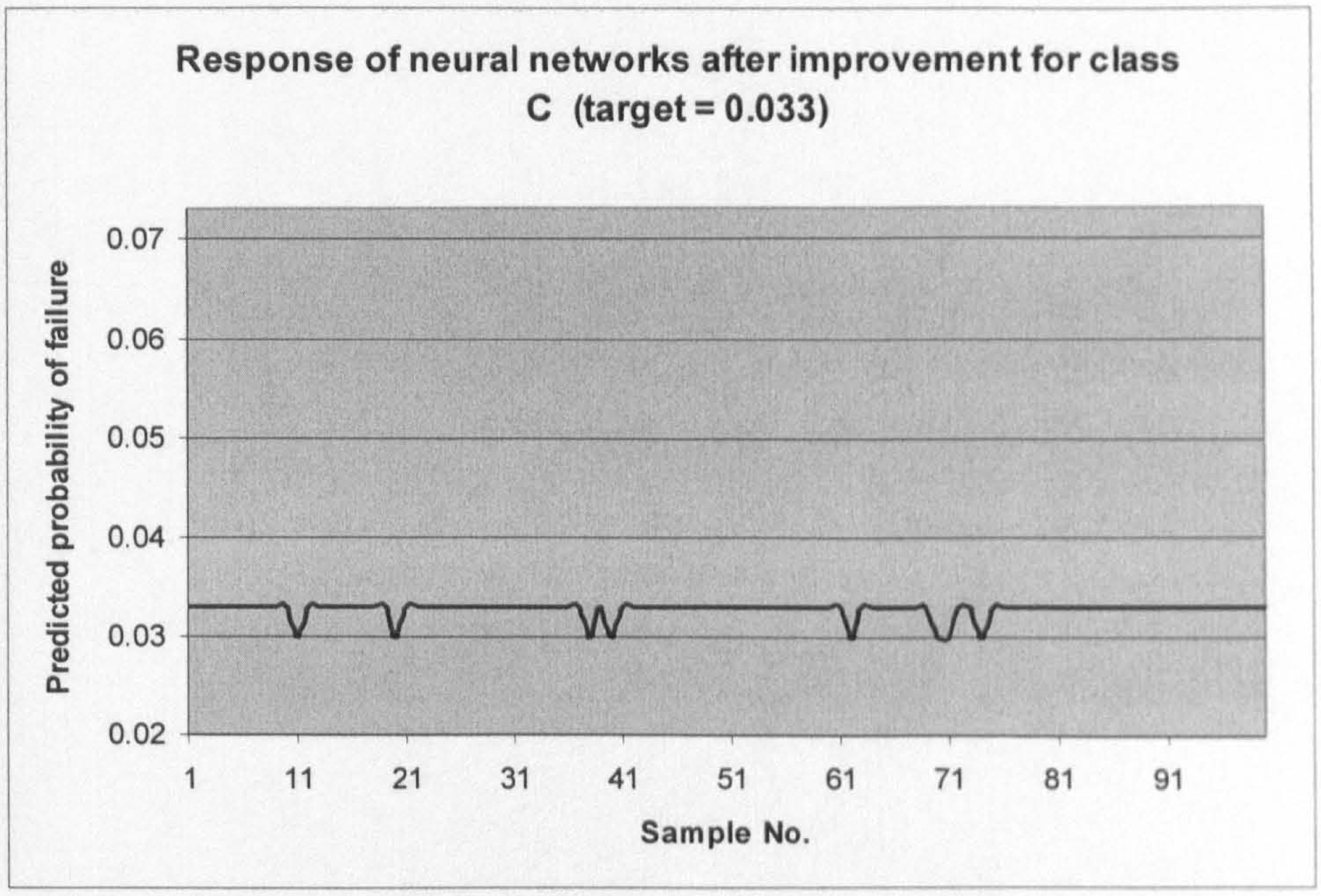


Fig.7.44. Response of neural networks for class C (after improvement)

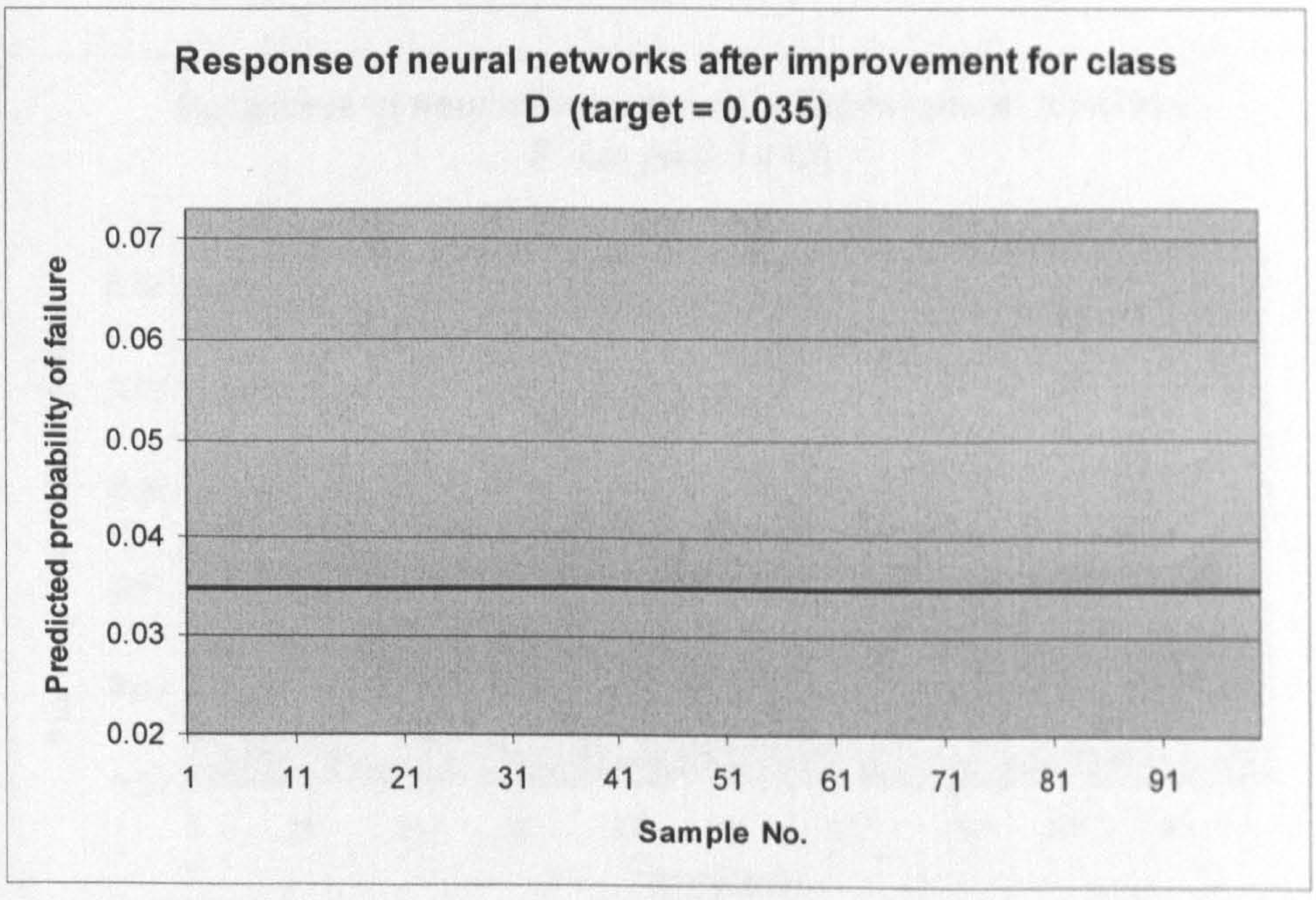


Fig.7.45. Response of neural networks for class D (after improvement)

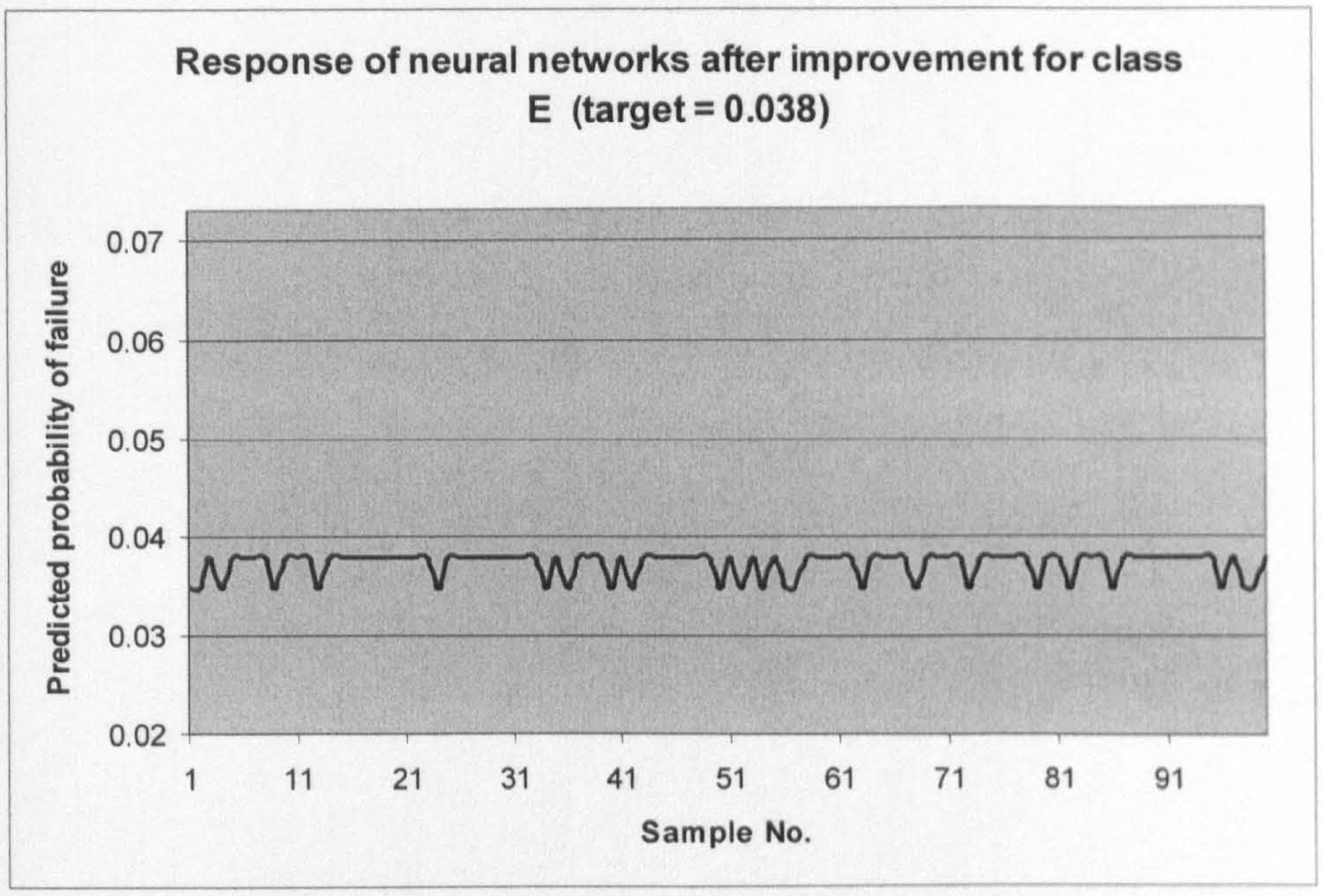


Fig.7.46. Response of neural networks for class E (after improvement)

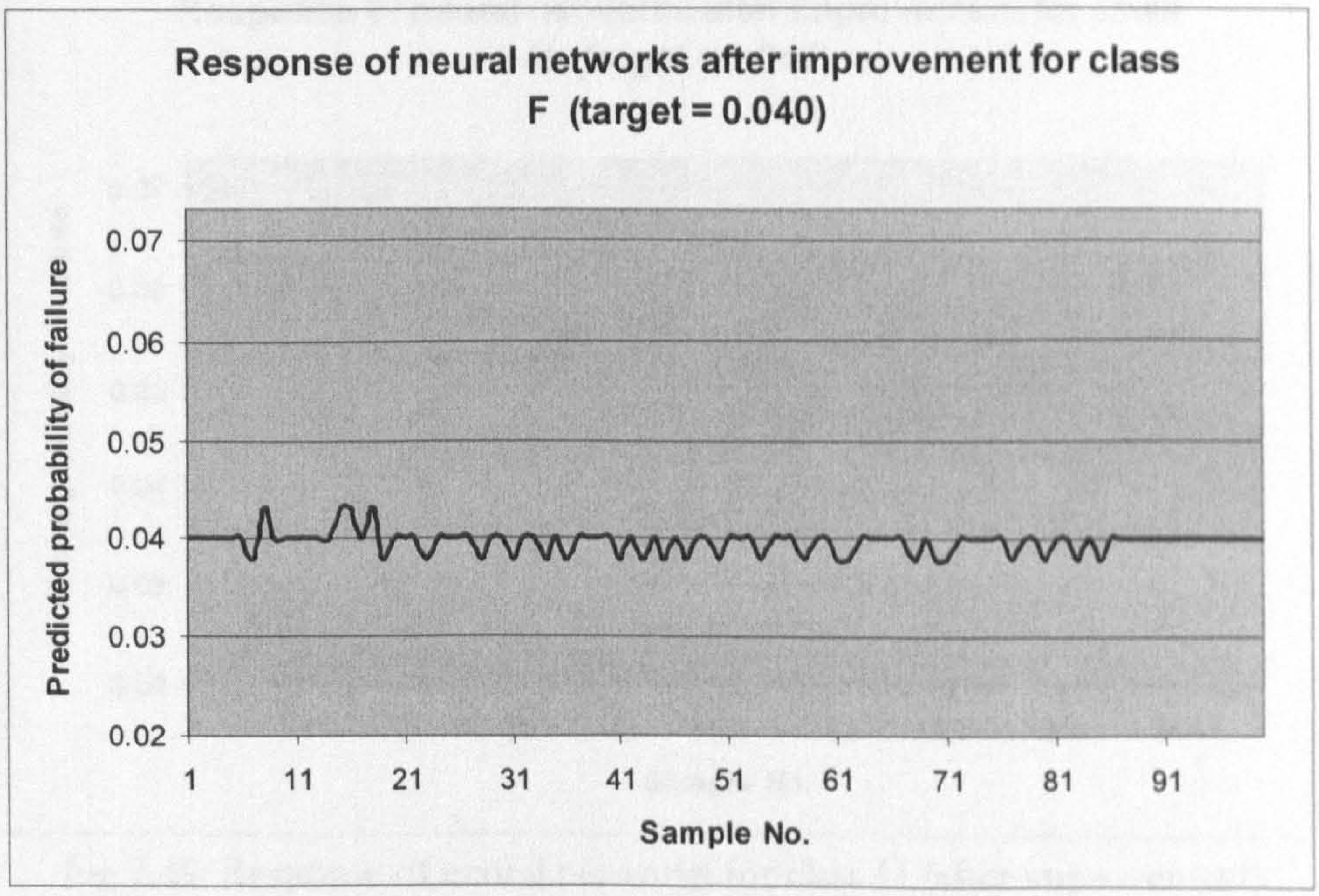


Fig.7.47. Response of neural networks for class F (after improvement)

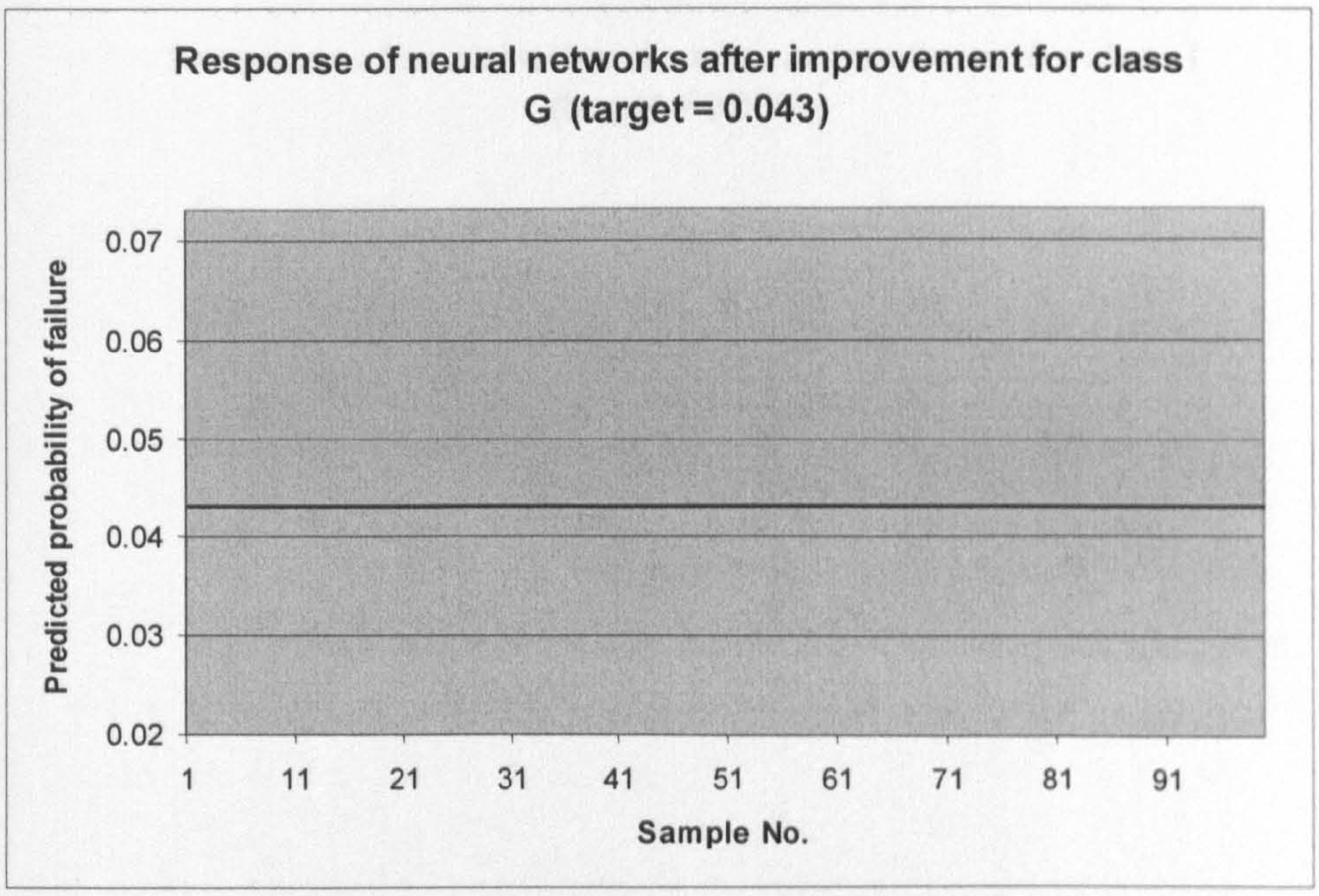


Fig.7.48. Response of neural networks for class G (after improvement)

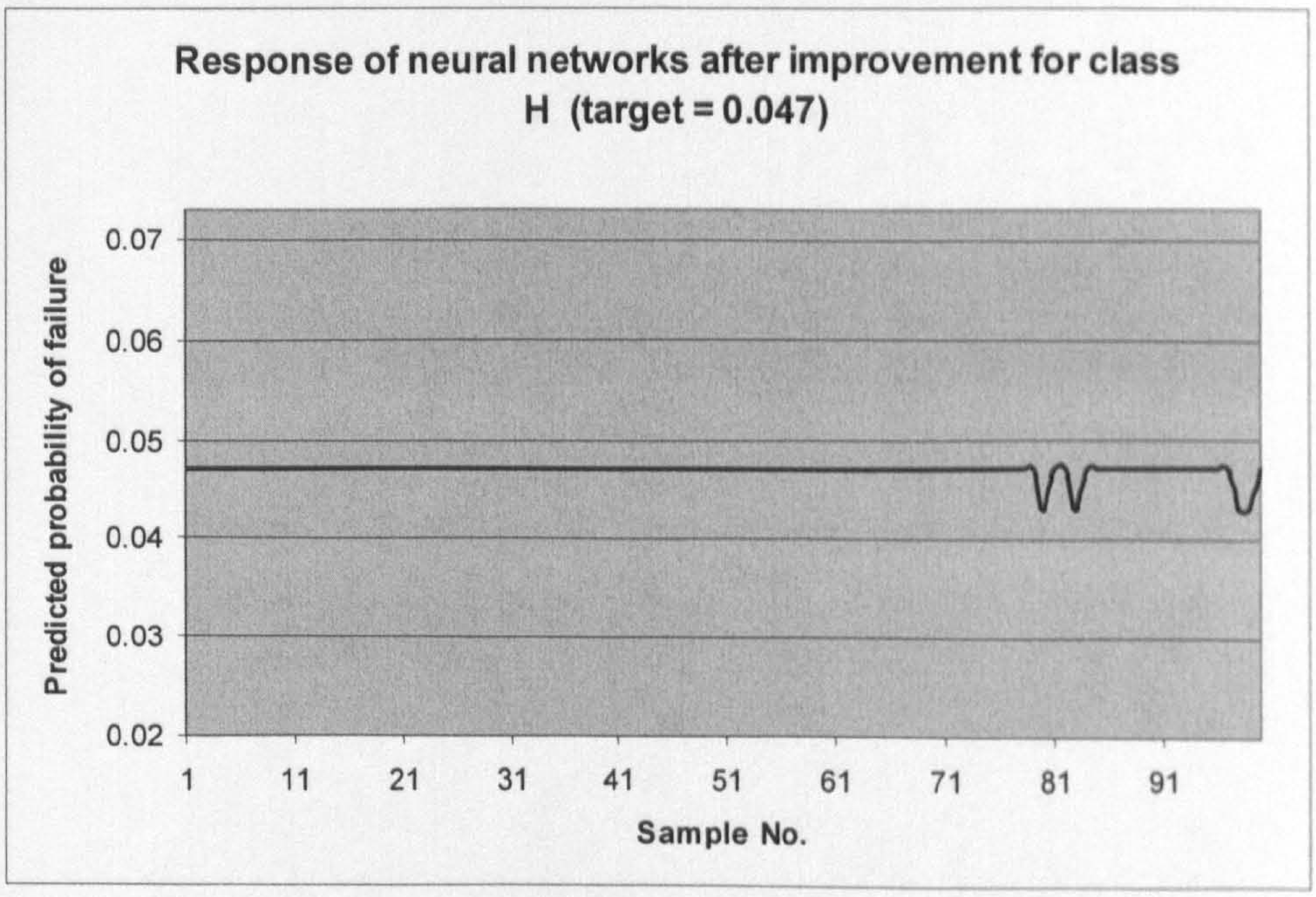


Fig.7.49. Response of neural networks for class H (after improvement)

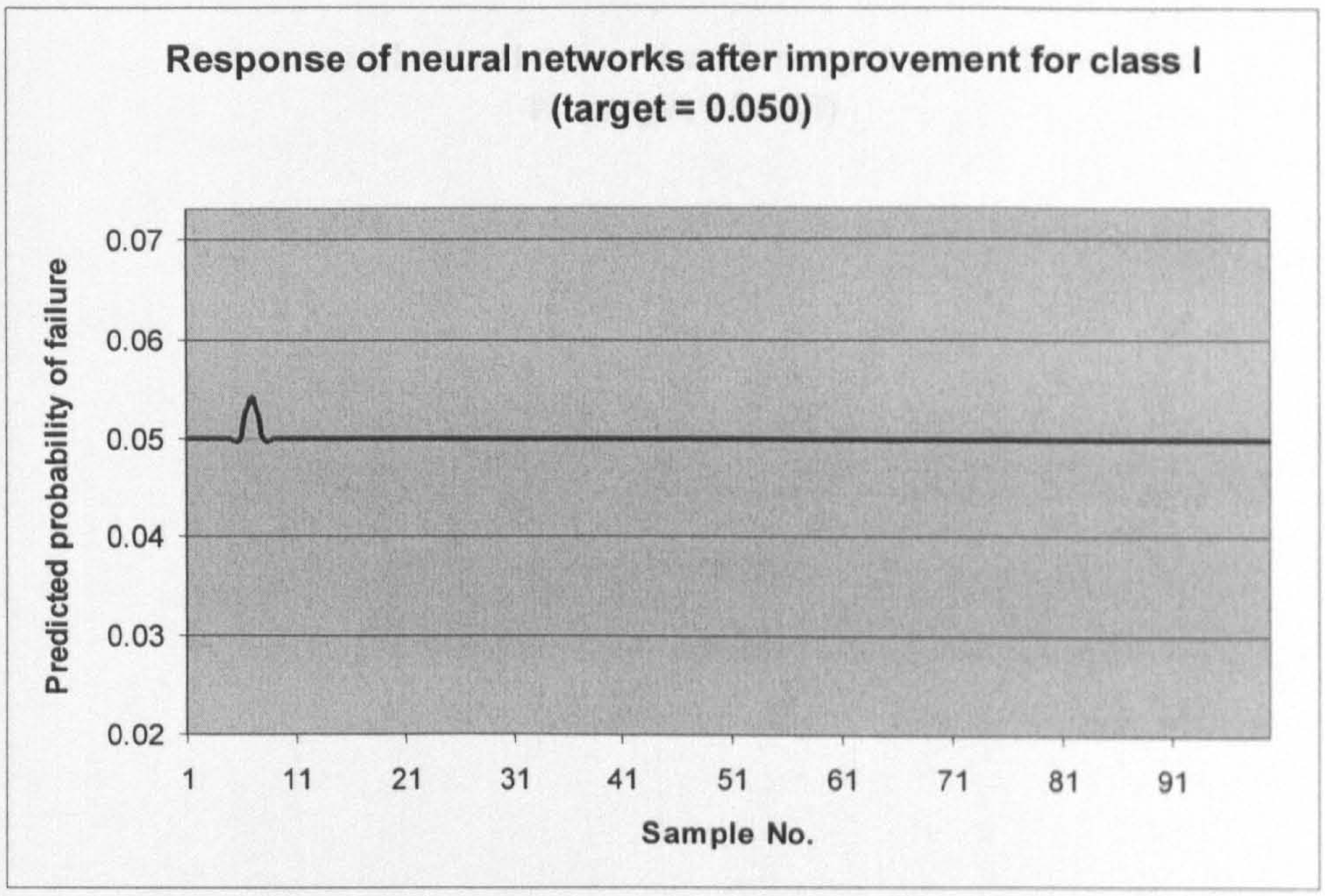


Fig.7.50. Response of neural networks for class I (after improvement)

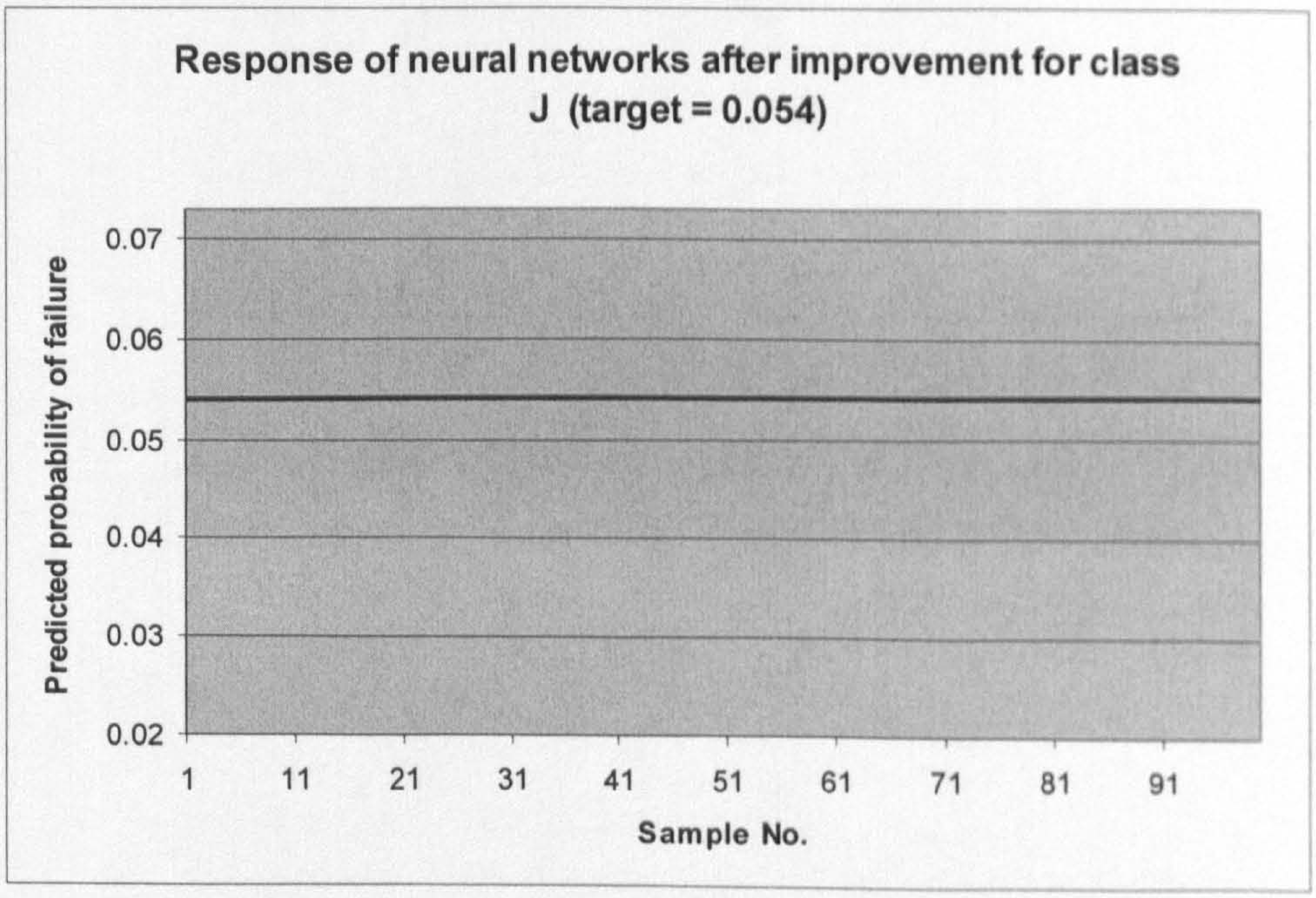


Fig.7.51. Response of neural networks for class J (after improvement)

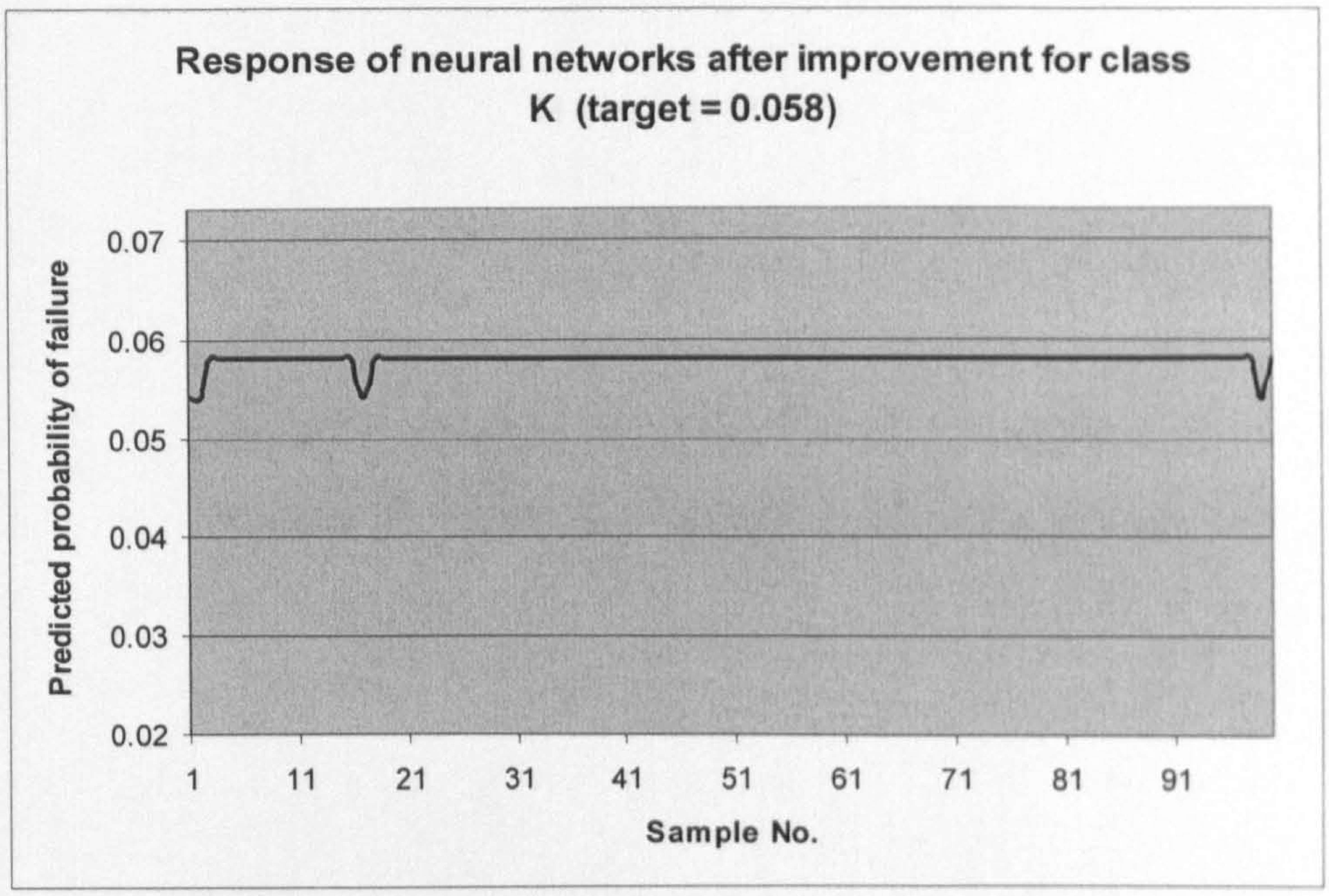


Fig.7.52. Response of neural networks for class K (after improvement)

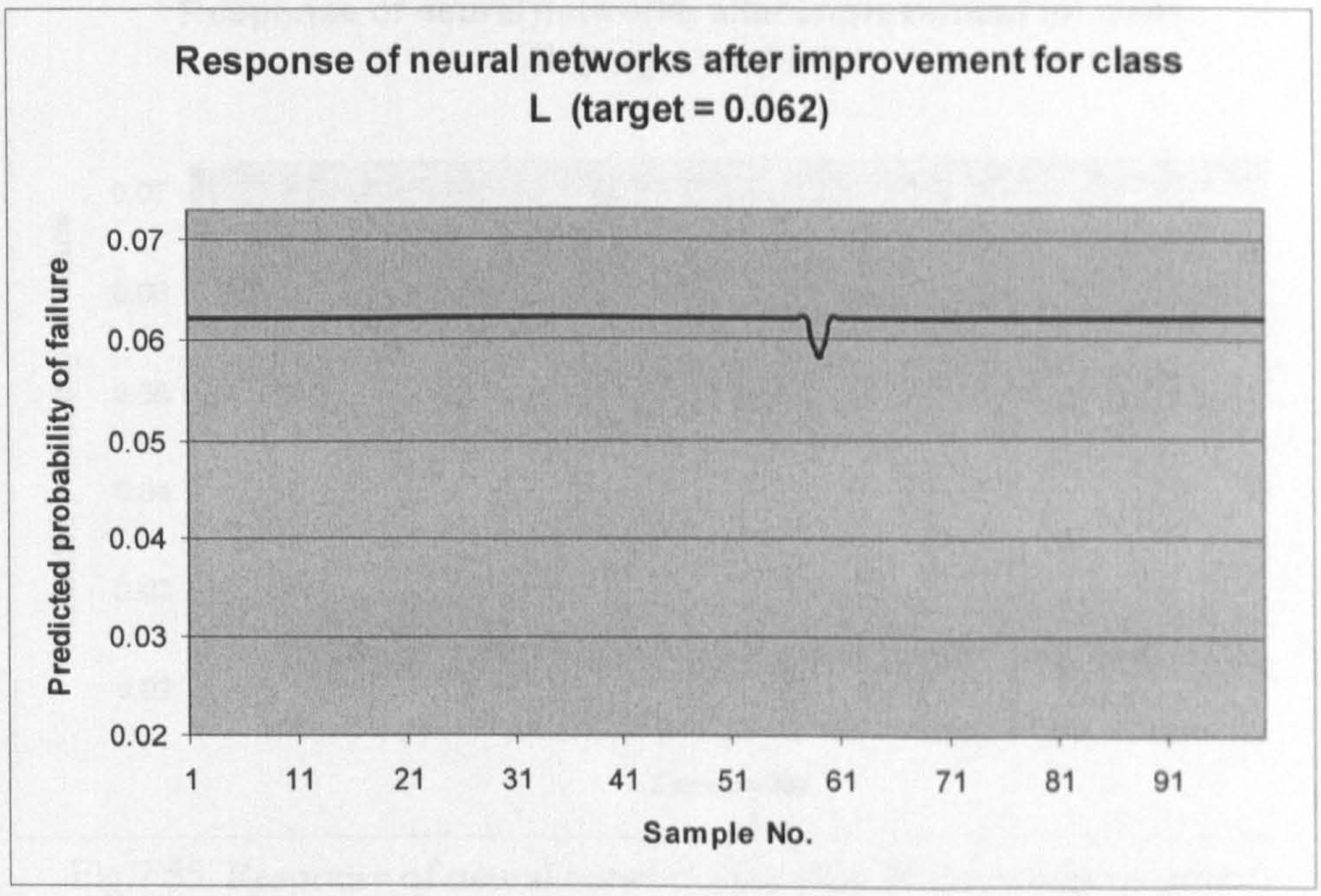


Fig.7.53. Response of neural networks for class L (after improvement)

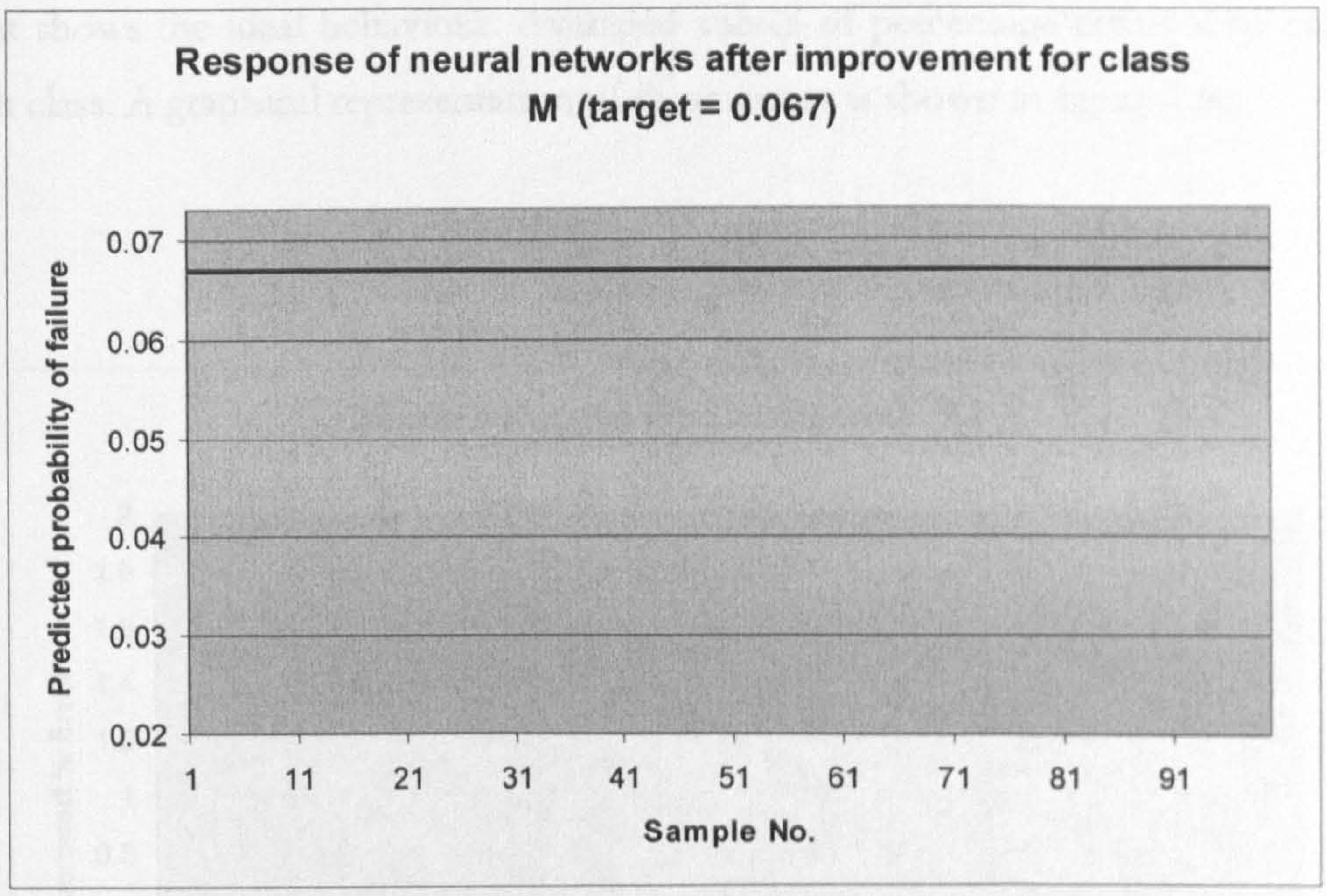


Fig.7.54. Response of neural networks for class M (after improvement)

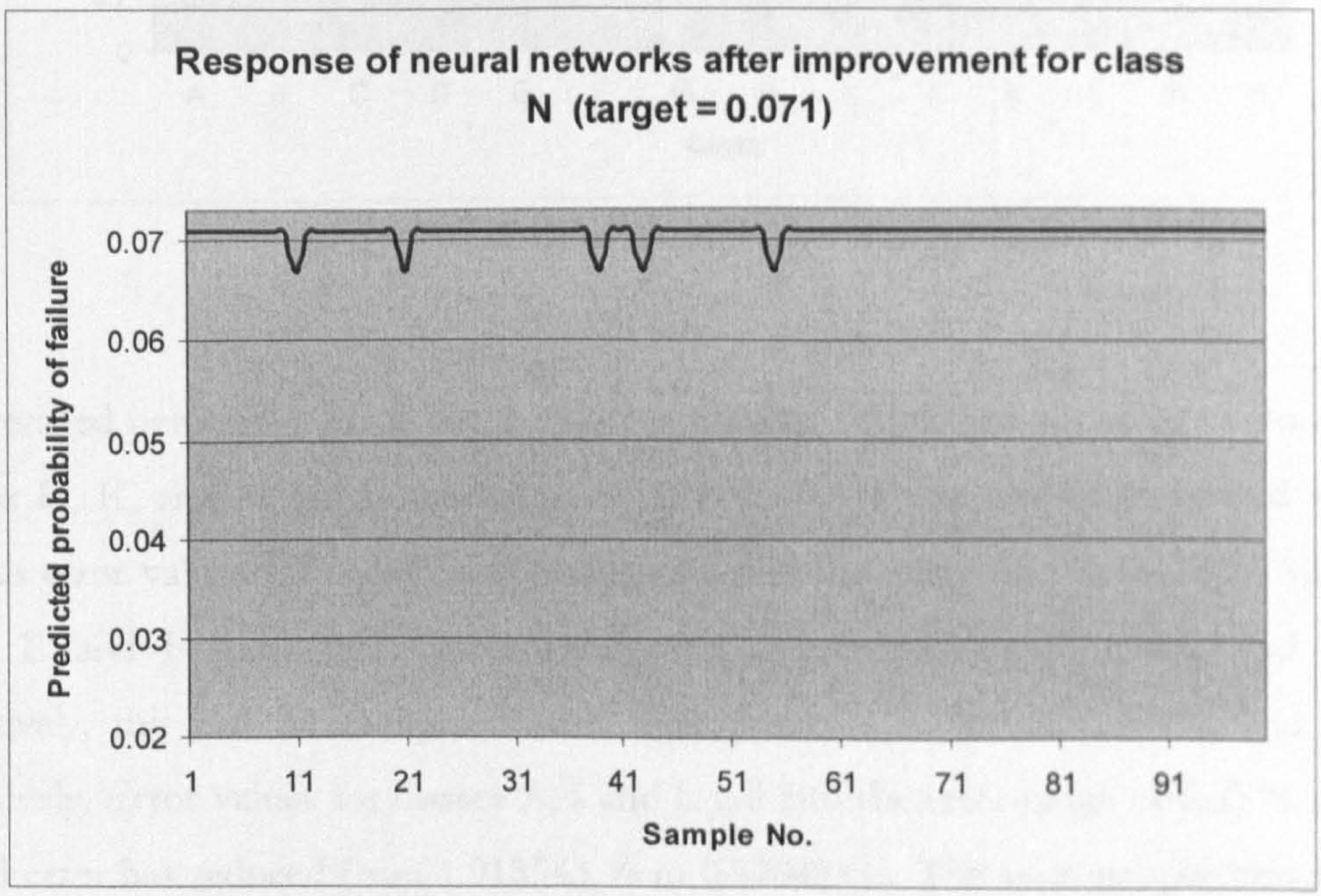


Fig.7.55. Response of neural networks for class N (after improvement)

If we consider the graphs of classes B (figure 7.43), D (figure 7.45), G (figure 7.48), J(figure 7.51), and M (figure 7.54) then we can see that these graphs are totally a straight horizontal line that shows the ideal behaviour. Averaged values of percentage errors were calculated for each class. A graphical representation of these errors is shown in figure 7.56.

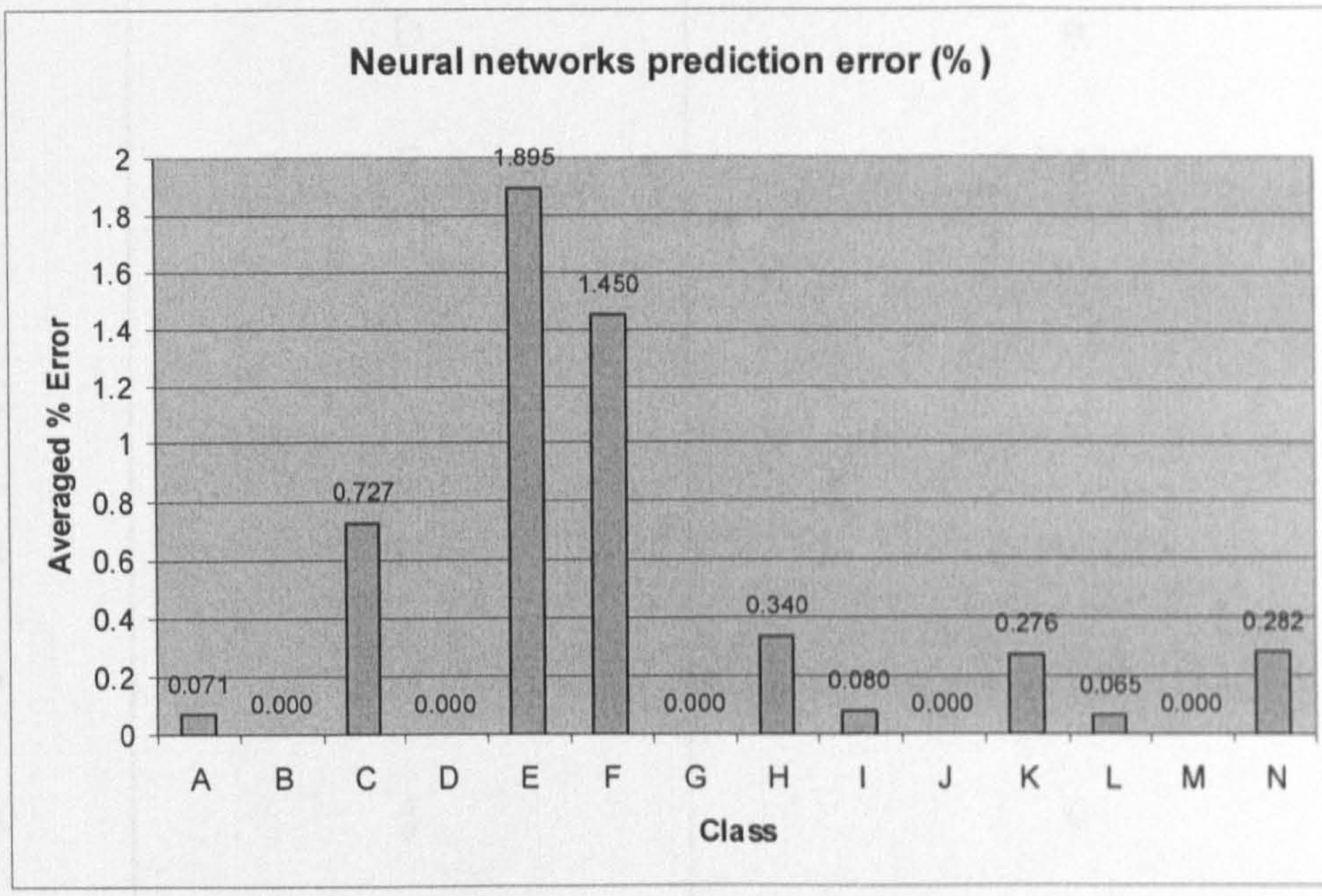


Fig.7.56. Bar chart of averaged percentage error

The averaged percentage error for the classes that are mentioned above has reduced to 0, whereas H, K, and N fall in the range of 0.2% to 0.4% that can be compared with the previous error values for these classes which were in the range of 1% to 2.5%. Moreover, classes E and F have error percentages after improvement of 1.896%, and 1.450% respectively, this can be compared with their previous values of 2.447%, and 1.791% respectively. Error values for classes A, I and L fall into the error range of 0.05 % to 0.1%. Overall error has reduced from 1.913543 % to 0.370424%. The averaged percentage errors for each class are presented in table 7.9.

S No.	Class	Averaged % Error
1	A	0.071429
2	B	0
3	C	0.727273
4	D	0
5	E	1.894737
6	F	1.45
7	G	0
8	H	0.340426
9	I	0.08
10	J	0
11	K	0.275862
12	L	0.064516
13	M	0
14	N	0.28169
Average		0.370424

Table 7.9. Values of averaged % Error (after improvement)

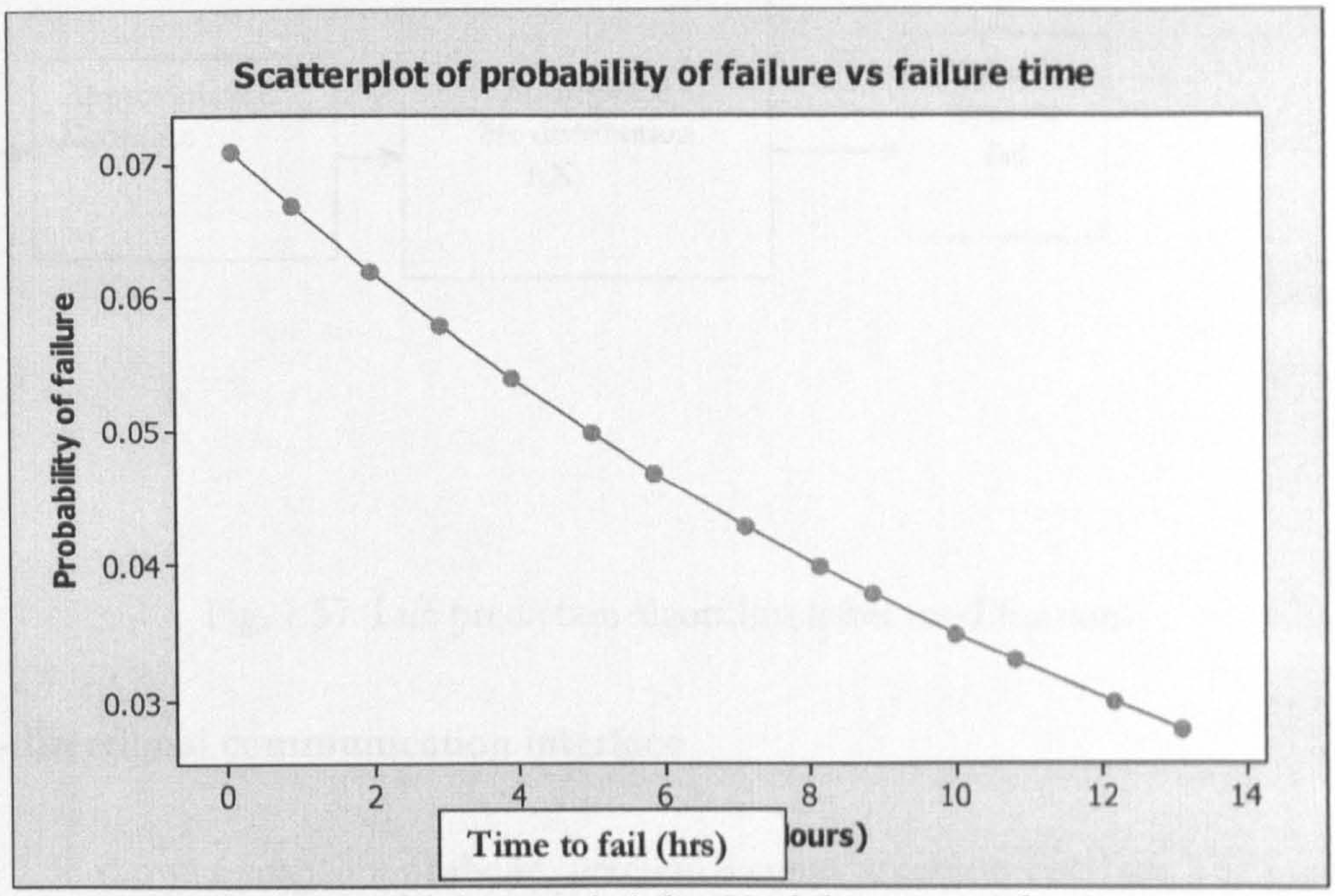


Fig.7.57.Scatter plot of failure probability Vs failure time (after improvement)

Now if we consider the scatter plot that is presented in figure 7.57 then we can see a clear difference in how the predicted values are concentrated as compared to the scatter plot presented in figure 7.41. Figure 7.41 shows that the values are widely scattered so that the connection line is not clearly visible. In addition to this, we can see that none of the calculated time values go below zero. It means that there are no negative time values. The scatter plot is now similar to the plot of the probability density function of an exponential distribution.

Hence, we can say that the improved algorithm provides a better way to calculate the lifetime in hours. The modified version of the life prediction algorithm is illustrated in figure 7.57.

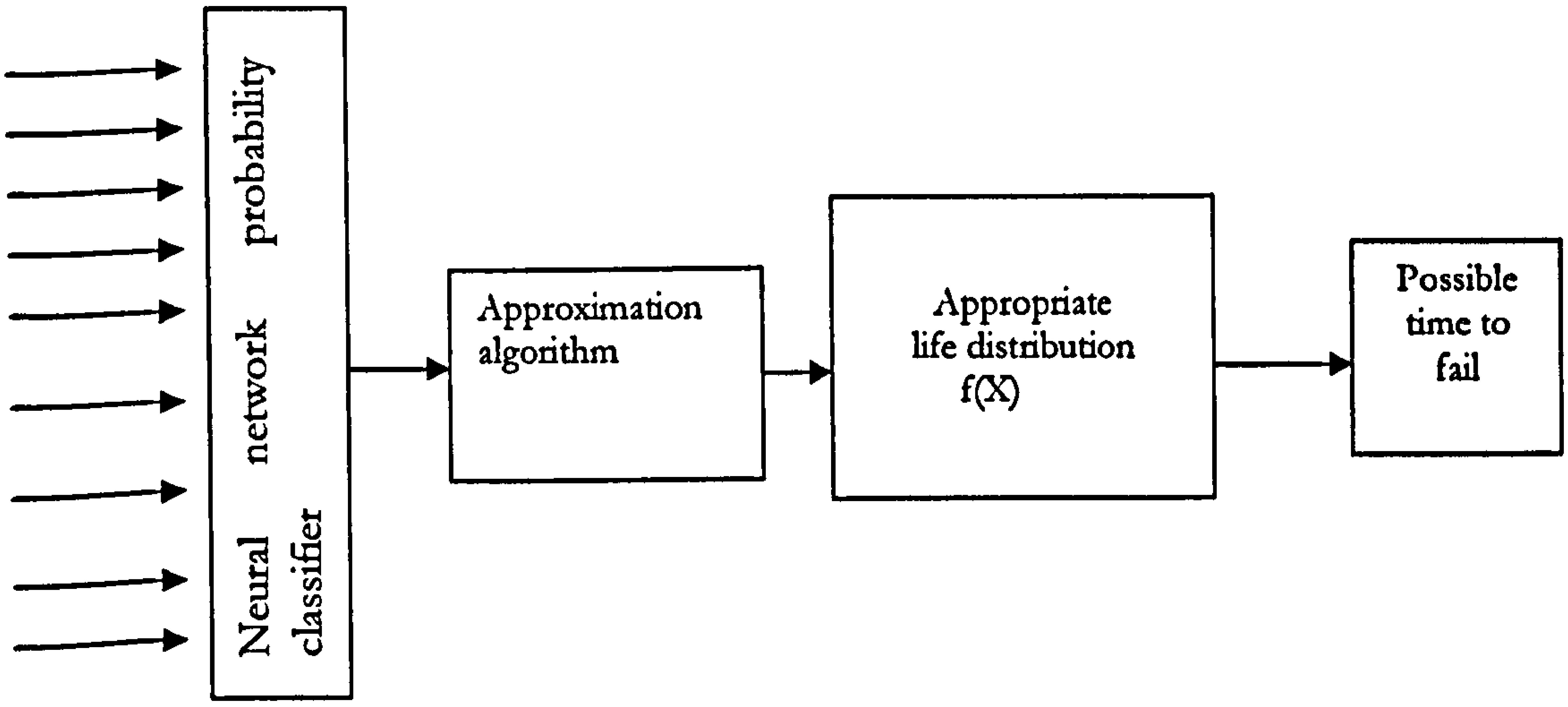


Fig. 7.57. Life prediction algorithm (after modification)

7.4 Bi-directional communication interface

Figure 7.58 shows a snapshot of the bi-directional communication interface. The purpose of this software is to enable intelligent EID to communicate with the external world. As it is explained earlier that the lifecycle data of the gearbox is stored in the USB mass storage device of the intelligent EID, bi-directional communication interface is responsible to program the intelligent EID in order to send the lifecycle data to the external world. This data then can be stored into some database in order to facilitate the vendors, recyclers, and the concerned parties, in terms of knowledge exchange. Bi-directional communication interface uses FTP (File Transfer Protocol) in order to communicate with the intelligent EID. The reason behind using the FTP as the communication protocol is this that it is a standard protocol for data transfer, especially, over the internet. Another strong advantage of using this protocol is this that this protocol can be used to transfer data between two systems regardless of this that what operating systems they have.

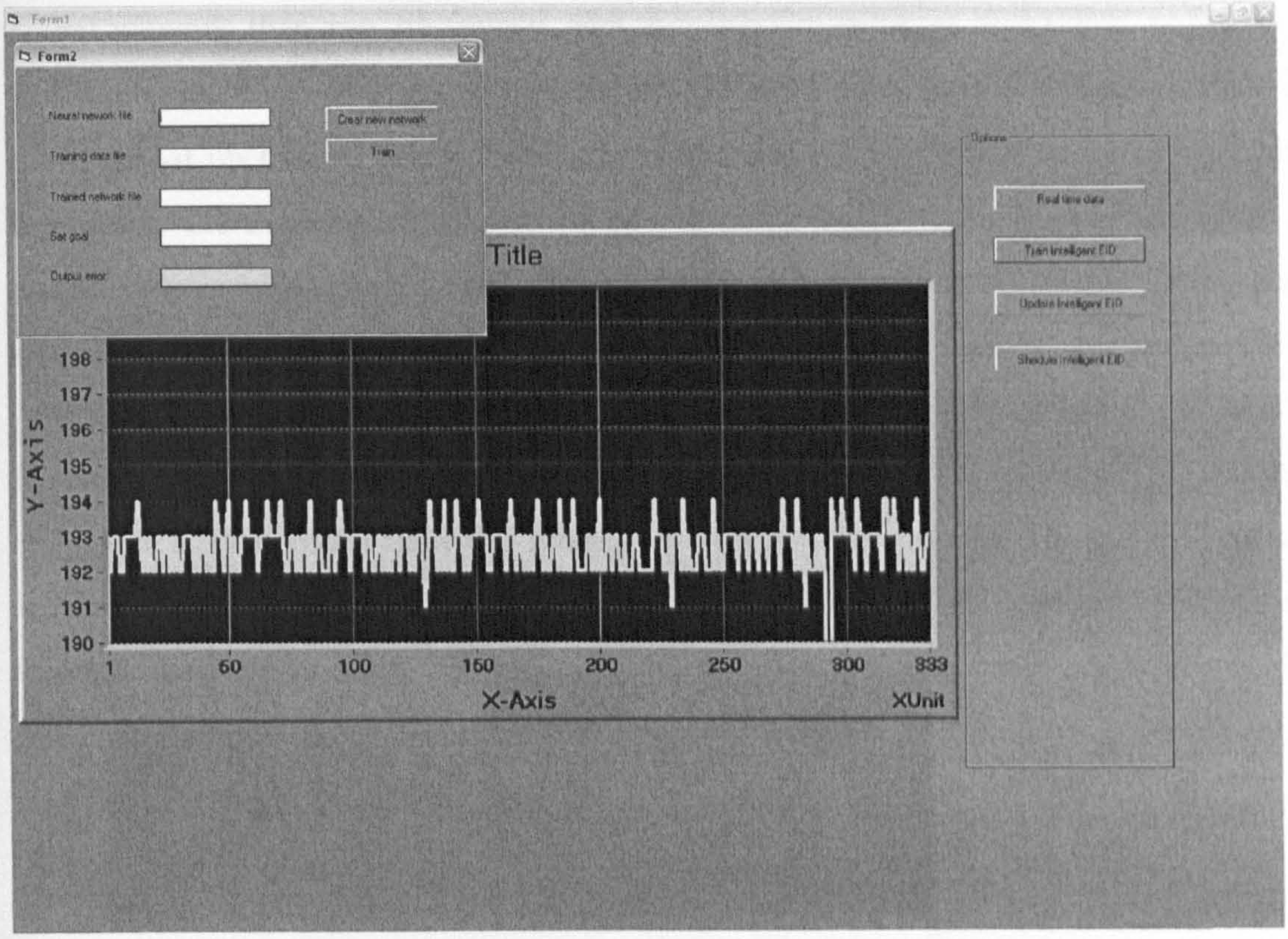


Fig. 7.58. Bi-directional communication interface

The bi-directional communication interface provides provision to the user to program intelligent EID that after how many days backup of data is required. The software asks the user for the start date and also that after how many days the backup is required. Once the number of days are entered, the software automatically sends a request to the intelligent EID to send the logged data file to the FTP server after the period when backup is required. In addition to this, bi-directional communication interface is also responsible to train intelligent EID and to update it with the new training file. For this purpose, the code that was developed to train intelligent EID in GNU C was recompiled in MinGW (Minimum GNU for Windows) in order to make it compatible with bi-directional communication interface that is developed under Visual Basic, which is a Windows based programming language. The training module of the bi-directional communication software provides an option to the user to create a neural network with random weights for intelligent EID. This neural network then can be trained with the help of training dataset that is fed to the software in the form of a simple text file. The bi-directional communication interface asks the user that up to how much extent, the output error should be reduced. The software then trains the neural network until the error is minimised up to the desired level, and creates a file of trained neural networks. The update module of bidirectional communication interface is then used to send this trained neural network file to the program memory of Axis device server. The life prediction algorithm to predict the life of gearbox then uses this file of trained neural network. Therefore, whenever a change in the training dataset of intelligent EID is made then the intelligent EID can be updated through this software. Similarly, this software can be used to maintain product-related archives or maintenance logs into the product itself. Overall, bi-directional communication software has successfully demonstrated the idea of information exchange from the product to the environment and vice versa.

7.5 Summary of chapter 7

- Results of accelerated life test show that the tested gearbox has gone through severe degradation.

- The exponential distribution has been chosen as a reliability distribution model to be used in the life prediction algorithm.

- The averaged percentage error before improvement in the life prediction algorithm is found to be 1.9135%

- The averaged percentage error after improvement in the life prediction algorithm has been reduced to 0.3704%

- The idea of intelligent EID has proved the concept that intelligent logic can be embedded into the product itself. This proves the idea of intelligent products that can assist their users in order to increase their useful lifetime and can take part in decision making for their own destiny.

- Bi-directional communication software has successfully demonstrated the idea of knowledge exchange between a product and its environment. This proves the concept that products can behave like intelligent agents that receive information from their external environment, act according to it, and provide useful information to their users.

Chapter 8

OVERALL DISCUSSION

As defined in section 2.8 the aims of the project are as follows:

To develop an intelligent embedded information system and technique to predict the remaining life of a product in terms of hours, based on the product usage mode.

To make an intelligent EID independent of an external processing system for the process of life prediction.

To develop an interface for bi-directional communication between the product and its external environment to make the product intelligent enough in terms of knowledge exchange.

To investigate and demonstrate the potential of passive and smart EIDs for the purpose of product lifecycle management.

The system and scheme proposed in chapters 5, 6 and 7 fulfil the above three aims as follows:

a) The proposed system for intelligent EID provides an intelligent way to predict the remaining life of a product in terms of numbers, depending upon its usage mode. We can say this for the following reasons:

i) In general, existing systems for life prediction employ tedious and complex graphs or performance coefficients for the prediction of a product's reliability. These graphs and performance coefficients need further interpretation in order to understand the process of product degradation. This approach seems good if the user is skilled; however, from the perspective of adding intelligence to the future products, especially white goods and other customer products, this approach seems unfeasible. This is so because the end-user is interested, not in the complex performance graphs and coefficients, but in something which he or she finds familiar. The proposed system is quite efficient in that it tells its user the remaining life of the product in terms of hours instead of any complex graph or performance coefficient and this prediction depends upon the product usage mode. This fulfils some of the requirements of an intelligent product that are mentioned in section 1.6; that it should be capable of communicating with its external environment and deploy a language to display its features, production requirements etc. The proposed system is efficient in a manner that, irrespective of the level of user, it communicates with the user in terms of numbers; therefore it deploys a language as well. Hence, we can say that the proposed system provides an intelligent way to predict a product's life or can make a product intelligent.

ii) The proposed system has the capability to record data about the product itself. The proposed system has a USB mass storage device that stores product dynamic data throughout the product's lifecycle. This fulfils the requirement of an intelligent product as mentioned in section 1.6; that an intelligent product must have the capability to store or retain data about itself. The proposed intelligent EID stores vibration data of a gearbox for every cycle of operation. From an experimental perspective, the intelligent EID was programmed to record data continuously, as the storage capacity of the USB device used was 1GB. If it is needed, then an intelligent EID can be programmed easily to record only the critical events.

iii) The life prediction technique is a combination of standard tools that are in general use in the fields of artificial intelligence and reliability. It employs neural networks that are similar to a human brain in that they work on the same principles as a human brain. The use of artificial networks has enabled the system to percept from the external environment, learn and then act in response and to behave exactly like an intelligent agent. Due to their ease of programming and implementation, the proposed technique employs back propagation neural networks that are in common use. Though it is recommended that the implemented system should have an unsupervised learning mechanism, due to the limitations of computing capacity, such a paradigm of neural networks is difficult to implement. However, the implemented back propagation neural networks are efficient in that they employ a trained neural network that is stored in the program-memory of the Axis board. Therefore, whenever, any change in the trained network parameters is required then there is no need to change anything in the code This trained neural network is stored in the form of a simple text file; therefore, the stored network parameters can be easily understood as compared to any other data formats, e.g. binary . As the proposed life prediction technique is a combination of standard tools, therefore, the proposed technique can be easily customised for other systems as well. In case of a more complicated system with more sensory inputs, the inputs of back propagation neural networks can be increased easily. As for the process of life prediction, the algorithm utilises the standard exponential distribution, therefore, irrespective of the system, it requires only one parameter that is the failure rate of the system under consideration. This failure rate is determined experimentally. Therefore, the proposed technique is generic and can be used for other systems provided that the failure rate is determined and the neural networks are trained with the failure patterns.

b) All the approaches that are discussed in the literature review are dependent on some external system for the process of life prediction. However, the proposed system is totally independent in terms of prediction and does not use any external processing system for the life prediction process. The life prediction algorithm was first programmed in GNU C and then it was compiled under a Criss cross-compiler to make it executable under the embedded environment of an Axis device server. The programmed code is stored in the program memory of the Axis device server in the form of a binary executable file. Hence, it can be said that the proposed life prediction algorithm is a totally on-chip algorithm. This ensures the integration of intelligent EID into future products because this approach gets rid of the user having to plug equipment into a full-time, dedicated PC. In addition to this, new versions of the Axis device server are very small. Advancements in micro-fabrication technology have already reduced the size of electronic components. Therefore, in future, such kinds of systems can be easily embedded into products. Although, in order to attain the research objectives, results were displayed using a terminal, the Axis device server has provision to integrate an LCD for display and a keypad for input.

c) A bi-directional communication interface has been developed in Microsoft Visual Basic in order to receive information from the intelligent EID and to update it with new training data or maintenance records. For this purpose, the bi-directional communication interface uses the very popular FTP (File Transfer Protocol). Ideally, the bi-directional communication application should be web-based. This can be seen in the scenario of plug and play products. If the manufacturers maintain some product-related website, whenever the user connects the product to the Internet there should be some information exchange taking place between the product and the concerned parties. For example, the manufacturer updates the product with new and improved training data and in return retrieves the stored data from the product to some centralised database for product feedback and further improvement. The bi-directional communication interface demonstrates this by providing the user with a data retrieval option after a particular number of days. In a real scenario, manufacturers have to manage a web-based application. Users should be allowed to register their products by product ID to the manufacturer's website. In the case of an intelligent EID, it can also be a domain name as it uses the Axis device server that can be accessed by a domain name as well.

d) Demonstration of a smart EID has proved the idea of storing product maintenance logs on the product itself. This information can play a very important role at the time of product recovery. The subject for the smart EID application was a domestic refrigerator. The most important and valuable component of a domestic refrigerator is the compressor. These compressors are designed for a life span of 16 to 20 years. If sensory data of the compressor and maintenance log of a refrigerator is available at the time of recovery, it can then play an important role in EOL decision-making. Sometimes, a refrigerator with a compressor in the working state is discarded due to some other technical fault. Implementation of such smart EID ensures the recording of sensory data as well as storing the maintenance log within the product itself. Moreover, using Bluetooth technology to write the maintenance log to the product provides an easier way to the maintenance person by using a laptop or PDA device.

Implementation of the smart EID idea to products like white goods can be proved to be very useful at the time of product recovery.

e) In the light of experiments with passive EIDs, it has been proved that these technologies have a great potential to support a sustainable approach to product lifecycle management. RFID and i-button technologies cannot only be used to store static information but they can store information of a dynamic nature as well. These devices can be used to store static and dynamic information about small electronics items of low functional complexity, such as hairdryers, shavers, blenders and microwave ovens.

i-buttons are preferred to RFID tags due to their robustness, whereas, RFID technology has merits over i-buttons because it is a non-contact-based technology. However, experiments have already proved that the performance of RFID tags is affected in the presence of metals. The usage of i-button technology in this regard is proposed for the very first time in the literature.

Though experiments were not performed with barcodes, in the light of extensive literature review it was found that barcodes can be used to encode product-related information of simple and very low cost products.

Chapter 9

CONCLUSION AND SUGGESTIONS FOR FUTURE WORK

9.1 Conclusions

This thesis provides an extensive account of the work done on the utilisation of embedded information devices to support a sustainable approach to product lifecycle management. It fulfils the aims and objectives that were defined earlier in section 2.8 of the thesis.

- An intelligent EID system and technique have been successfully developed to predict the remaining life of the product exactly in terms of hours depending upon the product usage mode. The proposed technique has been implemented successfully on the intelligent EID to predict the remaining life of a gearbox in terms of hours.

- The life prediction algorithm is stored in the program memory of the intelligent EID itself, thus making the intelligent EID system independent of any external processing system for the process of life prediction. The implemented program or code has proved successful as an on-chip implementation of the life prediction algorithm and thus the independency of an intelligent EID has been demonstrated.

- A bi-directional communication interface has been developed for the intelligent EID that enables it to communicate with the external world in terms of knowledge exchange. The bi-directional communication interface can be used to improve the intelligence of the intelligent EID by sending intelligence updates from the external environment, which in turn receives MOL data from the intelligent EID, thus making the information exchange bi-directional.

- The proposed intelligent EID approach is closer to the watchdog approach as mentioned in the section 2.3.3 in the sense that it also has a focus on MOL activities of product. Like the watchdog agent, the proposed intelligent EID also aims to prolong the useful lives of functionally complex products through predictive maintenance. Despite of the fact that the watchdog approach is one of the latest techniques that are proposed in the area of predictive maintenance, however, the proposed intelligent EID approach has preference over watchdog approach in the sense that the intelligent EID is very independent for the process of life prediction i.e. it has an on-chip life prediction algorithm. On the other hand, the major shortcoming in the watchdog agent is its dependency on an external PC for the process of performance measurement and forecasting. This gives preference to the proposed intelligent EID over watchdog agent, as independency of the intelligent EID ensures its integration into the future products for the purpose of life prediction. In addition to this, with the help of proposed life prediction technique, the user is informed regarding the remaining life of product in terms of hours, whereas, the watchdog agent predicts the degradation in performance of a product by showing a performance coefficient or complex graphs. The proposed intelligent EID also has the capability of getting intelligence updates i.e. the intelligent logic inside the intelligent EID can be updated with the help of bi-directional communication software that aids the intelligent EID in terms of information exchange. On the other hand, intelligence of the watchdog agent cannot be updated. In addition to this, the watchdog agent has no on-board facility to store product lifecycle data as it uses an external database. On the other hand, the proposed intelligent EID has capability to retain lifecycle data into an external database and into itself as well with the help of a USB mass storage device. Briefly, we can say that the intelligent EID has preference on the watchdog agent due to its on-chip and bi-directional communication features that proves the intelligent EID more suitable for integration into the future products in order to prolong their useful lives.

- The potential of smart and passive EIDs has been investigated. Successful implementation of a smart EID has proved the idea of keeping products up to date with their maintenance logs. In addition to this, the potential of passive EIDs (Barcodes, RFID tags, and i-buttons) have been thoroughly investigated.

Demonstration software has been developed for RFID tags and i-buttons to store product-related information with the help of these technologies.

9.2 Future work

- Further improvement of the life prediction algorithm in terms of improving the learning paradigm should be undertaken, possibly by developing further self-learning techniques. This has not been possible so far because of the limited computational capability of the Axis Linux board. Implementation of such kind of a self-learning technique can make intelligent EID more advanced in terms of providing the feedback to itself and capability of self-adjustment to improve its own performance. In addition to this, future work also includes the deployment of an on-chip fault classification technique. This technique will enable intelligent EID to predict the fault type. However, this technique requires a large amount of training data from different test scenarios.

- There is an indispensable need for some scheme to classify different types of EIDs for different types of products. Therefore, future work should aim to develop some standards, indices, and metrics for the choice of EIDs for different types of products based on their functional complexities. This may also involve the development of some technique that take these standards, indices, and metrics as inputs to suggest an EID type for a particular product.

- There is also a need for a standardised database management system to store product lifecycle data. Therefore, future work also includes development of a generic database that provides basic structure to hold necessary lifecycle information associated with a product.

9.3 Contribution to knowledge

The thesis contributes knowledge in the area of embedded systems with respect to product lifecycle management. Initially, the research explores different technologies for the purpose of product lifecycle management, however, the main contribution of research is in the area of MOL management of products through predictive maintenance. The research provides an on-chip life prediction technique that ensures the integration of intelligence into the future products, which enables these products to predict their own lifetime against different usage profile that can aid their users to prolong their useful lives. The thesis contributes to the idea of intelligent products that behave like intelligent agents that percept information from their environment and act in response to it. These products are able to store their own lifecycle data and provide useful information to their users. Briefly, we can say that this thesis strengthens the concept that in future, smart and intelligent products will play an important role in the sustainability paradigm.

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Appendix: PUBLICATIONS

Application of embedded information devices, an advanced approach to support sustainable product lifecycle management

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ABSTRACT

Huge landfills from solid waste generated by the massive utilisation of different products from domestic sources are badly affecting the environment. About 70% of the solid municipal waste, two thirds of which comprises of household waste, is dumped as landfill all over the world. For efficient product lifecycle management via upgrade, maintenance, reuse, refurbishment, and reclamation of components etc, storage of product related information throughout its lifecycle is indispensable. Efficient use of information technology integrated with product design can enable products to manage themselves in a semiautomatic and intelligent manner. It means that products themselves should contain information that what to do with them when they are of no use. More advanced products may locate themselves and communicate with their recyclers through internet or some other communication technology. Consortium like PROMISE(PROduct lifecycle Management and Information tracking using Smart Embedded Systems) is trying to manage and track lifecycle information during the use and end of life phase of the product. In this regard, we have investigated different types of technologies. These technologies are broadly classified as passive embedded information devices and active embedded information devices. Methods of automatic identification in combination with information technology can act as passive Embedded Information Devices (EID) to make products intelligent enough in order to manage associated information throughout their life cycles. This paper highlights the need for adoption of eco-design approaches in smart and medium enterprises through two case studies in terms of active and passive EIDs. Experiments demonstrated that some of the technologies have the capability to store information in the form of small maintenance logs as well. Barcodes, Radio Frequency Identification tags, and a new technology called i-button technology are being discussed as possible candidates for passive EIDs. The i-button technology from perspective of product lifecycle management is being presented for the very first time in literature. As passive EIDs are unable to monitor the sensory data therefore in addition to these demonstrators for passive EIDs, an advanced active EID demonstrator for lifecycle management of products with high functional complexity is also presented..

1 INTRODUCTION

Huge landfills from solid waste generated by the massive utilisation of different products from domestic sources are badly affecting the environment. About 70% of the solid municipal waste, two thirds of which comprises of household waste, is dumped as landfill all over the world. This waste includes various products like batteries, waste electrical and electronic equipment, chemicals, vehicle maintenance items, etc. It is reported that about 6 million tonnes/year of end of life electronic waste is disposed of by the European Union countries (Goggin and Brown 1998). This domestic waste, when disposed to landfill with the municipal solid waste, gives rise to various hazardous emissions like volatile organic compounds (VOCs) and liquid solutions of landfill called leachates. These leachates and VOCs are affecting the underground water and air thus disturbing the overall ecosystem. This gives the world a new concept of sustainability and product lifecycle management The next section explains the different phases of product lifecycle.

2 PHASES OF PRODUCT LIFECYCLE

The product life cycle is segmented in to three stages:
a) BOL (Beginning of Life)
b) MOL (Middle of life)
c) EOL (End of Life)
Beginning of life (BOL) involves the development stages of the product. The data regarding this stage is comprehensive i.e. information related to design and production. For example, we have the details like manufacturing date and time as well as we have the process and design information like drawings and other manufacturing parameters. The comprehensive information regarding the product at this stage is available due to the employment of MIS (Management Information Systems), DBMS(Database Management Systems), and CAD(Computer Aided Design) software by the manufacturers. At BOL, the product is similar to a newborn baby whose details are to be entered in the council register. MOL (Middle Of Life) includes the period after the delivery of product to the customer. This involves usage, service, and maintenance of product whereas EOL (End Of Life) can be seen as the time where the product is unable to perform its function due to failure or wear out. The next section explains product lifecycle data.

3 PRODUCT LIFECYCLE DATA

There are two types of product lifecycle data. One is called static data and the other is called dynamic data. Static data of a product is related to the product specification like manufacturing date, manufacturer information, material type, number of components, drawings, and assembly instructions, instructions for preventive maintenance and service, etc. A more comprehensive static dataset may include disassembly instructions for proper EOL management. This data does not change and remains static throughout the life cycle of product. Therefore, static data can be stored on some sort of an external database and can be accessed by using a unique product identification code.
The dynamic data of a product contains information regarding the use phase of product. It includes the information regarding the product usage that how a product is used. What parts or components of the product have been repaired or replaced or how long the product has been used, etc. Briefly, we can say that it is the data associated with the changes in product. As this data changes constantly, it is termed as dynamic. This dynamic data can be used at the time of product take back to get useful information regarding the product such as use patterns, length of usage, service and maintenance history, etc. This dynamic data can also be used to improve product design and reliability as well as for preventive and predictive maintenance in order to avoid any break down or failure. Most of the dynamic data mainly consists of sensory data captured by some sort of an electronic device or data logger embedded in the product.

4 INTELLIGENT PRODUCT AND LOUGHBORUGH UNIVERSITY APPROACH OF EMBEDDED INFORMATION DEVICES

Absence of proper structure for product recovery, high recovery costs, and unavailability of information regarding product, are the factors that have made EOL product recovery a little bit difficult. These constraints can be minimised by shifting the product management responsibility to the product itself. Due to the involvement of IT in every sector of life, the product life cycle management and waste management systems are also dependent on the

tools of IT. Efficient use of information technology integrated with product design can enable products to manage themselves in a semiautomatic manner at the end of their useful lives. It means that product themselves should contain information that what to do with them at EOL. More advanced products in a rubbish bin may locate themselves and communicate with their recyclers through internet or some other communication technology. McFarlane et al. (2003) define an intelligent product as follows:
"An intelligent product is a physical and information-based representation of a product which:
possesses a unique identification;
is capable of communicating effectively with its environment;
can retain or store data about itself;
deploys a language to display its features, production requirements etc.;
Is capable of participating in or making decisions relevant to its own destiny".

Methods of automatic identification in combination with information technology can act as Embedded Information Devices (EID) to manage product-related information throughout their life cycles. Moreover, advancements in micro-sensor technology have now made it possible to integrate various kind of sensory devices on a single electronic chip in order to store sensory data as well. This can be considered as a progress towards intelligent products. According to the proposed approach of Loughborough university, embedded information devices can be classified into passive and active EIDs.

4.1 Passive EID
Passive EID can be defined as an information device that stores or refers the information associated with design, production, and assembly activities that can be used at product EOL for selecting the most suitable EOL option for a product.

4.2 Active EID
Active EID has characteristics of passive EID plus some additional features. It can be divided into two classes:

4.2.1 Smart EID
Smart EID has capability to monitor sensory data plus it keeps product update with repair and service records throughout the product life cycle in order to increase the product functionality.

4.2.2 Intelligent EID
Intelligent EID has characteristics of smart EID plus it has capability to predict the product remaining life as well as it advises the user against different usage modes from the view of life optimisation of product.

5 CANDIDATE TECHNOLOGIES FOR PASSIVE EID

Two types of automatic identification or tag technologies, the optical tag technology and RFID tag technology are the possible candidates to be used as passive EIDs, whereas, a new technology called i-button technology is also being proposed in this paper.

5.1 Optical tags
Optical tags include simple barcodes also called one-dimensional or linear barcodes, and two-dimensional (2D) codes.
The use of barcodes is in common practice for about 20 years. The very famous EAN (European Article Number) internationally and its subset UPC (Universal Product Code) in USA are frequently used on almost every grocery item. The data storage capacity of linear

barcodes ranges from 8 to 30 characters. Beside UPC and EAN, other famous linear barcodes are Interleave 2-of-5, Code39, Codabar, and Code128.

1D codes normally contain a unique number, which serves as a reference key in the computer database carrying the detailed information of a product. However, in the harsh industrial environments where it is not possible to access a computer database, 2D codes can serve as portable data files, as they carry large amount of information as compared to conventional 1D codes. Hence, 2D codes eliminate the requirement of an external database system. 2D codes basically consist of various 1D barcodes stacked together in the form of rows and columns. With the use of 2D codes, it is possible for the product to carry out its own information in the form of a portable data file. Moreover, due to their large size, conventional barcodes cannot be placed or printed over small items like electronic components; also, it is difficult to place them on mechanical components, which are subjected to harsh environment. On the other hand, 2D codes are scaleable; easy to read even they are very small and can be marked directly on components giving them preference over conventional barcodes. PDF-417, Data Matrix Code, QR Code, and Maxi Code are some popular examples of 2D codes. Barcodes provide the cheapest way of low cost labelling to products. However, this type of labelling cannot be used for all types of products. Overall, this type of labelling is a more suitable and perfect tagging solution for low cost simple products having shorter lives, which are exposed to less harsh environments.

5.2 RFID tags

Unlike barcode technology RFID technology does not require line of sight because this technology employs electromagnetic waves. An RFID system consists of three components:

a) Tags or transponders that serve as electronic data carriers bearing an ID code and are attached to different objects.

b) A reader or interrogator that corresponds with tags through electromagnetic waves at radio frequency

c) A host computer to process and distribute the data over some network.

A tag consists of an integrated circuit (normally a resonating circuit), an antenna, and memory. The tag and reader communicate with each other through electromagnetic waves. Radio frequency tags can be broadly classified into two types. Active tags that require a power source and passive tags that do not require power source. In active systems, their own battery drives the tags or transponders. As active tags have their own power, it is easy to increase the read range in active systems but they have short lives as their lives are totally dependent upon the battery. However, active RFID systems can perform more complicated tasks as they have the capability to integrate various kinds of sensors and even the microcontroller with them. Passive systems do not have their own power source. They derive their power from the electromagnetic field generated by the reader. As compared to active RFID systems the passive RFID systems are cheap and can be produced at low cost. Due to this reason passive systems are nowadays in major focus. Passive systems have a shorter range as compared to active systems. For passive systems, the reader energises the tag by inducing a constantly changing electromagnetic field in to the tag when it comes in the interrogation field of a reader. When the field of reader affects the tag, a DC voltage is produced in the tag's antenna and the tag begins to oscillate in response to the reader. The memory capacity of RFID tags ranges from 64 to 32,678 bytes. Active tags are read/written from the distance of approximately 5 to 100 feet whereas passive tags can be read or written from less than six feet and in various cases it is limited up to 2 feet (Jaselskis and El-Misalami 2003). The operating frequency of RFID tags is disturbed, if they are placed over or near especially metallic objects or objects containing liquids because metals, liquids and some materials absorb electromagnetic waves. The inductance of a tag decreases due to loss in electromagnetic waves thus disturbing the resonant frequency of the tag. Therefore, inductive tags need special tuning by adjusting their capacitance or inductance to maintain their performance when placed over metallic objects.

5.3 i-button technology

One simple technology developed by Dallas semiconductors is i-button, which is simply a semiconductor chip enclosed in a tiny can of stainless steel. Each i-button has two contacts, the lid, and the base. The lid is the data contact, which is the top of can whereas the base is the ground contact that is the bottom of the can. Each i-button is provided with a unique factory etched number in its silicon chip. The unique identity inside the i-button can be accessed using a probe or a blue dot receptor that uses the 1-wire protocol. The 1-wire protocol uses a single wire that is employed for both device signalling and power. The probe or blue dot receptor are connected to PC via serial or parallel port. The ID inside the i-button can be read by simply making a physical contact between the i-button and the probe or blue dot receptor. These buttons are available in various varieties. The ID only i-buttons consist of 64 bit ROM that contains a factory etched unique ID.

Other flavours of i-button include memory devices that have capability of read/write and have capacity ranges from 1 Kbit to 64 Kbits. EEPROM i-buttons have also read/write capability with limited write cycles but their capacity ranges between 256 bits to 32 KB. These devices are also available in the form of data loggers. Standard versions of these devices can take 2048 readings with time interval of 1 to 255 minutes whereas advance versions are capable to make 8192 readings for interval ranges from 1 second to 273 hours (Website Maxim Dallas Semiconductors accessed 24th May 2005). As these devices need physical contact for data transmission, this makes this technology little bit labour intensive.
The next section explains the research in the area of active EID.

6 RESEARCH IN THE FIELD OF ACTIVE EID

Very few attempts are made in the area of active EID. (Scheit and Zong 1994) proposed a concept of green port to capture the life cycle data in order to get information for reuse of electronic items. According to them, electronics products should consist of a modular structure rather than traditional design. Because having modular product structure, individual functional modules of products can have a better possibility for reuse. According to the proposed approach, each module should be provided with a memory unit, called identification (ID) unit in order to store the static and dynamic data. The life cycle data from product can be retrieved using a port, which they named the green port. All ID units installed in individual modules of products will be connected to each other through a common bus called the green bus. The green bus will be further connected to green port for the purpose of data retrieval from the product.

Klausner and Grimm (1998) proposed a system called ISPR (Information System for Product Recovery). The ISPR consists of an electronic device called EDL (Electronic Data Log) embedded in the product to record the dynamic data related to the product. This EDL was mainly developed to use in electric motors in order to retrieve dynamic information to judge the reuse of electric motors in other products (Klausner et al. 1998). The proposed EDL contained a circuit board with a microcontroller and EEPROM. EDL also had temperature and current sensors. An LED was employed to transmit data from ISPR to an electronic reader. A DC power supply was used to power the EDL. The EDL was supposed to be embedded inside the housing of product. It had capacity to log data for about 2300 hours of operation. The logged data was then transferred through LED read by an electronic reader containing photo diodes and an electronic circuit to amplify the received signal from LED. The electronic reader could be connected to the PC via an RS-232 communication port in order to make data available for the visualisation and interpretation. Unlike EDL, which was just able to record sensory data LCDA (Life Cycle Data Acquisition) system proposed by Simon et al. (2001) was able to store the other MOL activities like maintenance, service, and repair updates. The proposed LCDA consist of sensors for data acquisition, a clock, and a microprocessor to manipulate the sensory data plus a non-volatile memory, and a communication system to retrieve data from the LCDA. The LCDA was supposed to perform different functions like counting the starts and stops of a machine, controlling various functions like controlling an actuator, recording the date and time stamps for the start of each individual cycle, recording the duration of operation for each machine cycle, thus giving the total running hours for the machine. The embedded software in the microcontroller took 8 KB of memory. The software was responsible to perform basic control operations. The LCDA was provided with a socket for data communication to a host computer. The host computer then employed a software for online monitoring during operation.

Djurdjanovic et al. (2003) proposed the concept of watchdog agent. The basic objective of watchdog agent is the efficient MOL management through predictive and proactive maintenance. Main functions of watchdog agent are to assess and predict the machine performance degradation by using data from multiple sensors, prediction of fault, and finding the reason or cause of the fault. These features are not only useful from maintenance point of view but also useful to predict the product remaining life. Various tools can be employed in such type of an agent like fuzzy logic, neural networks, signature analysis etc., to predict and assess the performance of a machine. The functional elements of watchdog agent are sensory system, signal processing, condition monitoring, performance assessment, prognostic, decision-making, and representation. Next section explains experiments with passive EIDs

7 EXPERIMENTS WITH PASSIVE EIDS

In order to determine and demonstrate the capability of passive EIDs, experiments were performed with RFID tags and i-buttons, which are explained below.

7.1 Experiments with RFID

For information encoding, experiments were performed with RFID technology. Experiments were performed using Texas Instrument RFID evaluation kit (RI-K10-001A). This kit includes Texas Instruments RFID 6350 reader board. The board is enclosed in a plastic housing with an antenna. The kit can be connected to the host computer via serial communication port. A 9-pin D type male-female connector is used to connect the reader module to the PC. The reader is powered by a 9V DC power supply. Texas Instruments 6350 reader operates at 13.56 MHz frequency. The reader has a very limited range in inches. Sample inductive RFID tags (RI-I03-110A and RI-I1-110A) of Texas Instruments provided with the kit were used for experimentation. These tags have etched aluminium antennas of rectangular shape with PET substrate. Their data storage capacity is just 32 Bytes and they can retain data for more than 10 years. As explained before that the data storage capacity of RFID tags used in the experiment was limited to 32 Bytes only, therefore, experiment was performed in the limited conditions. The memory of used RFID tags was divided in to 8 blocks each has capacity of 4 Bytes. The data is stored on the tags in hexadecimal format. Each block of data can contain an eight-digit number.

7.1.1 Information storage

Authors attempted to store necessary product related information in this limited data capacity. In this regard software called RFID demonstrator was developed. The software was developed in the Microsoft Visual Basic environment using the specific command set provided by Texas Instrument for 6350 13.56 MHz reader. Though 6350 reader is compatible with ISO commands and protocols as well, but due to familiarity and availability of Texas

Instrument command set authors preferred to use that command set. The software consists of two interfaces, the read interface to read information from the tag, and the write interface to write and update information on the tag.

Data can be written block wise on the tag. Data cannot be written simultaneously on all data blocks. Therefore, user has to select a particular field in the write mode to update or change the information. Different types of information were then stored in RFID tags like manufacturer ID, product ID or serial number, and manufacturing date, etc. Each field was assigned a single data block. It is also possible to store the product and manufacturer information in RFID tags in the UPC and EAN style. However, the purpose of experiment was just to know and demonstrate the capability of RFID technology to store information. Attempts were also made to store product specifications, like, length, width, height, and weight. To do this, authors used a single block of data to store product length, width, height, and weight. As mentioned before, an eight-digit information can be stored in a single block of data, therefore, two digits were used to define each of the four attributes i.e., length, width, height, and weight. Thus, if an eight-digit number is stored as 12131404 then its length, width, height and weight can be decoded as 12, 13, 14, and 4 receptively. By explaining this, it does not mean that some coding scheme is proposed, but the purpose is to mention that how information can be written on RFID tags in an efficient manner. Other information, like, purchase date was also stored on RFID tags as an eight-digit number; this type of information may be useful to get an idea about the product's age. Location information can also be stored and updated as required in case of a supply chain. Location information can be encoded in terms of country code, city code and area code, or any standard way of coding location information can be used like GLN (Global Location Number) by EAN-UCC can be used, to write location information on the tag. Maintenance information like date of last inspection was also stored on the tags. Tags with greater data capacity are able to store more detailed maintenance information like maintenance logs or service history. However, it is demonstrated in experimentation with i-buttons.

7.2 Experiments with i-buttons

Experiments were also performed on information storage with i-buttons. As explained before that i-buttons are available in various varieties. However, in this experiment Dallas Instruments DS1996 memory i-button was used to store product related information due to its large data capacity. The DS1996 is a read/write non-volatile memory that has data capacity of 65536 bits. Moreover, it has a 64-bit memory to store a factory etched unique ID or registration number that cannot be changed, and a 256-bit scratchpad memory, which verifies the data before copying in to the memory. The read/write memory of DS1996 is divided into 256 memory pages, having memory of 256 bit or 32 Bytes each. DS1996 has communication speed of 142 kbits/sec. It can retain data for more than 10 years. To link the i-button with a PC, a DS1402D blue dot receptor was used. The receptor can be easily connected to any serial or parallel 1-wire adapter. However, in this experiment DS9097U-S09 one wire adapter was used which can be connected to the PC through a 9-pin serial interface.

7.2.1 Information storage

In order to judge and demonstrate the information storage capability of i-buttons, an information encoding software called i-button demonstrator is developed. The software has capability to read and write product related data on read/write memory i-buttons using DS9097U-S09. The software was developed in the Microsoft Visual Basic programming environment using the one wire API (Application Programming Interface) provided by Dallas Instruments to aid the development of i-button based applications. The software has basically three interfaces. The identification interface, the write interface, and the read/edit interface.

The identification interface is used to identify the type and unique factory etched identity of i-button device. It also identifies the type of one wire adapter that is used to read the i-button as well as the connected port. Second interface, the write interface is developed to write different type of information on i-button, whereas the third interface, the read/edit interface is developed to read, edit and update information on i-button. Product information like maintenance information during the use phase of product can be updated through this interface.

Various types of information for product identification like product name, model no., manufacturer name, product serial number, product weight, dimensions, etc., was written on i-button using the write interface of this software. In addition to this product information of dynamic nature like customer name, location information as well as dynamic information related to maintenance like date of maintenance, nature of maintenance, description of identified fault, description of customer complaint, information regarding faulty part, etc., can be updated or appended through the read/edit interface. However, the author is of the view that all necessary product related information of a static nature, like manufacturer ID, serial no., model no., etc., should be factory programmed.

Information like supplier name, customer details should be written at the time of selling the product, whereas, maintenance associated information should be updated throughout the product life cycle. Therefore, the read/ edit interface of the software allows updating those fields only, which need to be appended, while other fields are kept locked. Each memory page of DS1996 i-button was assigned to each field. So, each field can be 32 Bytes or 256 bits long. In other words, each field can be 32 characters long as an ASCII character consists of 8 bits. As DS1996 i-button has 256 memory pages, therefore, 256 fields of data can be stored. In order to optimise the information storage it is also possible to assign one memory page to two fields or to assign multiple memory pages to a more descriptive field. For demonstration purpose, software uses 29 memory pages of DS1996 i-button, whereas 227 memory pages were left blank and can be used in future to store more information. Table 4 shows the attributes of information stored in i-button during experiment.

8 INTELLIGENT EID DEMONSTRATOR

As the passive EIDs were explained above were not able to record the sensory data, therefore, an intelligent EID is developed to monitor the sensory data as well as to predict the remaining life of products with high functional complexity. The intelligent EID demonstrator consists of a test rig, electronic hardware, and software. Due to the nature of wear and tear mechanisms, gradual performance degradation over a prolonged period of time mostly happens in mechanical systems instead of electrical or electronic ones. Also to justify the economic worthiness of installing intelligent EID, the demonstration object should be a high cost mechanical system with multiple lifecycles, and the research on its performance degradation have gained enough attentions worldwide. Having considered these factors the gearbox has been chosen as the demonstration object for the intelligent EID prototype.

The gearbox, a BL15-2 right angle bevel gearbox, is driven by an AC motor and an electro-magnetic power brake applies a load on its output shaft, the test rig setup is shown in Figure 1. The motor speed is 40 rpm and at this speed the rated torque of the gearbox is 2.2 Nm. The gearbox is subjected to accelerated life test by applying a brake load of 5 Nm.

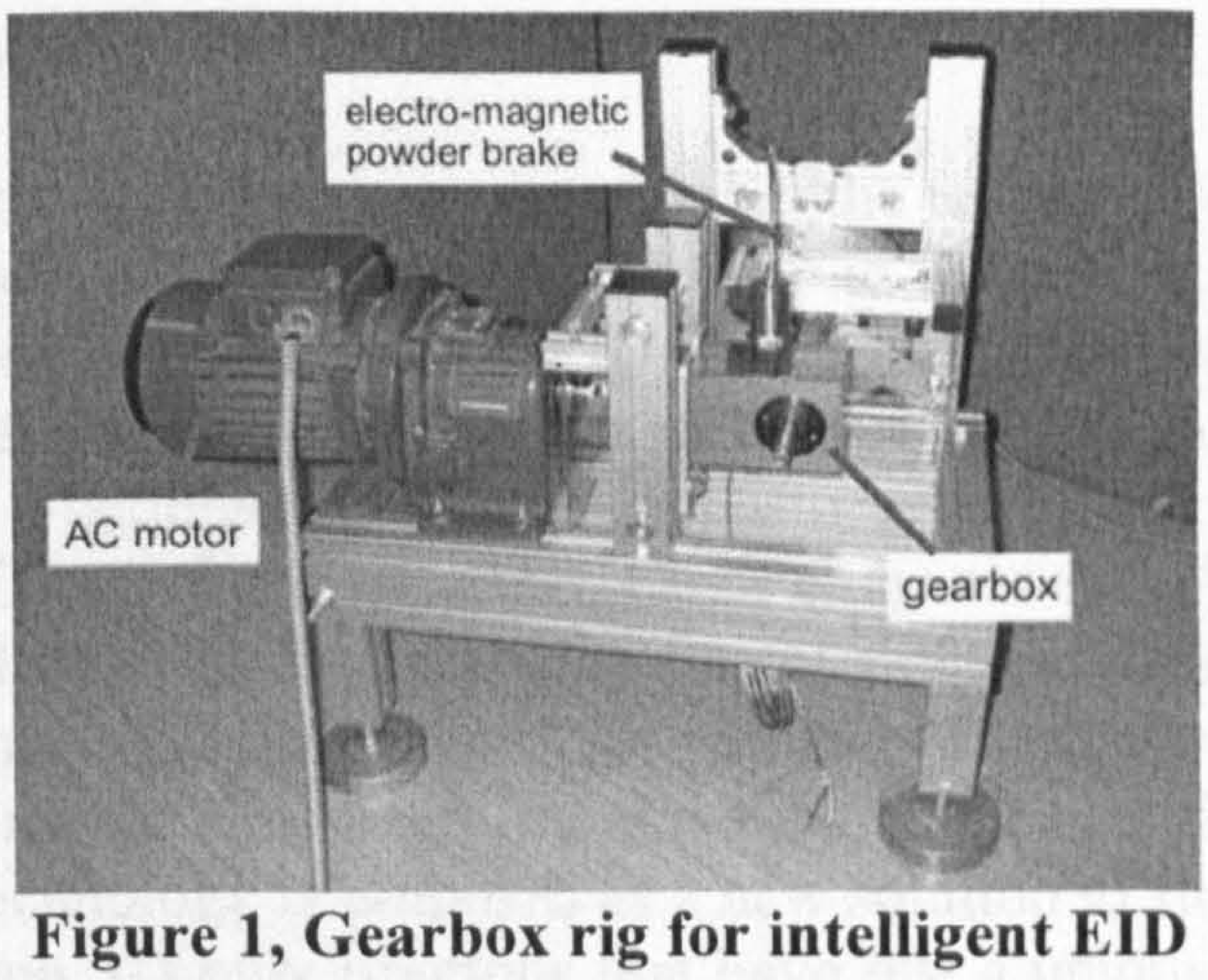

Figure 1, Gearbox rig for intelligent EID

The major electronic hardware elements of the prototype are sensor nodes, the central module and the USB device to record the sensory data. There are two nodes in the Intelligent EID prototype and they are connected with CAN bus, namely vibration node and temperature node. The temperature node is reserved for future use and the vibration of gearbox is considered as a major signature to monitor degradation. The microcontrollers used in both nodes are Microchip's PIC18F4680, which has built-in CAN module and ADC module with selectable reference sources. The AXIS-82 developer board is used as a host computer in this prototype, it features 2 Mbyte of Flash memory and 8 Mbyte of SDRAM memory, runs under Linux environment and equipped with input/output supports like RS232, RS485, USB, parallel ports, and Ethernet. The most important software element in the intelligent EID is the life prediction algorithm.. The life prediction software contains a back-propagation neural network algorithm, which is widely used for mechanical system degradation monitoring. The algorithm had been tested in the AXIS-82 board using synthetic data sets to justify the sufficiency of computing resource for its implementation within the EID. The life prediction algorithm itself occupies 300 Kbyte of Flash memory, whereas, the sensory lifecycle data can be stored in the USB mass storage device, which has memory space up to 2 Gbyte nowadays. As the gearbox tends to degrade, its vibration is increased. The back propagation neural network is used as a classifier to classify the gradual increase in vibration into corresponding probability of failure. A new gearbox is failed by applying excessive torque using the rig. The gearbox was run in this state. After 14 hrs, the level of degradation seems to be constant and did not increase further. It means the threshold limit for degradation can be taken as 14 hrs. The different levels of degradation of gearbox recorded by the intelligent EID are shown in figure 2. Work on intelligent EID demonstrator is still in progress and it is expected that it will be fully functional in the near future.

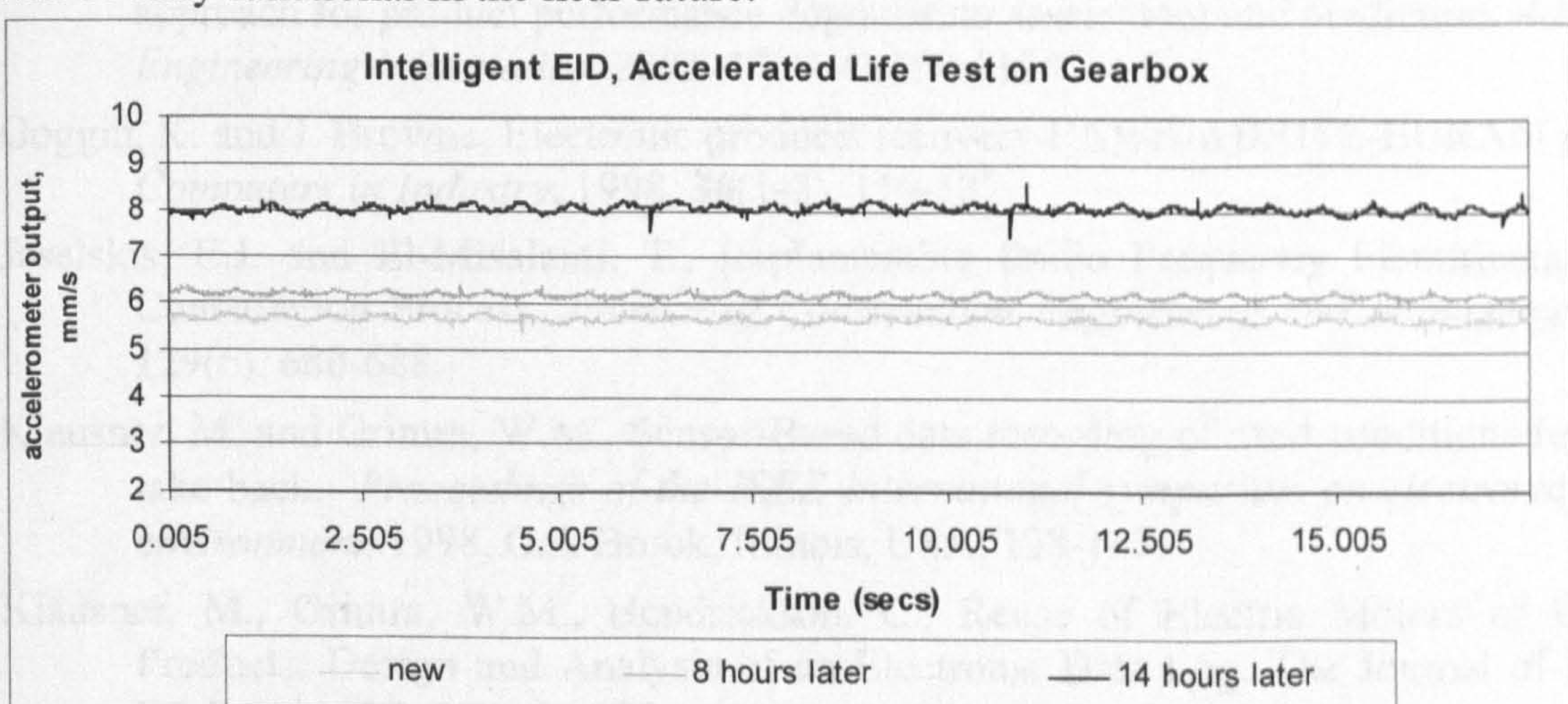

Figure 2, Different levels of gearbox vibration

9 CONCLUSION AND FUTURE WORK

In light of above experiments, it has been proved that the technologies explained above have great potential to be used as passive EIDs in order to support a sustainable approach to product lifecycle management. Moreover, RFID and i-button technologies have the potential to store not only the static but the dynamic data like small maintenance logs as well. Experiments prove that i-buttons due to their robustness and large data capacity are more advantageous than RFID tags for their use in harsh environments. Unlike i-buttons that are contact-based devices, RFID tags do not require line of sight but their performance is affected sometimes in the presence of metals, therefore, specialised tags are required to tag metallic objects. This makes choice for RFID tags little bit application specific. Therefore, in addition to RFID tags, i-button technology is proposed as a new solution to store product identification and use-phase information. ID only i-buttons that have just a unique factory programmed ID can be a good solution for CMMS (Computerised Maintenance Management System) to tag and link equipment related information to a centralised plant database. Though i-buttons need detection through physical contact, which makes the use of this technology little bit labour intensive but compromise can be made on the basis of their large memory capacity that enables their use as a portable data carrier for product life cycle management. Barcodes can be used to encode product related information for low cost and simple products that are not exposed to harsh environments. However, as data once written on barcodes cannot be changed, therefore, barcodes cannot be used to store product use-phase information. They can be used only to store information like, product ID, manufacturer name, recycling or packaging information for very simple products. Barcodes may also be used to encode the website address to refer someone to get useful information. A single technology cannot be proposed as a solution to apply on every product. There is an urgent need of proper classification to apply different technologies on different products on the basis of various factors like product complexity, data requirements, or exposed environment, etc.

For long life products with high functional complexity, the requirement of a fully integrated mechatronic system or an intelligent embedded information device (EID) is indispensable in order to prolong their use phase in an efficient manner through predictive and proactive maintenance. Therefore, future work involves improvement of intelligent EID demonstrator for products with high functional complexity.

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