ARTIFICIAL NEURAL NETWORK MODELLING OF REVERSE OSMOSIS PROCESS

Thesis by:

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Dedicated to my family and loved ones.

ABSTRACT

With the increase in population and the scarcity of fresh water in the Middle East desalination has taken an important role in the provision of water for everyday use and for industrial purposes. Reverse osmosis water treatment process is of particular interest as it is one of the key processes in a desalination plant. The modelling of this process and the prediction of permeate flow is useful in better understanding the process. In the present study, an artificial neural network based model was developed based on plant data for the prediction of permeate flow performance.

Plant data was collected and a number of variables determined. Principal component analysis was then carried and factor loadings obtained to identify the main variables. Once the main input variables were obtained a statistical analysis of the data was done in order to remove outliers present in the data. This was done because the presence of outliers in data to be analysed using ANN models renders the models ineffective in prediction of an output. Once the removal of outliers was done, the data was then analysed using the developed model. 1081 sets of data were originally used with twelve input variables. After principal component analysis was done the input variables were reduced to five with one output variable. With the removal of outliers 981 sets of data were obtained and these were then used in the model.

The model was able to predict the output accurately with r^2 at 0.97. Key factors determined from the process were that to obtain an optimum network one has to consider the epoch size, the transfer function, the learning rate and finally the number of nodes in the hidden layers. The number of hidden layers also had an effect on the overall prediction of the data. It is also important when using ANN models to obtain the correct input variables and to remove any outliers that are present in the data in order to be able to predict the output. The use of plant data severely limited optimisation of the process due to it already being heavily optimised.

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Chapter 1 INTRODUCTION

1.1 RESEARCH MOTIVATION

Several factors have led to the development of membrane separation technology recently. The most important ones are the necessity of fresh water production for drinking, domestic, agricultural, landscape or industrial uses, the requirement of higher performance level methods for waste water reclamation and reuse applications, as well as lower regulatory maximum allowed levels of contaminants. Membrane processes are often chosen in water treatment technology since these applications achieve high removals of constituents such as dissolved solids, organic carbon, inorganic ions, and regulated and unregulated organic compounds. Reverse osmosis (RO) and nanofiltration (NF) membrane processes are used around the world for potable and ultra-pure water production, chemical process separations, as well as desalination of seawater (salinity around 35 g/l) and brackish water (less salty than the seawater). Moreover, lately there has been a growing interest in the integration of such membrane technologies for municipal and industrial water treatment, since they have been recommended as suitable for cost-effective desalination and removal of a wide range of low-molecular-weight trace organic constituents [1-9].

Reverse osmosis is a pressure driven membrane separation process, used for removing low molecular weight solutes, such as inorganic salts or small organic molecules, from a solvent. It relies on the use of a semi permeable membrane, which allows solvent molecules to pass through it, impeding the pass of solutes. When two solutions of different concentrations are separated by such a membrane, the solvent from the lower concentration solution will move through the membrane into the concentrated one, in a process called osmosis. The osmotic flow is attributed to the tendency to equalize the both size's solute concentrations. However, if the liquid on one side of the membrane is pure solvent, the two concentrations can never be equal. In this case, the process of osmosis continues until the chemical potentials of both solutions are equal. This happens when the pressure exerted by the concentrated solution against the membrane is high enough to prevent any further solvent flow. The hydrodynamic pressure difference between the two solutions found at chemical potential equilibrium is called the osmotic pressure difference. In a reverse osmosis process, a pressure must be applied to the concentrated solution in order to overcome the osmotic pressure and to force the solvent to cross the membrane against the concentration gradient, as represented schematically in Figure 1.1 [3].

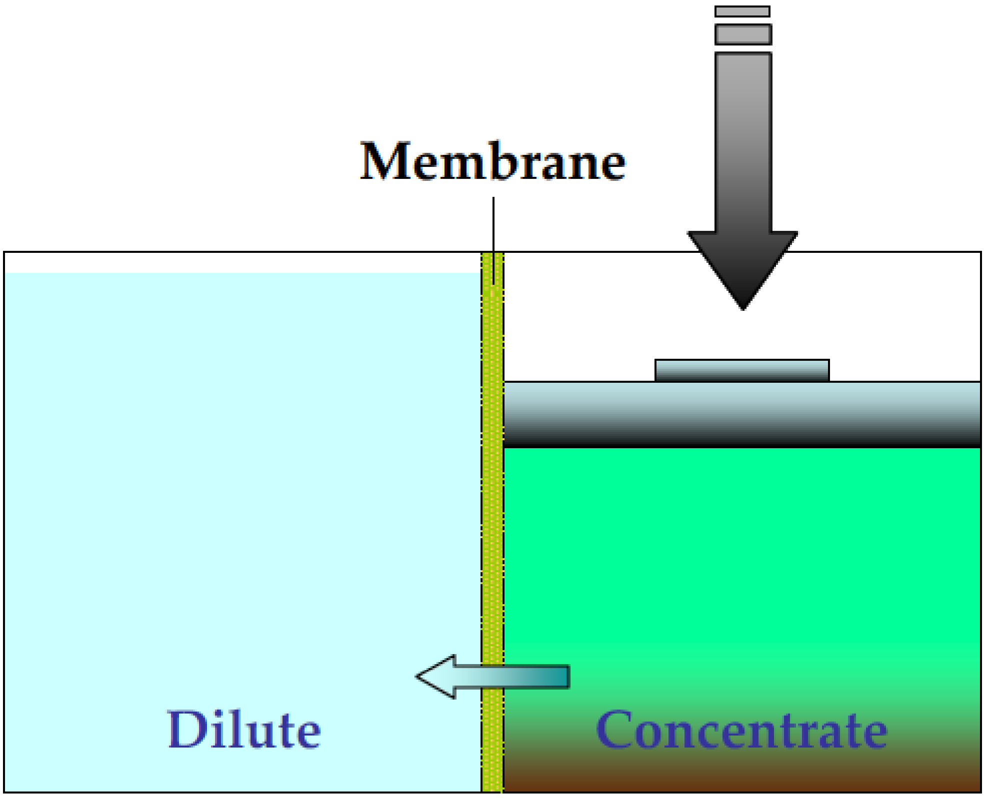

Figure 1.1: Schematic diagram of reverse osmosis process (Mulder, 1997)

1.2 AIMS AND OBJECTIVES

The main aim of this research was to develop an artificial neural network model that would help in the prediction of permeate flow data of a reverse osmosis process from the Institute of Research for desalination in Saudi Arabia. The stages involved in achieving this aim were as follows:

1. Reverse osmosis data collection
2. Data preparation such as statistical analysis
3. Identification of outliers
4. Creating the ANN model
5. Analysis of the data using the ANN model

1.3 THESIS STRUCTURE

The thesis consists of six chapters; Chapter 1 puts the thesis into general context. Chapter 2 reviews relevant literature, Chapter 3 outlines the basics of artificial neural networks, Chapter 4 discusses how the raw data used in this research was collected, Chapter 5 then discusses findings from this research and finally Chapter 6 concludes the thesis by providing overall conclusion and suggesting possible future work.

Chapter 2 LITERATURE REVIEW

This chapter introduces desalination processes starting with the history of desalination and its needs and moving on to the classifications of desalination processes. We next illustrate the principle and operational variables in multistage flash and reverse osmosis desalination plants.

2.1 NEED FOR DESALINATION

Water is an important resource for use of mankind. It is essential for agricultural and industrial growth, as well as for supporting growing populations who require a safe drinking water supply. We find 97% of all water in oceans, 2% in glaciers and ice caps, and the rest in lakes, rivers and underground. Natural resources cannot satisfy the growing demand for low-salinity water with industrial development, together with the increasing worldwide demand for supplies of safe drinking water. This has forced mankind to search for another source of water. In addition, the rapid reduction of subterranean aquifers and the increasing salinity of these non-renewable sources will continue to exacerbate the international water shortage problems in many areas of the world. Desalination techniques are capable of providing the solution (Temperely, 1995). Desalination refers to water treatment processes that remove salts from saline water.

2.2 DESALINATION TECHNOLOGIES

Desalination technologies enable the reduction of salinity in water thus converting it to suitable water for human consumption. It can be divided into two processes; thermal and membrane separation. The thermal process is one of the most ancient ways of desalting brackish or seawater; it is based on distillation and involves boiling or evaporation. Steam generators and boilers provide the thermal energy required.

2.3 CLASSIFICATION OF DESALINATION PROCESSES

Figure 2.1, shows the major desalting processes.

Two of the most popular methods for classifying the well-known desalination processes are as follows:

A. Phase change desalination process. There are three main methods:
    - Multi-effect distillation
    - Multistage flash distillation
    - Vapour-compression distillation
B. Non phase change desalination processes. These include the following two main methods:
    - Reverse osmosis
    - Electrodialysis
    - Nanofiltration

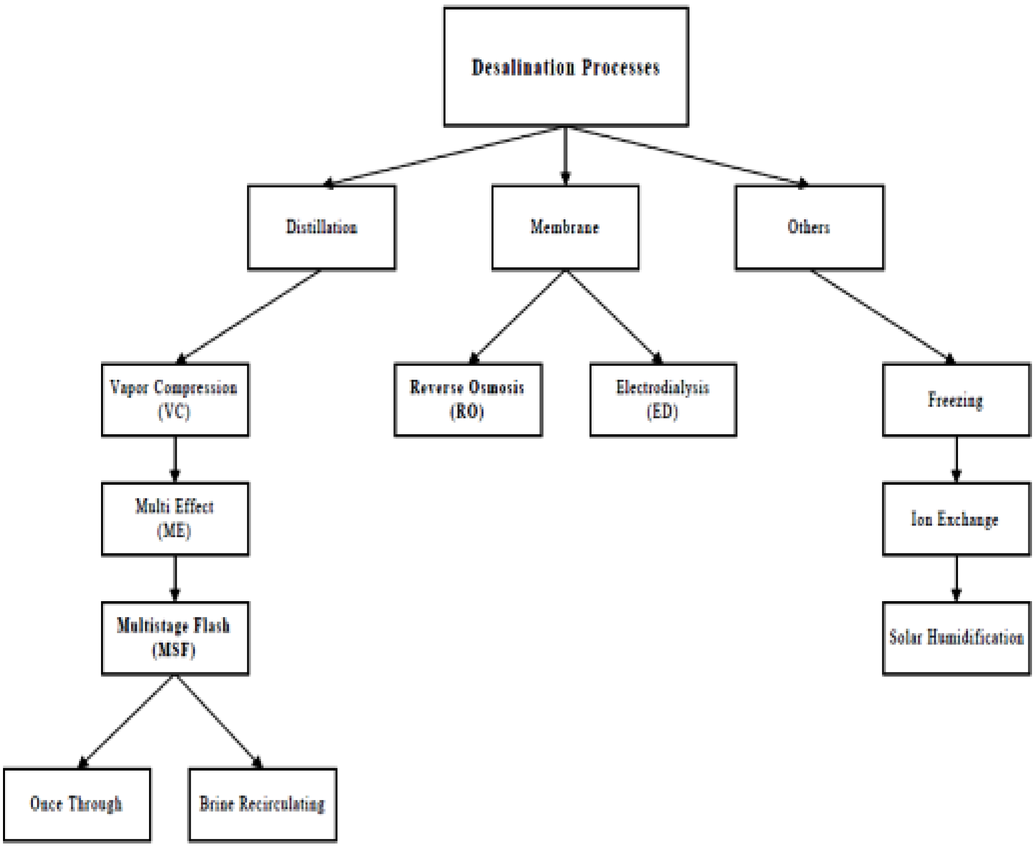

Figure 2.1: Desalting processes classification (Khan, 1986).

The use of a particular process of desalination depends on the salt concentration in the feed water and on its water unit cost. Distillation is the oldest and most commonly-used desalting techniques. It involves the evaporation of the saline water and condensation of the generated vapour occurring in order to obtain fresh water. More often than not the water produced is of superior quality as compared to that produced through crystallisation and membrane processes.

2.3.1 Distillation: thermal processes

2.3.1.1 Vapour Compression

Vapour-compression distillation uses mechanical energy rather than thermal energy. Saline water is sprayed over an evaporator tube bundle and the vapour formed at some temperature and pressure is then compressed either thermally in a steam ejector, or mechanically in a compressor. The condensation temperature and pressure increase and the volume decreases. Compressed vapour is passed through the evaporator bundle, where it condenses and forms distilled water. Vapour-compression plants have single effects however multi-effect configurations could be used for a larger product capacity. Figure 2.2 illustrates the principle of vapour compression. The process utilises little energy and as a result unit operation costs are low. However the water produced is of low quality.

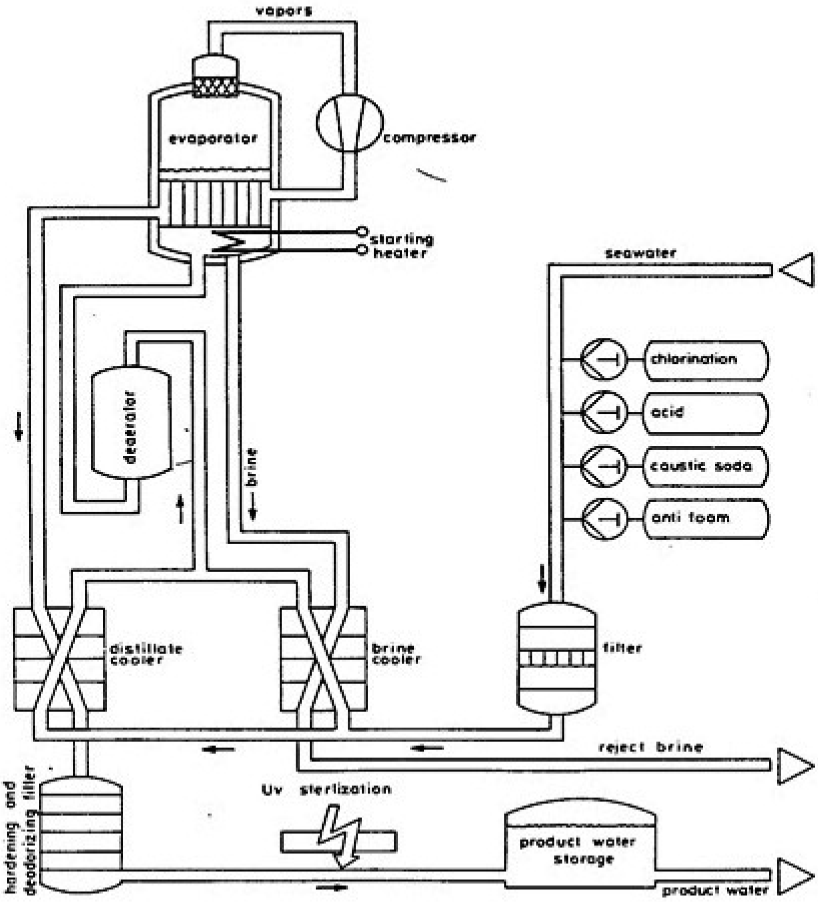

Figure 2.2: Principle of vapour compression (Khan, 1986).

2.3.1.2 multieffect distillation (MED).

One of the pioneering processes used to produce a significant amount of water from the sea is Multieffect distillation. It takes place in a series of vessels and uses the principle of reducing the ambient pressure in the various vessels in order of their arrangement. This causes the feed water to undergo boiling in a series of vessels without supplying additional heat after the first effect. MED units are usually built for capacities of 2000-

20000 m^3/day and the energy consumption is about 15 kWh/m^3 (Al-Sahili, *et al.*, 2007). Figure 2.3 illustrates the arrangement of a multieffect distillation. Vapour generated in the first vessel gives up heat to the second effect for evaporation and is condensed inside the tubes.

The seawater is distributed onto the surface of evaporator tubes in a thin film to promote rapid boiling and evaporation. The condensate is recycled to the boiler for reuse.

The larger the number of vessels, the less heat that is required as heat sources. There are vertical and horizontal tube evaporation vessels. In horizontal vessels evaporation takes place on the outer surfaces of the heating tubes and thus steam is condensed in the inner tubes.

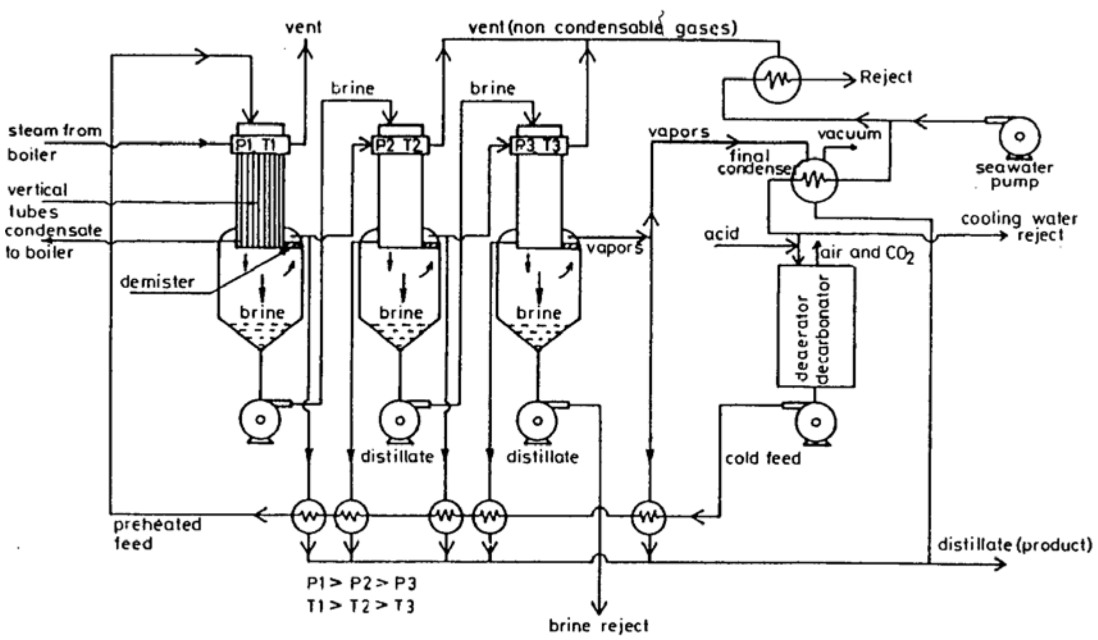

Figure 2.3: Schematic diagram of a multieffect distillation plant (Khan, 1986).

2.3.1.3 Multistage flash distillation (MSF)

Multistage flash distillation processes work on the principle that seawater will evaporate as it is introduced into the first evaporator (flash chamber) with lower pressure than saturation pressure. It condenses and cools down to a saturation temperature equivalent to chamber pressure. It enables to produce fresh water with low salt concentrations (< 10 mg/l) from feed water with salinities of up to 70 g/l. MSF units are built for capacities of 4000-57000 m^3/d. It is an energy intensive process consuming about 18 kWh/m^3 which is the highest of all established technologies. It is up to three times higher than that of a reverse osmosis unit. It is still often used due to its high reliability and its easy layout and process control (Al-Sahili, *et al.*, 2007).

The multistage flash distillation plants consist of three sections: heat-rejection, heat-recovery, and heat input (brine heater). The heat-rejection and heat-recovery consist of a number of flash chambers (stages) connected to one another.

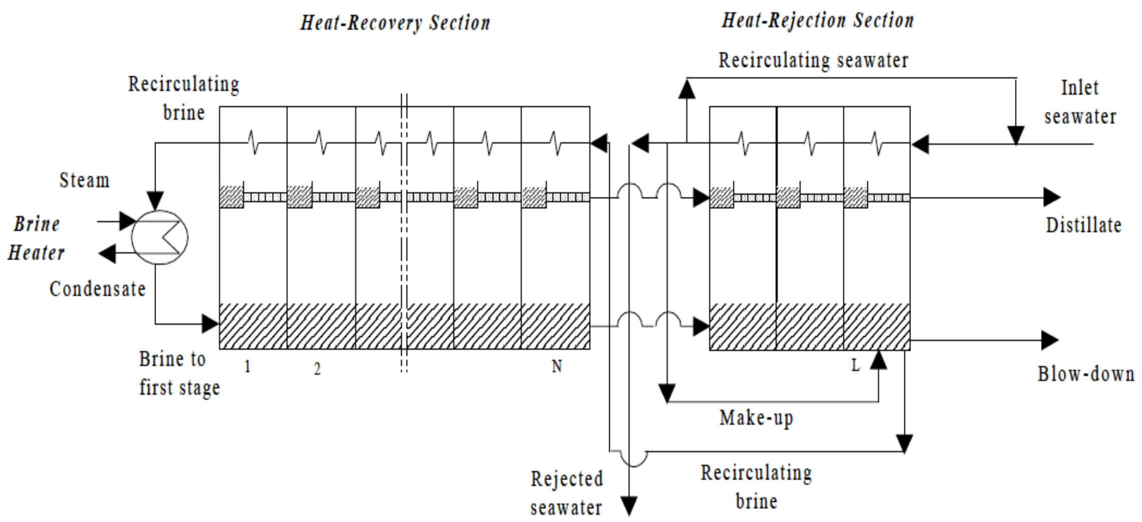

Figure 2.4: A recirculating-brine multistage flash desalination plant (Khan, 1986).

2.3.2 Membrane processes

Membrane processes are based on the separation of water and salts via a semi-permeable membrane. The reverse osmosis process uses pressure to separate the dissolved salts from the feed water. In electrodialysis, electricity is used.

2.3.2.1 Reverse osmosis

Reverse osmosis processes are of high interest in two fields; in the biological science, because of the importance of selective transport through cell membranes to life processes and in chemical processing, including water and waste water treatment.

The process is simple and highly effective thus generating a lot of interest in research as well as general application in industry. It is generally a very fine filtration process that uses a membrane to filter out salt from a solution using minimal driving pressure, osmotic pressure difference below which it fails (Hanbury et al., 1993).

In the reverse osmosis process feed water is pressurised by high pressure pumps up to 80 bats and passes through special membranes to an enclosed vessel. The vessels selectively block most dissolved solids including salts and let pure water through. The amount of fresh water produced is dependent on the applied pressure and salt content of the feed water. It goes without saying that energy consumption increases with growing membrane pressure however recent methods of energy recovery mean that the energy consumption can be reduced to about 3 kWh/m^3 (Buros, 2000).

Its efficiency depends on the type of membrane used, its ability in separation and its resistance to chemical and environmental effects. Recent developments in membrane technology and construction material have made reverse osmosis plant attractive for large desalting capacities. The membranes used are fine in nature.

The process is widely used in the desalination of sea water for plant use, wastewater reclamation and most importantly in water production for human consumption (Van der Kooij, Hi- jnen & Cornelissen, 2009).

2.3.2.1.1 Principles of reverse osmosis

During the separation of pure water and a salt solution through a semipermeable membrane, the pure water diffuses through the membrane and dilutes the salt solution. The membrane rejects most of the dissolved salts and allows water to permeate. This phenomenon is known as natural osmosis (Figure 2.5a).

As water passes through the membrane, the pressure on the dilute side drops and that of the concentrated solution rises. The osmotic flux continues until equilibrium is reached, where the net water flux through the membrane becomes zero (Figure 2.5b).

At equilibrium, the liquid level in the saline water will be higher than that on the waterside. The amount of water passing in either direction will be equal. The hydrostatic pressure difference achieved is equal to the effective driving force causing the flow, called osmotic pressure. This pressure is a strong function of the solute concentration and the temperature, and depends on the type of ionic species present.

Applying a pressure in excess of the osmotic pressure to the saline water section slows down the osmotic flow, and forces the water to flow from the salt solution into the waterside. Therefore, the direction of flow is reversed, and that is why this separation process is called reverse osmosis (Figure 2.5c).

Between two solutions with different concentrations a difference in osmotic pressure exists. The osmotic pressure is the minimum pressure which prevents the movement of water molecules to the concentrated solution. To make reverse osmosis possible the external pressure has to exceed osmotic pressure. When osmotic pressure and external pressure are equal, no water is flowing. When external pressure exceeds the osmotic pressure, the water starts to flow from left to right. (Crittenden, Trussel, Hand, Howe & Tchobanoglous, 2005)

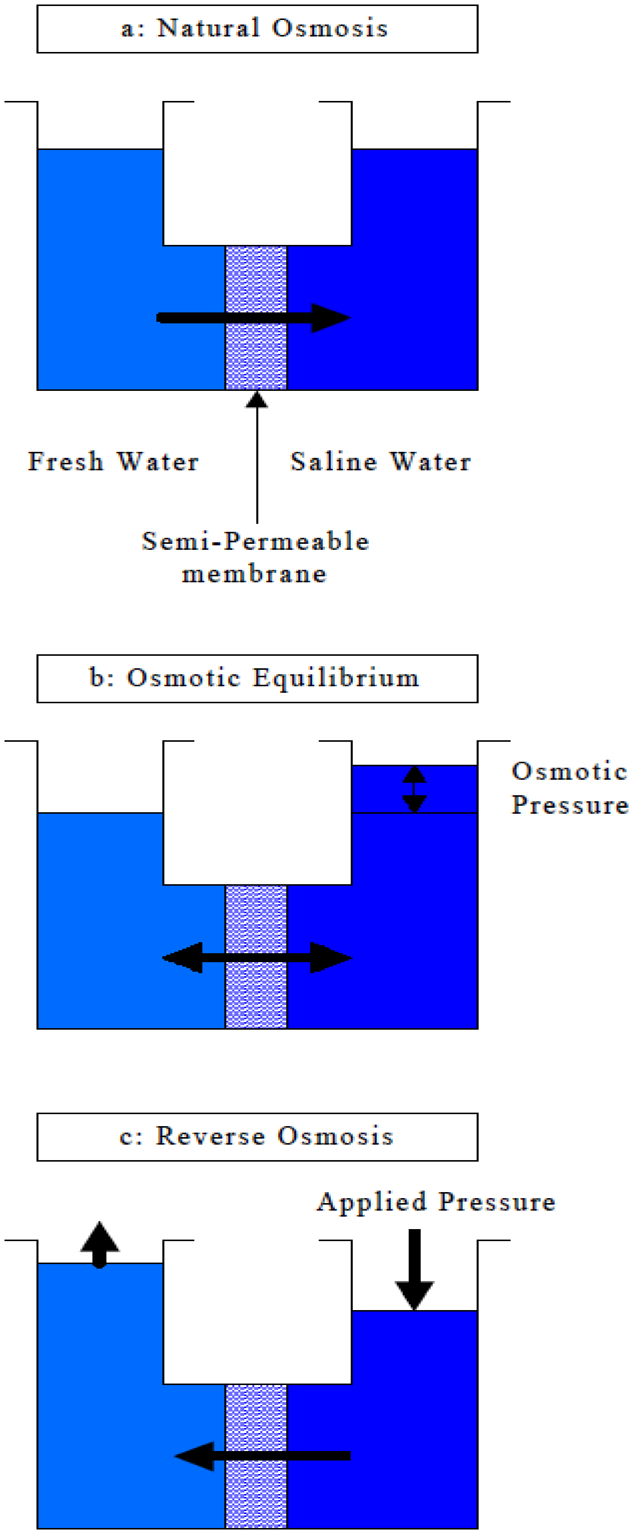

Figure 2.5: Principle of reverse osmosis (Mulder, 1997).

2.3.2.1.2 Process description and terminology

A reverse osmosis system consists of four major components, shown in Figure 2.6. They are:

- pre-treatment system
- high-pressure pump
- membrane assembly
- post-treatment system

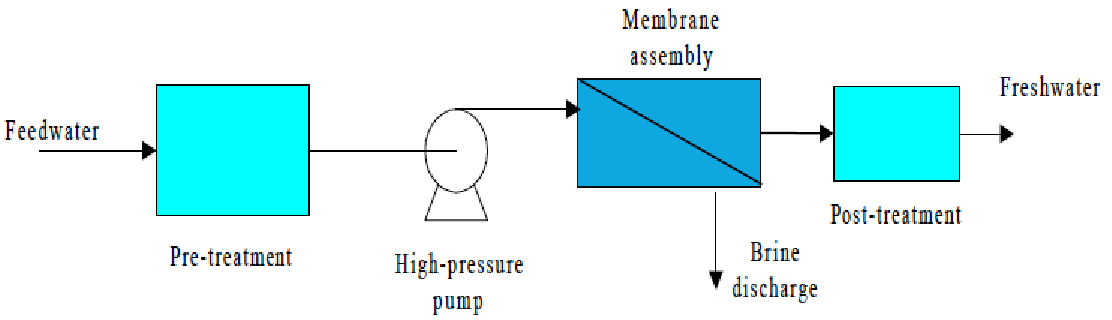

Figure 2.6: Flow diagram of a reverse osmosis system (Mulder, 1997).

2.3.2.1.2.1 pre-treatment system

Feed pre-treatment is necessary in all desalination methods. Proper pre-treatment of water before it reaches the membrane key to successful operations of a reverse osmosis plant. The need for pre-treatment depends on the feed water composition, the recovery of the RO system, and the solubility of the particular salt. Specifically, a pre-treatment step has the following objectives:

- To remove excess turbidity and suspended solids.
- Inhibiting and controlling scaling and precipitate formation which would block the membrane.
- To disinfect and prevent bio fouling and equipment contamination.

A new method for pre-treatment is the use of micro- or ultrafiltration. They give defined protection against particles. Membrane filtration has the advantage of non-chemical treatment and it can replace the granular filtration of conventional pre-treatment which needs chemical dosing. Micro and ultrafiltration membranes have also backwash possibility. They are more flexible to changes in feed water quality than conventional pre-treatment methods. Because of the good rejection of micro and ultrafiltration, reverse osmosis membranes age slower. (Greenlee, Lawler, Freeman, Marrot & Moulin 2009) Recent studies show that ultrafiltration has become the most tested and studied membrane filtration pre-treatment (Van Hoof, Minnery, Mack 2001, 164-166. Halper, McArdle & Antrim 2005). The disadvantage of pre-treatment with membrane filtration is fouling of the pre-treatment membranes themselves. Fouling can be reduced by the use of inline coagulation. Coagulant cannot be applied at the same time with antiscaling agent. Coagulant and antiscaling chemical form together a complex which is a very difficult foulant (Greenlee, Lawler, Freeman, Marrot & Moulin, 2009). Ultrafiltration has yet another disadvantage, according to studies, ultrafiltration results in a very good rejection of particles but it does not remove material that causes bio fouling. (Van der Kooij, Hijnen & Cornelissen, 2009), (Vrouwen velder, van Paassen, van Agtmaal, van Loosdrecht, Kruithof, 2009).

2.3.2.1.2.2 high-pressure pump

It raises the pressure of the pre-treated feed water to the required feed pressure. The pressure required depends on the concentration and temperature of the feed water. Osmotic pressure increases with increasing concentration, so that the operating pressure must exceed the osmotic pressure corresponding to the concentration of the rejected brine at the membrane outlet. It can be up to three times the osmotic pressure for seawater desalination. Brackish water requires 17-27 bar, whereas seawater operates in the range of 50-80 bar (Al-Sahili, *et al.*, 2007).

Figure 2.7 depicts the osmotic pressure of sodium nitrate, chloride and sulphate, and seawater as a function of salt content 25°C. In addition, osmotic pressure increases with temperature, so that any increase in the temperature must be accompanied by an increase in the applied pressure.

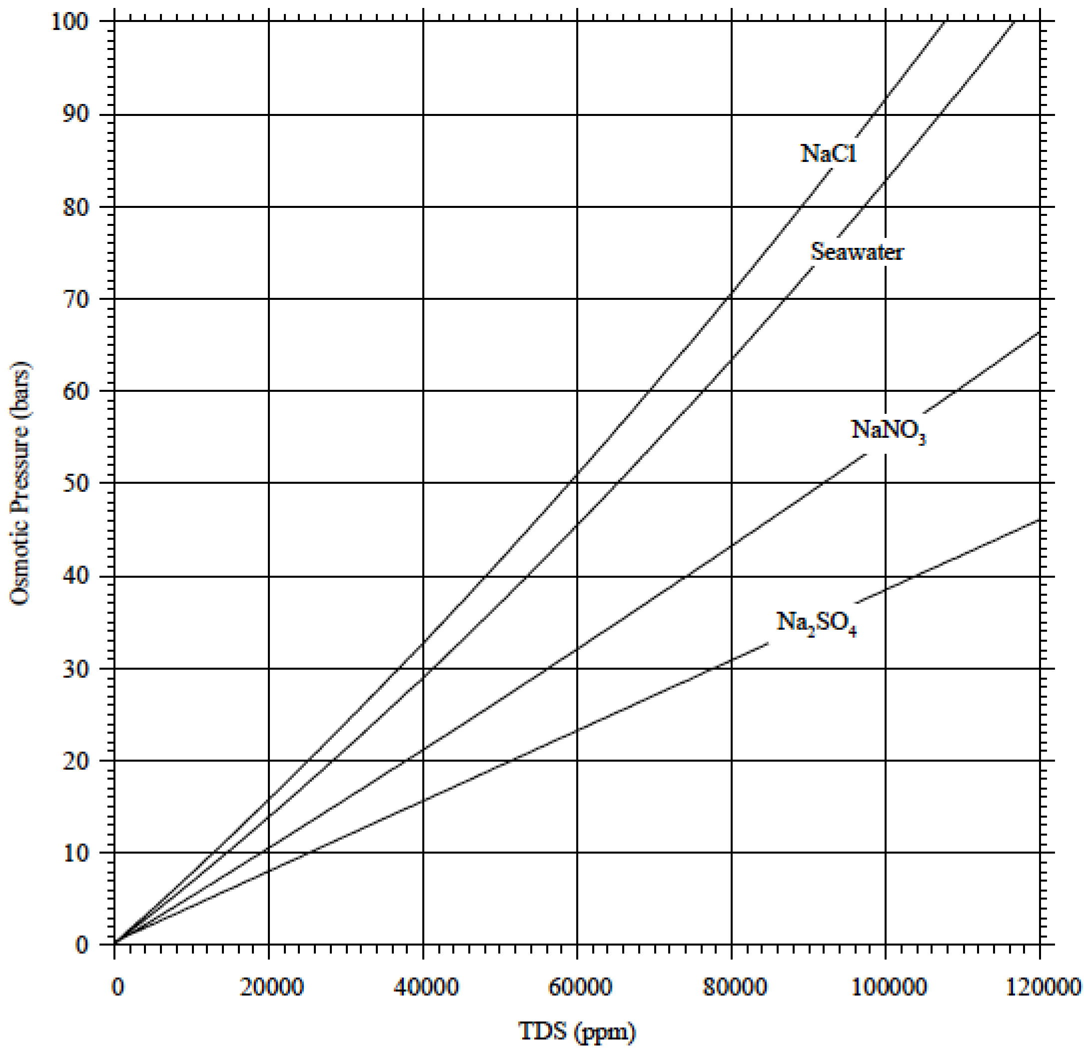

Figure 2.7: Osmotic pressures of sodium nitrate, chloride and sulphate, and seawater at 25°C (Hanbury, et al., 1993).

2.3.2.1.2.3 membrane assembly

Membranes were originally made from cellular acetate but with advances in technology reverse osmosis processes use a variety of blends or derivatives of cellular acetate, polyamides. Plate-and-frame, tubular, spiral-wound and hollow-fine-fibre membranes are the most popular reverse osmosis devices.

An ideal membrane should have the following characteristics (Mulder, 1997):

- High salt rejection
- High permeability to water
- Resistant to high temperature
- Resistant to oxidizing agents
- Resistant to all kind of fouling
- Chemically, physically, and thermally stable in saline water.
- Capable of being formed to yield high membrane area-to-volume ratio
- Long and reliable life.
- Inexpensive.

Figure 2.8 shows the factors influencing the membrane performance.

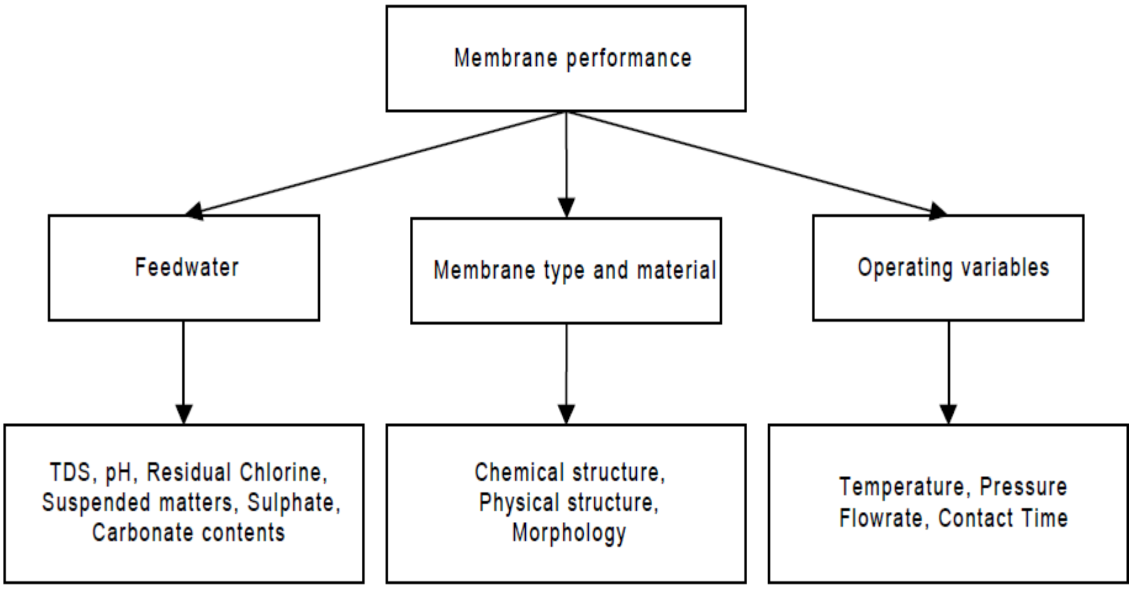

Figure 2.8: Factors influencing the membrane performance (Mulder, 1997).

2.3.2.1.2.3.1 Spiral-Wound Systems

Originally developed in the mid-sixties, they became commercially available in the late sixties and replaced tubular membranes in water producing installations. They are characterised by their high packing densities in the order of 600 m^2/m^3 and can operate at pressures of up to 80 bar.

Figure 2.9 shows the spiral-wound membrane assembly consisting of two or more leaves (envelopes). Each leaf has two flat sheets of semipermeable membrane separated and supported by a porous backing material, and sealed together at the edges by special epoxy or polyurethane adhesives. The edges of the membrane are sealed on three sides only to form a flexible envelope. The open end of the envelope is sealed around a central product collection tube from which the permeate flows. A flexible spacing, plastic netting is placed on top of the sealed membrane sandwich and the whole roll material is wrapped around the central tube, to form a spiral wound unit. This unit is then inserted into a glass-fibre, pressure vessel for use.

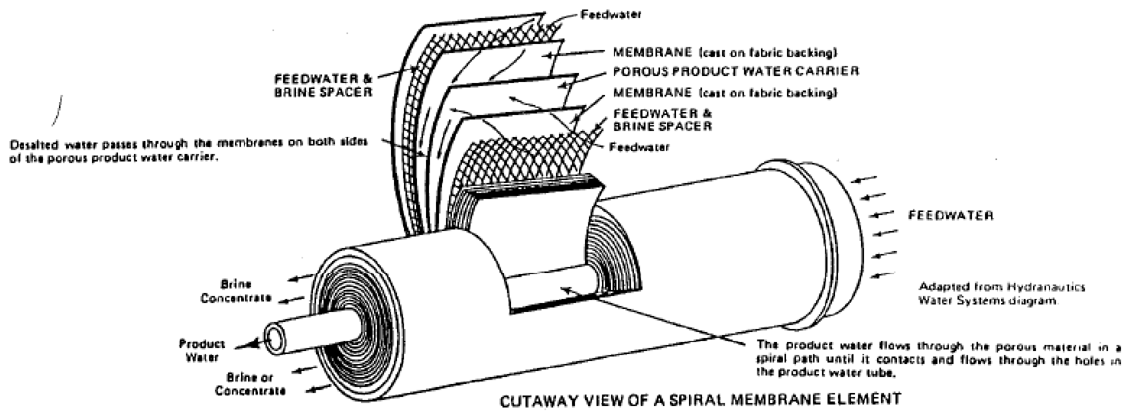

Figure 2.9: Spiral-wound membrane assembly (Khan, 1986).

2.3.2.1.2.3.2 Hollow Fibre Membranes

Developed in the late sixties, they became commercially available in the early seventies. They have a maximum area per unit volume (about 30,000 m^2/m^3). They are designed as long capillary tubes with a diameter of about a human hair. The capillary tubes have an outside diameter of 80-200 microns, about twice the inside diameter of 40-100 microns, so they are relatively thick-walled tubes. An outside-to-inside diameter ratio of 2 to 1 gives the fibres the strength to resist the high pressure involved.

Figure 2.10 shows the hollow fibre membrane configuration. Millions of membrane fibres are arranged and wound around a backing cloth as a bundle which is rolled up around a feed distribution pipe, and then assembled into a sealed cylindrical pressure vessel made of a glass-reinforced plastic. Each end of the fibre bundle is set into epoxy resin blocks so that the bores are exposed. One end remains sealed, while the other is then cut away to expose the open end. This arrangement is much like a shell-and-tube arrangement, with the fine tube open at one end.

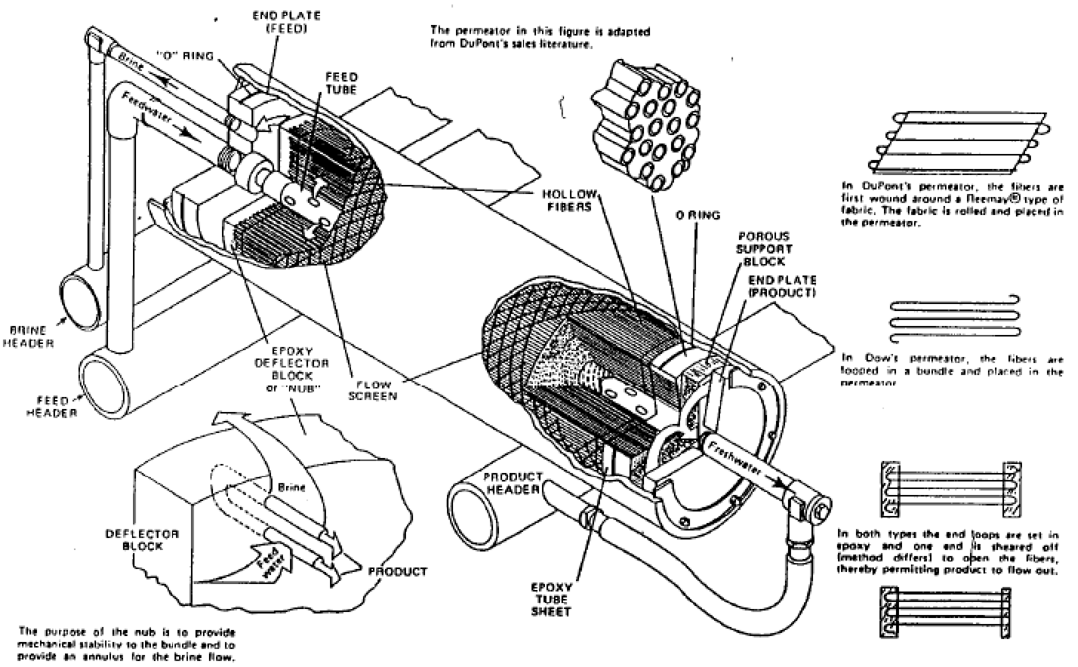

Figure 2.10: Hollow fibre membrane assembly (Khan, 1986)

2.3.2.1.2.4 Post-Treatment System

The water produced as a product from the reverse osmosis plant requires further treatment before storage and transmission to consumers. This is necessary as the product water can cause serious corrosion problems in the pipe transmission system. (Hanbury, 1993).

The produced water requires pH adjustment. This is done by adding a base or by degasification (H_2S and CO_2). Most reverse osmosis membranes reject calcium in preference to sodium thus necessitating the addition of calcium salts. The water further requires disinfection to curb bacterial growth.

2.3.2.1.3 Reverse osmosis working equations

The reverse osmosis membranes must be tested for fluxes, salt rejection, and recovery under various temperatures, pressures, and feed water salinities.

2.3.2.1.3.1 Water flux

Water flux is defined by Equation 2.1, (Mulder, 1997) ;

$$J_1 = K_1(\Delta P - \Delta \pi) \tag{2.1}$$

$$K_1 = K_w \frac{A}{\tau} \tag{2.2}$$

$$\pi = 1.21T \sum M_i \tag{2.3}$$

Where

J_1 Water flux ($m^3/m^2/sec$)

ΔP Hydraulic pressure differential across the membrane (atm)

$\Delta \pi$ Osmotic pressure differential across the membrane (atm)

K_1 Pure water transport coefficient, i.e. the flux of water through the membrane per unit driving force, (m^3/m^2/sec atm)

K_w Membrane permeability coefficient for water.

A Membrane area (m)

τ Membrane thickness (m)

T Feed water temperature (K)

M_i Molarity of the i[th] ionic or non-ionic materials

K_1 is given by the membrane manufacturer or may be found by solving the equation at the standard test conditions. It depends on the membrane properties, temperature of the system and the chemical composition of the salt solution.

2.3.2.1.3.2 salt flux

It is an indicator of membrane effectiveness in the removal of salts from water. The salt flux as defined by Equation 2.4 (Mulder, 1997) is a function of the system temperature and the salt composition. Therefore, it is a property of the membrane itself and indirectly related to the feed pressure. It is proportional to the salt concentration difference across the membrane, according to the following equations;

$$J_2 = K_2 \Delta C \qquad (2.4)$$

$$\Delta C = C_f - C_p \qquad (2.5)$$

where

J_2 Salt flux (Kg/m^2/sec)

K_2 Salt transport coefficient (m/sec)

C_f Salt concentration in the feed (Kg/m^3)

C_P Salt concentration in the product (Kg/m^3)

Due to water flux being higher than that of salt through the membrane, an accumulation of salt on the membrane surface on the pressurised side of a membrane arises. This phenomenon is called concentration polarization. The increase in concentration polarization has two effects 6 (Mulder, 1997)

- Increases the osmotic pressure thus reducing the water flux across the membrane.
- Increases the driving force of the concentration difference across the membrane thereby reducing the driving potential and increasing the salt passage thus impacting negatively on product quality.

2.3.2.1.3.3 Salt Rejection

Salt rejection expresses the effectiveness of a membrane to remove salts from the water. It can be calculated from Equation 2.6 (Mulder, 1997);

$$\%\ salt\ rejection = \left(1 - \frac{Product\ concentration}{Feed\ concentration}\right) \times 100\% \quad (2.6)$$

The salt passage depends on the feed water temperature and composition, operating pressure, membrane type and material, and pre-treatment.

Salt passage and bundle pressure drop are the two indicators of membrane fouling.

2.3.2.1.3.4 Recovery

Recovery rate of a RO system is defined by Equation 2.7(Mulder, 1997).

$$R = \frac{Q^p}{Q_f} \times 100\% \tag{2.7}$$

where

Q_P Product flow (m^3/day)

Q_f Feed flow (m^3/day)

The recovery is specified by the feed water salinity. For example, seawater plant's recovery varies between 20-35%.Increasing the recovery raises the brine concentration and the osmotic pressure, thus decreasing the permeate flux and increasing the total dissolved solid in the product. We can increase the recovery by increasing the number of banks in the system.

2.3.2.1.4 Reverse osmosis process variables

When a reverse-osmosis system is used on a commercial level, it is important to check its performance periodically. As time passes, the membrane performance deteriorates continuously due to pressure compaction and fouling. This causes its transport parameters to change, and the performance of the module to decline. Therefore, data monitoring is an important step in optimizing the performance of an RO plant. The important operating variables of a RO desalination process are as follows;

2.3.2.1.4.1 Permeate flux

At a given feed salinity, the feed flow rate affects the production rate of the plant, water recovery, and the number of modules. A low production rate, below design specifications, could be an indication of membrane fouling. Every stage in an RO plant is designed to operate at a certain recovery, which is the ratio of product flow to the feed flow. If the recovery is above the design specification, then the brine concentration and the osmotic pressure will increase, causing a decrease the permeate flux and an increase in dissolved solid content in the product.

Since the feed flow is maintained constant during operation, the product flow must be controlled to maintain a constant recovery during operation.

2.3.2.1.4.2 Permeate conductivity

The main objective of an RO process is to produce product of a low total dissolved solids content. However, since the TDS is not easily measured except under controlled conditions in laboratories, the plant operators use conductivity to estimate the quality of the water produced.

Monitoring the product conductivity is necessary to produce good water product. A gradual or rapid increase in the product conductivity is an indication of membrane fouling or mechanical damage in the membrane module, respectively.

Both permeate flux and conductivity are affected by (Mulder, 1997);

- pH
- Temperature
- Pressure

2.3.2.1.5 MEMBRANE FOULING

Fouling is the most important issue for membrane applications. It causes flux decline and shortens the membrane life. Fouling can be categorized by different characters: mechanism, reversibility and foulants (Crittenden, Trussel, Hand, Howe & Tchobanoglous, 2005). Surface fouling and fouling in pores are the two fouling mechanisms that are commonly detected. Fouling causes water flux decline, increase of trans-membrane pressure drop and feed channel pressure drop, and salt passage through NF/RO membranes (Greenlee, Lawler, Freeman, Marrot & Moulin, 2009). Permanent loss of performance after cleaning is called irreversible fouling. Reversible fouling is fouling that could be removed by backwashing or cleaning (Crittenden, Trussel, Hand, Howe & Tchobanoglous, 2005). The next sections describe four common types of fouling: particulate fouling, organic fouling, scaling, and bio fouling.

2.3.2.1.5 .1 Particulate fouling

Source water for reverse osmosis is often sea water or brackish water and compared to fresh surface waters sea water has less particle content. However sea water treatment plants that treat water from open water intake are typically fouled by particles and organic matter. Particle fouling is caused by sand, sludge, silicates, salt precipitates and remains of micro- organisms. Particle fouling causes cake formation on the membrane and plugging in the feed channel or piping. From micro and ultrafiltration membranes particle fouling is easy to remove with backwash but NF/RO processes do not have a backwash cycle. Big part of particles exits the membrane in the concentrate because of turbulence flow in the membrane elements. If the load of particles is too big or there is not enough turbulence, particles will start accumulating which results in salt passage through NF/RO membrane, pressure drop over membrane elements and a decrease in water flux. Ultrafiltration and microfiltration as a pre-treatment for reverse osmosis give excellent particle removal (Crittenden, Trussel, Hand, Howe & Tchobanoglous, 2005), (Greenlee, Lawler, Freeman, Marrot & Moulin, 2009),(Van der Kooij, Hijnen & Cornelissen, 2009).

2.3.2.1.5.2 Organic fouling

Natural organic matter is a term often used when describing organic material. Natural organic matter (NOM) is a term used to characterise a complex group of organic chemicals originating from biological activity in water bodies such as metabolic activity of algae or micro-organisms. It can also be washed from land into water. It is composed of biological matter, reaction products between NOM molecules or reaction products between NOM molecules and inorganic components. This makes it very complex mixture of different chemical features (Crittenden, Trussel, Hand, Howe & Tchobanoglous, 2005). NOM consist of particles, biological material and dissolved organic compounds. It can be partly removed by backwashing from MF/UF membranes (Crittenden, Trussel, Hand, Howe & Tchobanoglous, 2005). Also coagulation and activated carbon treatment as part of MF/UF can help to reduce organic content and thus decrease fouling.

In NF/RO processes NOM precipitates and adsorbs on the membrane surface and causes decrease in water flux (Van der Kooij, Hijnen & Cornelissen, 2009). Organic fouling can be reduced by pre-treatment with bio filtration or very tight ultrafiltration membranes are also able to reduce the organic load (Liikanen, 2007), (Mosqueda-Jimenez, Huck, 2009).

2.3.2.1.5.3 Scaling

Scaling is fouling by inorganic substances. Scaling occurs when the concentration of salts exceeds the solubility and they start to precipitate. They crystallise on the membrane surface. Micro and ultrafiltration membranes allow salts to permeate through the membrane so the salt concentration will not rise on the membrane surface. Scaling is mainly a problem of NF/RO membrane processes. In sea and brackish water there are lots of inorganic ions. The main ions are calcium, magnesium and barium. Concentration polarization is a phenomenon which occurs when dissolved ions accumulate in a thin layer of the feed water. It is the ratio of salt concentration at the membrane surface and in the bulk solution. Concentration polarization decreases water flux through the membrane and increases salt transport through the membrane. It leads also to scaling. Water flux declines because higher concentration on the membrane surface causes higher osmotic pressure which leads to the overall pressure difference decrease. Salt transport increases due to increase in concentration and decrease in water flux. Scaling is prevented by using antiscalants which increase the threshold of concentration when the ions start to crystallise and disturb the formation of crystal structure (Crittenden, Trussel, Hand, Howe & Tchobanoglous, 2005).

2.3.2.1.5.4 Bio fouling

Bio fouling is accumulation and attachment of micro-organisms on membrane surface where they form a biofilm. Bio fouling is troublesome because it cannot be controlled by reducing microbes in the feed water. If there is any microbe left, it will multiply as long as nutrients are available. (Crittenden, Trussel, Hand, Howe & Tchobanoglous, 2005.) Part of NOM can be used by micro-organisms as nutrient. Assimilable organic carbon (AOC) is a ready to use energy source for microbes and if it's available in big concentrations that means that microbes have a lot of potential to grow. So the bio fouling potential can be derived from nutrient concentration in the system. (Van der Kooij, Hijnen & Cornelissen, 2009)

A biofilm is formed always when micro-organisms have a surface to attach. Micro-organisms can attach to the membrane and they are difficult to remove during backwash. On the membrane they start to excrete gel-like extracellular material that protects them from cleaning and results in additional fouling. The possibilities to prevent bio fouling are disinfection, biocide dosing and nutrient reduction by bio filtration. Disinfection kills microorganisms but if the dead biomass is not removed a new biofilm will grow on it fast using the biodegradable compounds from the dead mass. According to studies limiting nutrient concentration is an effective way to control bio fouling (Griebe, Flemming 1998, 156. Hu, Song, Ong, Phua, Ng 2005, 128, 132). Biofilm forms in phases. It occurs when the biofilm growth exceeds the threshold of interference. Because it's impossible to kill all the micro-organisms from the system, the other option is to live with biofilm formation as long as it does not lead to bio fouling. The threshold of interference is the limit below which the biofilm does not interfere with membrane performance. Bio fouling results mainly in pressure drop increase but it can also decrease the permeate flux and salt rejection on NF/RO membrane.

2.3.2.2 Electrodialysis

Many salts in water are ionic in nature and thus can be attracted to an electric field. Electrodialysis involves the use of two membranes, that is the cation and the anion membrane. The cation membrane allows only positive ions to permeate whereas the anion membrane allows only negative ions to permeate. The membranes are alternately immersed in salty water in parallel, and an electric current is passed through the liquid. The cations migrate to the cathode and the anions migrate to the anode. Water passing between membranes is then split into two streams, pure water and brine. Due to the energy being used in the process being directly proportional to the quantity of salt removed it is usually used in the desalination of brackish water. Figure 2.11 illustrates an electrodialysis process.

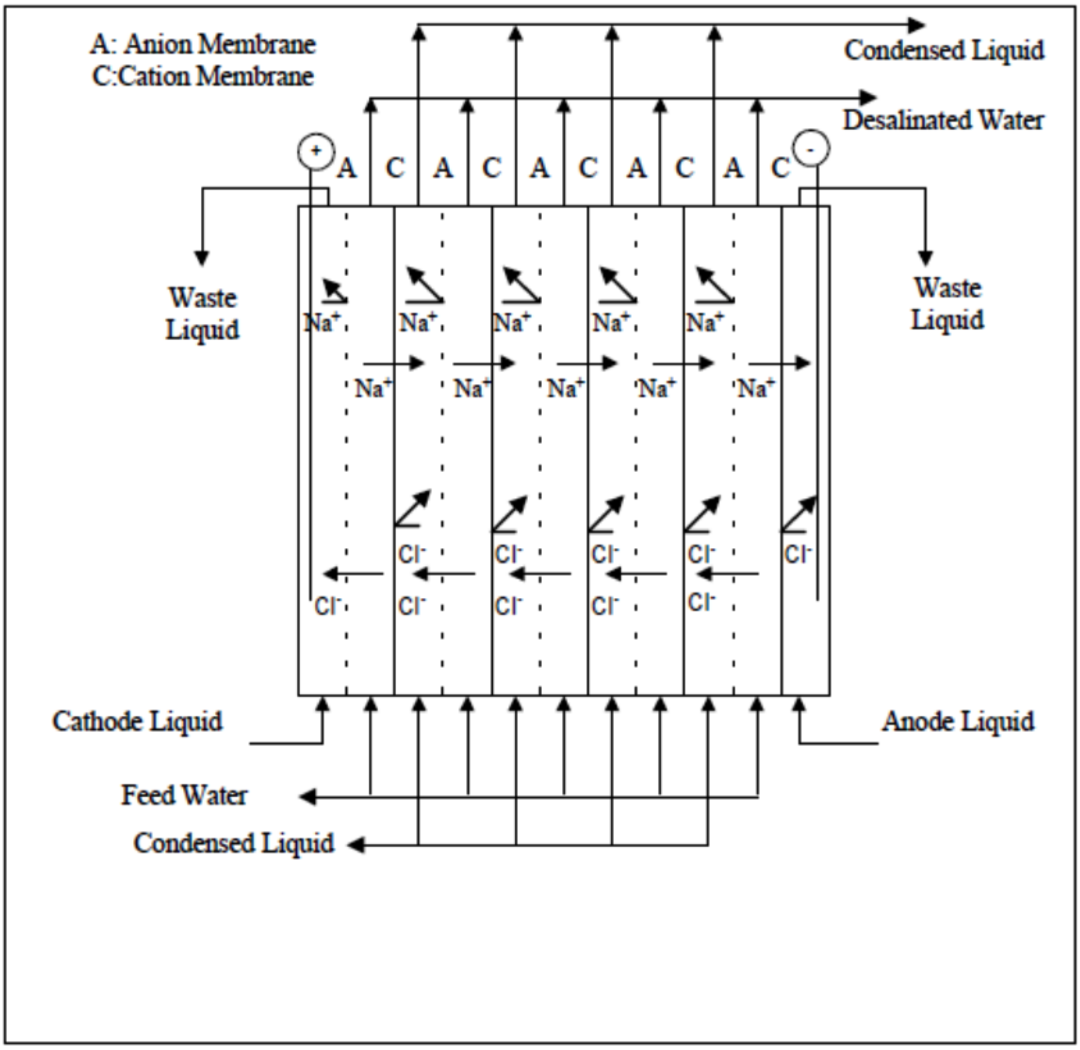

Figure 2.11: Principle of electrodialysis (Khan, 1986).

2.4 ADSORPTION

Selective adsorption concerns the separation of components in a fluid mixture by the transfer of one or more components (the adsorbates) to the internal surface of a porous solid (the adsorbent) where they are held by intermolecular forces. Desorption is the reverse process in which the adsorbates are removed from the solid surface so that the adsorbent becomes partially or fully regenerated for reuse.

Selective separation may depend on one or more of three mechanisms (Crittenden B.D. and Thomas J., 1998):

1. Differences in adsorption equilibria between adsorbates and the adsorbent (the equilibrium mechanism)

2. Differences in the rates of adsorption and/or desorption of different adsorbents within the adsorbent structure (the kinetic mechanism)

3. Complete exclusion of one or more adsorbates from the adsorbent pores because they are too small (the true molecular sieving mechanism)

The phenomenon of adsorption- the accumulation of concentration at a surface is essentially an attraction of adsorbate molecules to an adsorbent surface. Adsorption occurs when molecules diffusing in the fluid phase are held for a period of time by forces emanating from an adjacent surface. The surface represents a gross discontinuity in the structure of the solid, and atoms at the surface have a residue of molecular forces which are not satisfied by surrounding atoms like those in the body of the structure (5). These residual forces are common to all surfaces and the only reason that certain solids are designated ‘adsorbents’ is that they can be manufactured in a highly porous form, giving rise to a larger internal surface area (Coulson J.M., Richardson J.F., Backhurst J.R., Harker J.H., 1991). Interaction between adsorbate and adsorbent consists of molecular forces embracing (Crittenden B.D. and Thomas J., 1998):

- Permanent dipole
- Induced dipole
- Quadrupole electrostatic effects (van der Waal’s forces)-

The reason for the preferential concentration of molecules in the proximity of a surface to arise is because the surface forces of an adsorbent solid are unsaturated. When adsorption occurs, both short range (repulsive) and long range (attractive) forces between adsorbate and adsorbent become balanced (Crittenden B.D. and Thomas J., 1998).

The adsorption which results from the influence of van der Waals forces is essentially physical in nature. The forces in this case are not so strong and therefore the adsorption can easily be reversed. In some systems, additional forces bind adsorbed molecules to the solid surface. These are chemical in nature and they involve the exchange or sharing of electrons, or molecules breaking up into atoms or radicals. It is less easily reversed than physical adsorption.

Highly volatile components with low polarity, as represented by hydrogen in this case, are essentially non-adsorbable compared with other molecules.

When a molecule having three degrees of freedom approaches an unsaturated surface, at least one degree of freedom is lost. This is a consequence of its attraction to the surface where it is constrained to movement across the adsorbent surface. When spontaneous processes such as physical adsorption occur, there is a decrease in Gibbs free energy ($\Delta G < 0$). Further, there must also be a decrease in entropy because the gaseous molecules lose at least one degree of freedom (of translation) when adsorbed as seen in Equation 2.8 balanced (Crittenden B.D. and Thomas J., 1998).

$$\Delta G = \Delta H - T\Delta S \tag{2.8}$$

It follows then from the expression above that delta H becomes negative, that is to say heat is released. Physical adsorption is normally characterized by the liberation of between 10 to 40 kJ/mol of heat which is close to condensation values.

2.4.1 Granular activated carbon

Many adsorptions of organic substances by GAC result from specific interactions between functional groups on the sorbate and on the surface of the sorbent. There are three primary rate steps in the adsorption of materials from solution by GAC, that is the transport of the adsorbate through a surface film to the exterior of the adsorbent, film diffusion, second is the diffusion of the adsorbate within the pores of the adsorbent, pore diffusion, third is adsorption of the solute on the interior surfaces bounding pore and capillary spaces. For most operating conditions the transport of the adsorbate through the surface film or boundary layer is rate limiting, if sufficient turbulence is provided the transport of the adsorbate through the porous carbon may control the rate of uptake.

Factors affecting adsorption are (Crittenden B.D. and Thomas J., 1998);

- Surface area
- Solute properties
- Temperature
- Adsorbent properties

2.4.1.1 granular activated carbon from date pits

The final product of activation process of carbonaceous materials is activated carbon. The activation commences with carbonisation of the raw material to obtain high carbon content within this material. That is a material with a high degree of porosity and large inter particulate surface area which are the desired properties of activated carbon and useful particularly in the removal of organic compounds in filtration and separation process.

Activated carbon is predominantly used for water treatment, waste reclamation, gas purification and as a catalyst support. The adsorption capacity depends on method of preparation and initial structural property. They can be prepared by physical or chemical activation. Activated carbon produced by the physical method is obtained after two steps, the first step being carbonisation which involves pyrolysis of the carbon material at high temperature in inert conditions to aid in the removal of oxygen and hydrogen elements from the structural matrix. The second step is thermal activation at a higher range of temperature than the previous step in the presence of an oxidising gas such as water or carbon dioxide or both. Chemical activation usually involves one step, that is both pyrolysis and activation occur simultaneously in the presence of dehydrating agents.

Activated carbon can be produced from any organic substance with high carbon content, recently many agricultural by products have been used as raw material in the production of activated carbon such as; coconut shells, olive stones, cherry stones and pecan stones, very few studies have been conducted on date stones. As of 2004, world production of dates was approximately 6.7 million tonnes. The major producers happen to be in the Middle East. As can be seen in Table 2.1, dates have a significantly high source of carbonaceous material and hence would be ideal for the production of GAC.

Table 2.1: Approximate chemical composition of dates pits (% dry weight) (Bouchelta *et al*, 2008).

Compound	**%**
Moisture	5-10
Protein	5-7
Oil	7-10
Ash	1-2
Crude fibre	10-20
Carbohydrates	55-65

2.6 CLOSURE

Desalination means the removal of fresh water from saline water. Distillation is the oldest and most commonly-used desalting techniques. In this process, evaporation of the saline water and condensation of the generated vapour occur to obtain fresh water. Reverse osmosis is pressure-driven processes, to allow water, not salt, to diffuse from a salty solution across a semipermeable membrane. The pressure difference across the membrane should be high enough to overcome the osmotic pressure and push reasonable water flux across the membrane. The proper pre-treatment of water before it reaches the membrane is the key to successful operation of a reverse osmosis process.

Chapter 3 ARTIFICIAL NEURAL NETWORKS

This chapter discusses the artificial neural networks and there various methods especially those that will be employed in the modelling approach of the desalting process.

3.1 INTRODUCTION

Interest in the early development of neural networks arose from the desire of researchers to mimic human brain functionality (Barr and Feigenbaum, 1981). A neural network is an intelligent data-driven modelling tool that is able to capture and represent complex and non-linear input/output relationships (Robert Hecht-Nielson, 1990). Neural networks are used in many important applications, such as function approximation, pattern recognition and classification, memory recall, prediction, optimisation and noise-filtering.

The human brain has the ability to learn and classify. Neural networks take their name from the simple processors in the brain, called neurons, which are interconnected by a network that transmits signals between them.

3.2 NEURONS

The brain is made up of a large number of connected cells called neurons which are paired to receptors and effectors. The relationship between receptors and effectors is best understood through the study of a neuron. Figure 3.1 shows the major components of a typical nerve cell (neuron) in the central nervous system. The major structure of the cell includes dendrites, cell body, and axon. Dendrites are the receptive zones and form the major part of the input layer of the neuron. The axon acts as a transmission line or the output. Synapses connect the axon of a neuron to other neurons.

When an input signal is transmitted into the synapses local changes in the input potential in the cell body of the receiving neurons occurs. The potentials are weighted since some are stronger than others thus the resulting inputs are either excitatory or inhibitory. Polarisation increases with the later and decreases with the former.

When the input signals (nerve impulse) come into these synapses, this results in local changes in the input potential in the cell body of receiving neurons. The input potentials are summed at the axon hillock. If the amount of depolarization at the axon hillock is equal to or greater than the threshold for the neuron, then an action potential (output) is generated and travels down the axon away from the main cell body. Figure 3.2 shows the block diagram of the nervous system.

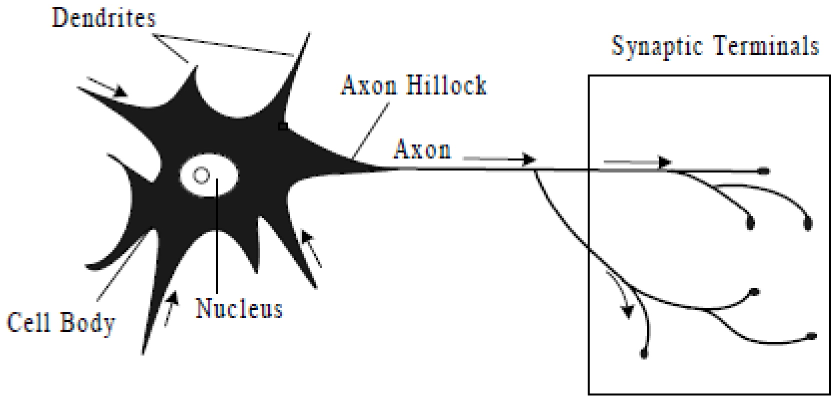

Figure 3.1: A simplified representation of a neuron (Haykin, 1994).

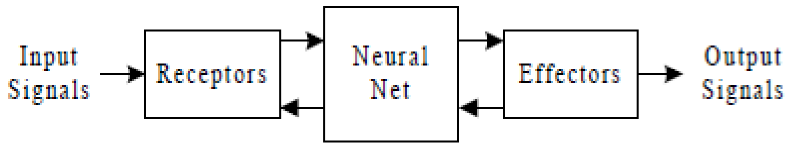

Figure 3.2: Block diagram of the nervous system (Haykin, 1994).

The nervous systems adjust to a signal which is termed learning and the rate of responding by firing an output is altered by the activities of the nervous system. Individual neurons process information by receiving signals from the dendrites and produce outputs that are transmitted to other neurons.

3.3 NEURAL NETWORK ARCHITECTURE

Neural networks can be thought of as black box devices into which specific inputs are sent to each node in the output layer. The network then processes the information through the interconnections between the nodes. The network then gives an output from the nodes on the output layer. One cannot view the processing step. Figure 3.3

shows a typical neural network structure. The layers are summarised as follows(Haykin, 1994):

- *Input Layer*: receives information from an external source and forwards this information for processing.
- *Hidden Layer*: it receives the information from the input layer and processes it in the background
- *Output Layer*: A layer of neurons that receives processed information and sends output signals out of the system.

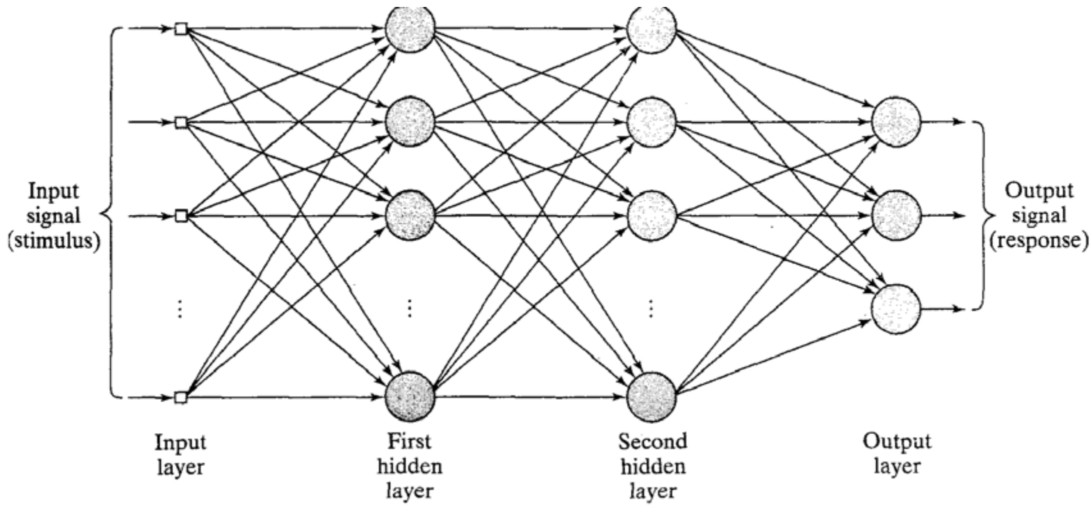

Figure 3.3: Structure of a typical multilayer neural network (Haykin, 1994).

The number of inputs and outputs determine the number of neurons on the input and output layer. The number of neurons on the hidden layer is dependent on the network application.

3.4 PROPERTIES OF NEURAL NETWORKS

3.4.1 Neural networks merits

Neural networks derive their computing power in solving complex problems through their parallel distributive structure, and their ability to learn and therefore generalize.

Table 3.1 summarizes some of the useful properties and capabilities of neural networks that give them advantages over conventional algorithmic techniques.

Table 3.1: Neural network properties and capabilities (Baugham and Liu,1995) .

STRENGTHS	REMARKS
In/Output Mapping	Network learns by identifying in/output relationship for the problem
Adaptability	A neural network trained to operate in a specific environment can be retrained to discover new input relationships
Non linearity	Neural networks are inherently non linear thus can model complex relationships
Effective in processing inconsistent or incomplete data	Easily minimises incomplete data in any given node as the nodes send continuous functions
Knowledge is disbursed throughout the system	In neural networks knowledge is not stored in specific memory locations thus greater flexibility of the system
Online use plausible	Initial training may take a long time but after training, the process becomes easier hence could be used online for a control system
No programming	Algorithms do not have to be known and written as the neural network programs its own solution to a problem
Knowledge indexing	Ease of indexing and storage of a large amount of knowledge between variables and ease of access of this data

3.4.2 Neural networks limitations

Neural networks are inappropriate for applications that require number crunching or for situations where an explanation of behaviour is required. Table 3.2 illustrates a number of concerns that must be understood before deciding to use neural networks for a specific application.

Table 3.2: Limitations of neural networks (Baugham and Liu,1995)

LIMITATIONS	REMARKS
Long training time	Training time is usually long and increases with the complexity of the problem
Not precise	If precision is required, neural networks cannot justify the accuracy of computed answers as training may get trapped in local minima
Not 100 % reliable	True with limited training data
Difficulty in selecting inputs	Whereas outputs are easy to select, the selection of the wrong inputs leads to poor predictions
Large amounts of training data	Neural networks need large amounts of training data to be effective and as such cannot be used if one has very little data or similar data

3.5 NEURAL NETWORK APPLICATION

Neural networks can deal with problems that are complex, nonlinear, and uncertain, due to the properties and capabilities listed in Table 3.2. Table 3.3 lists several typical neural network applications as provided by Matlab.

Table 3.3: Potential applications of neural networks (Baugham and Liu,1995).

APPLICATION	DEFINITION
Prediction	Uses input to predict an output
Classification	Uses input values to predict a categorical output.
Data Association	Learn associations of error free data and classify data which contain errors
Data Conceptualisation	Analyse data and determine relationships
Data Filtering	Smoothing input data
Optimisation	Determine optimal values

3.6 NEURAL NETWORKS ELEMENTS

The node/neuron is the basic component of the neural network. They contain mathematical processing elements governing the operation of the neural network. Figure 3.4 illustrates a single node of a neural network.

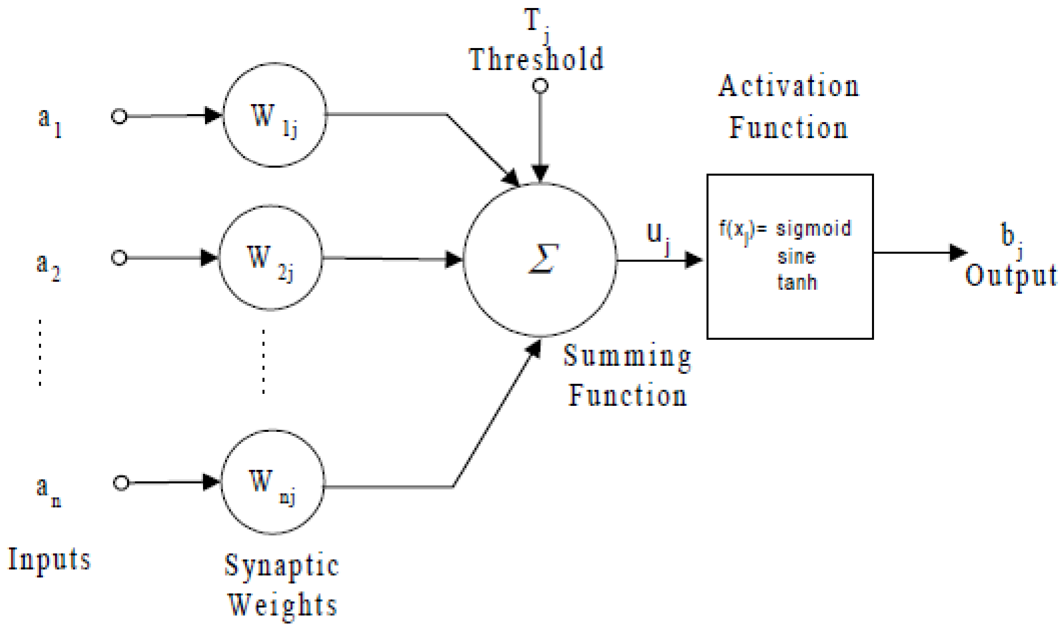

Figure 3.4: Single node anatomy (Haykin, 1994).

3.6.1 Inputs and outputs

The inputs are represented by a_1, a_2 and the output by b_j. Just as there are many inputs to a neuron, there should be many input signals to our nodes. The nodes manipulate these inputs to give a single output signal.

3.6.2 Weighting Factors

The values w_{1j}, w_{2j}, and w_{nj}, are weight factors associated with each input to the node. Weights are adaptive coefficients within the network that determine the intensity of the input signal. Every input (a_1, a_2, …, an) is multiplied by its corresponding weight factor (w_{1j}, w_{2j}, …, w_{nj}), and the node uses this weighted input (w_{1j} a_1, w_{2j} a_2, …, w_{nj} a_n) to perform further calculations. If the weight factor is positive, then (w_{ij} a_i) tends to excite the node and if negative it inhibits the node.
During the initial setup of the neural network, the weight factors are chosen according to statistical distribution. As the network is developed these are adjusted.

3.6.3 Internal threshold

The input T_j, is the node's internal threshold. This is a randomly chosen value that governs the activation or total input of the node through Equation 3.1 (Baugham and Liu,1995) .

$$\text{Total activation} = x_i = \sum_{i=1}^{n}\left(W_{ij} a_i\right) - T_j \qquad (3.1)$$

Total activation depends on the magnitude of the internal threshold T_j. If T_j is large or positive, the node has a high internal threshold and inhibits node-firing. If T_j is zero or negative, the node has a low internal threshold and excites node-firing. If no internal threshold is specified, we assume it to be zero.

3.6.4 Transfer Functions

When a nodes output is determined using a mathematical operation on the activation of the node, the operation is called transfer function. The transfer function can transform the node’s activation in a linear or nonlinear manner. Figure 3.5 shows several types of commonly used transfer functions.

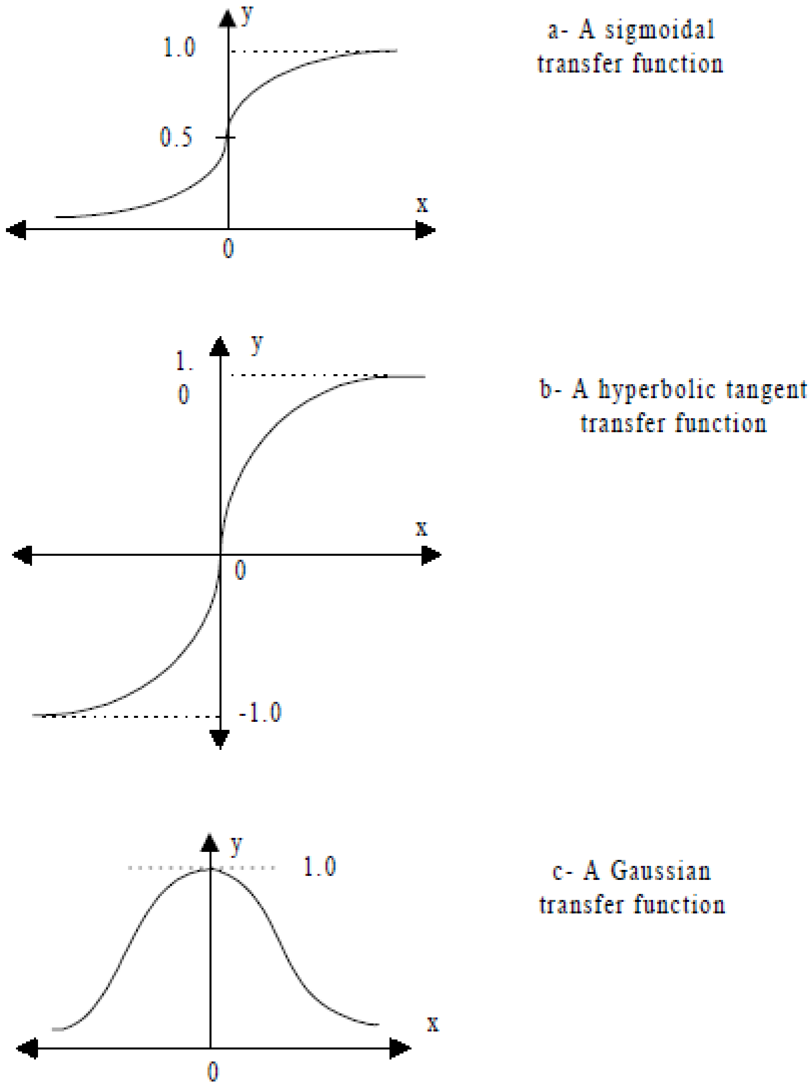

Figure 3.5: Commonly used transfer functions (Baugham and Liu,1995).

The corresponding equations for the transfer functions are as follows:

- Sigmoid transfer function is shown in Equation 3.2 (Baugham and Liu,1995):

$$f(x) = \frac{1}{1+e^{-x}} \quad 0 \leq f(x) \leq 1 \qquad (3.2)$$

- Hyperbolic tangent transfer function is shown in Equation 3.3 (Baugham and Liu,1995):

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad -1 \leq f(x) \leq 1 \tag{3.3}$$

- Gaussian transfer function is shown in Equation 3.4 (Baugham and Liu,1995):

$$f(x) = \exp\left(\frac{-X^2}{2}\right) \quad 0 \leq f(x) \leq 1 \tag{3.4}$$

The output, b_j, is found by performing one of these functions on the total activation, x_i.

3.7 NEURAL NETWORK LAYOUT

Two different classification levels of neural networks structures exist. The first level is known as the external structure which describes the overall arrangement of and connections between individual nodes both within and between the layers. The second level is the internal structure which refers to the actual connections between individual nodes both within and between layers. The various arrangements incorporate both internal and external connections, depending upon the specific application of the network, the available data, and the ease of use.

3.7.1 External neural network structure

Several general external arrangements for neural networks exist for example, single-input and single-output (SISO), multiple-input and single-output (MISO) and multiple-input and multiple-output (MIMO). The fourth arrangement, single-input and multiple-output (SIMO), is not generally used, because data for a single input are not sufficient to predict the behaviour of several output variables.

The simplest external structure is the single input single output network. It is designed to predict the behaviour of one output variable based on data for one input variable. It is only applicable to very simple systems or in cases where there is a direct relationship between two variables. A disadvantage of this type of network is that it is unable to consider the interactions between input variables. Figure 3.6 illustrates a single input single output network.

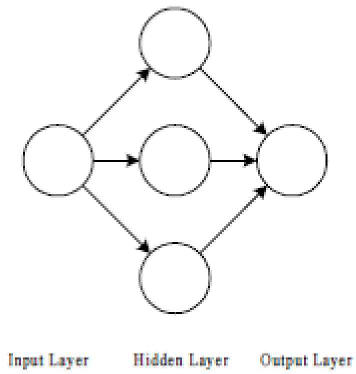

Figure 3.6: Example of a single input single output arrangement (Baugham and Liu,1995).

Multiple input single output networks take input data from many variables and use them to predict the value of a single output variable. Figure 3.7.shows an example of a multiple input single output network.

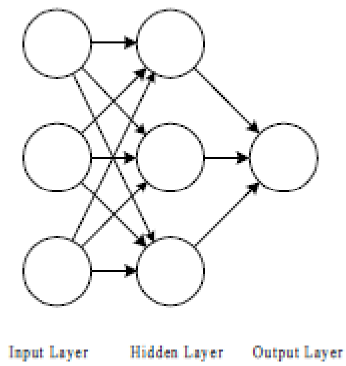

Figure 3.7: Example of a multiple input single output network (Baugham and Liu,1995)

Multiple input multiple output networks have the greatest degree of complexity. Input data from multiple variables is used to predict the values for multiple output variables. Figure 3.8 illustrates a MIMO network.

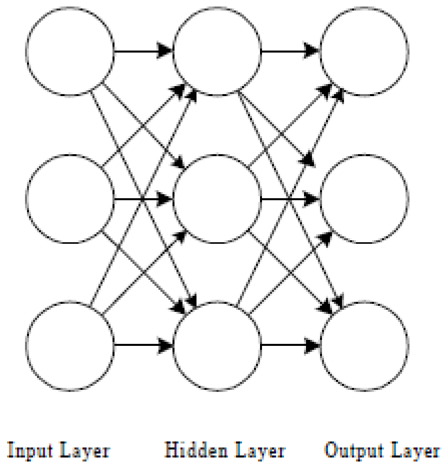

Figure 3.8: Example of a multiple input multiple output network(Baugham and Liu,1995)

3.7.2 Internal Neural Network Structure

Individual connections between nodes form the internal structure of a network. A node can be connected to any node in the network. The relative position of the origin to the endpoint of the connection defines the network's internal structure. Three types of connections are used: interlayer, intralayer, and recurrent. Figure 3.9 shows the three options for connecting nodes to one another. Layers *K*, *H*, and *W* could be any layer in the network.

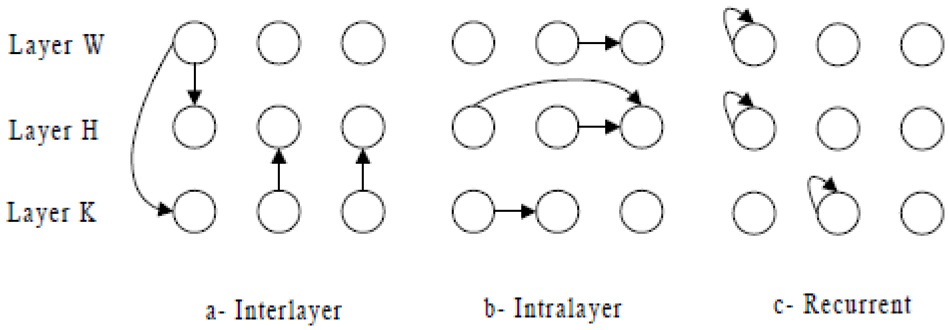

Figure 3.9: The connection options in a neural network (Baugham and Liu,1995).

- *Interlayer Connection*

  Outputs from nodes on one layer feed into nodes in another layer.

- *Intralayer Connection*

Outputs from nodes in one layer feed into nodes in that same layer.

- *Recurrent Connection*

  Outputs from a node feed into itself as inputs.

Within the interlayer connection, we have two main network architectures:

1. Feed forward network
2. Feed backward networks

shown in Figure 3.10 (Baugham and Liu,1995).

In the feed forward network, the direction of signal flow is from the input layer, through each hidden layer, to the output layer. We frequently use feed forward networks in process modelling and in most engineering applications of neural networks. In a feed backward network, signals flow from the input layers to the hidden layers. However, in a feedback network, the output from a hidden layer can return to the input layer.

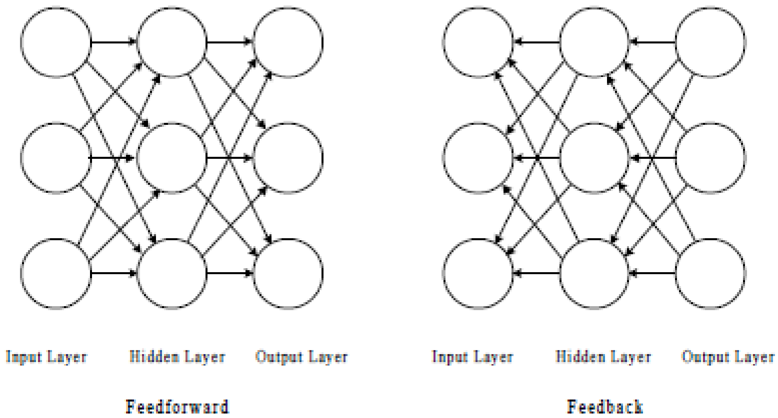

Figure 3.10: Feed forward and feedback networks (Baugham and Liu,1995).

3.7.3 Multilayer Networks

Most neural networks contain one to three hidden layers (Baugham and Liu,1995). The hidden layer intervenes between the external input and the network output. Multilayer networks are feed forward networks with one or more hidden layers between the input and output layers. These may be formed by cascading a group of single layers; the output of one layer provides the input to the subsequent layer. Figure 3.11 shows such a network with three hidden layers.

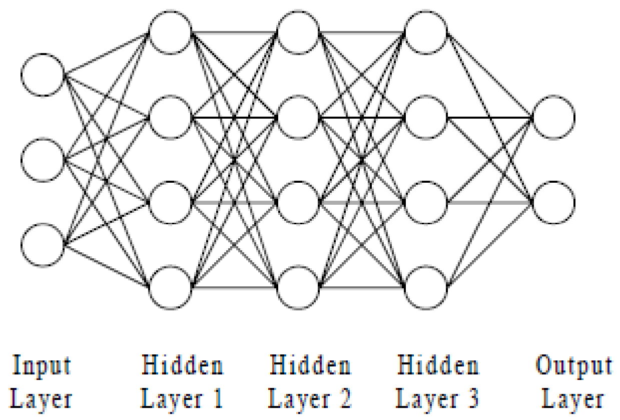

Figure 3.11: Feed forward network with three hidden layers (Baugham and Liu,1995).

Large, more complex networks generally offer greater computational capabilities. These multilayer networks have greater representational power than single-layer networks if nonlinearity is introduced.

3.8 LEARNING AND TRAINING WITH NEURAL NETWORKS

To effectively build a model two sets of data are used that is a training set and a testing set. The training phase needs to produce a neural network that is both stable and converges and us a result data selection to be used for training is a key step in building stable neural network models. Neural networks interpolate data very well, but are ineffective with extrapolation.

3.8.1 Training the network

Training involves the neural network adjusting the weights of interconnections between nodes so that the network can predict the correct outputs for a given set of inputs (Moody, 1992). In order to obtain the best learning, large sets of input/output data are needed.

3.8.1.1 Learning modes

There are a number of approaches to training neural networks. Most fall into one of two modes (Simpson, 1990):

- Supervised Learning: Supervised learning requires an external teacher to control the learning and incorporates global information. The teacher may be a training set of data or an observer who grades the performance. Examples of supervised learning algorithms are the least-mean-squire (LMS) algorithm and its generalization, known as the back propagation algorithm.
- Unsupervised Learning: No external teacher is used; the system must organize itself by internal criteria and local information designed into the network. Unsupervised learning is sometimes referred to as self-organizing learning, learning to classify without being taught.

3.8.1.2 back propagation fundamentals

Many different types of training algorithms exist (Baugham and Liu,1995) (cheng, 1994) . The most common class of training algorithms for feed forward interlayer networks is called back propagation. In back propagation, a set of inputs is fed to the network and outputs are returned. Then, the network compares its output with the output of the actual data source. The network calculates the amount of error between its predicted output and the actual output. The network works backwards through the layers, adjusting the weight factors according to how much error it has calculated in its output. Once all of the weight factors have been adjusted, the network works in a forward path, taking the same input data to predict the output, based on the new weight factors. The network again calculates the error between the predicted and actual outputs. It adjusts the weight factors and the process continues, iteratively, until the error between the predicted and actual outputs has been minimised

To describe the basic concept of back propagation learning algorithm, each of its elements and how they combine to form the back propagation topology are briefly looked at. Figure 3.12 illustrates a simple three-layer feed forward neural network.

- Input layer A: The input vector I is feeding into layer A. It has L nodes, a_i ($I=1$ to L), one node for each input variable.
- Hidden layer B: It has m nodes, b_j ($j=1$ to m).
- Output layer C: It has n nodes, c_k ($k=1$ to n), one node for each output variable: d_k is the desired output, and c_k is the calculated output.

- Interconnecting weight between the i^{th} node of layer A and the j^{th} node of layer B is denoted as v_{ij}.
- Interconnecting weight between the j^{th} node of layer B and the k^{th} node of layer C is denoted as w_{ij}.
- Internal threshold value for layer A is T_{Ai}, for layer B, T_{Bj}, and for layer C, T_{Ck}.

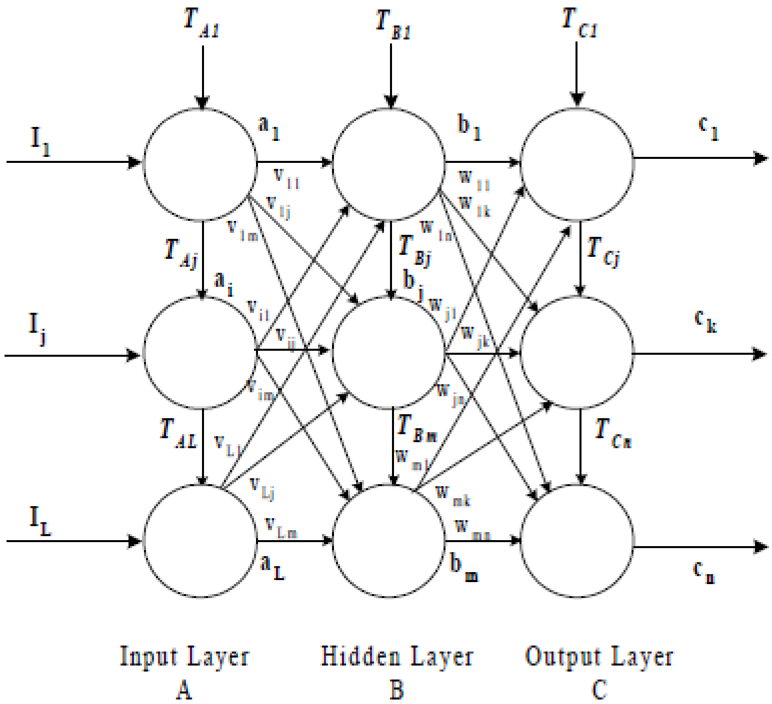

Figure 3.12: Three-layer feed forward neural network (Baugham and Liu,1995).

Back propagation learning attempts to map given inputs with desired outputs by minimizing the sum-of-square errors, by adjusting both sets of weight factors, v_{ij} and w_{jk}, along with the internal thresholds.

The total mean-square errors function, E, is described by Equation 3.4 (Baugham and Liu,1995): Figure 3.13 illustrates the step-by-step adjustment procedure.

$$E = (\text{Output error})^2 = \sum_k \in_k^2 = \sum_k (d_k - c_k)^2 \tag{3.4}$$

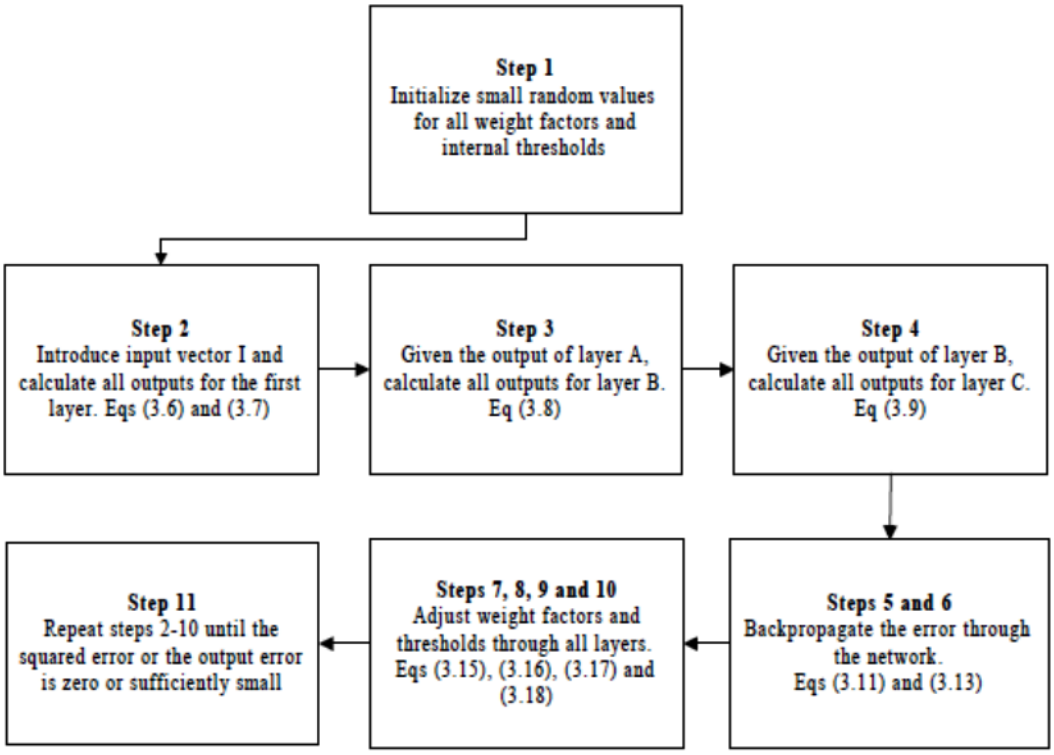

Figure 3.13: Back propagation learning steps (Baugham and Liu, 1995).

3.8.2 Network testing

In the development of the neural network it is important to determine how well the network performs after training (Baugham and Liu, 1995). Checking the performance of a trained network involves two main criteria:

1. how well the neural network recalls the predicted response, the output, from data sets used to train the network (called the recall step); and
2. how well the network predicts responses from data sets that were not used in training (called the generalisation step).

The networks performance in recalling initial input used in training is evaluated in the recall step. The network attempts to predict the corresponding output of a previously used input pattern. If the network has been trained sufficiently, the network output will differ only slightly from the actual output data. Note that in testing the network, the weight factors are not changed: they are frozen at their last values when training ceased. Generalisation testing is conducted in the same manner as recall testing; however, the network is given input data with which it was not trained. In the generalisation step, new input terms whose results are unknown to the network are fed to the trained network. The network generalises well when it sensibly interpolates these new patterns. In generalisation testing, the error between the actual and predicted outputs is larger than recall testing. These two errors converge upon the same point corresponding to the best set of weight factors for the network. A learning curve can be generated when both types of testing at various points during the learning process are done.

3.9 PRACTICAL ASPECTS OF NEURAL COMPUTING

Many neural network parameters control the network's performance and prediction capability. These parameters must be controlled as seen in Figure 3.14 if an effective neural network is to be developed.

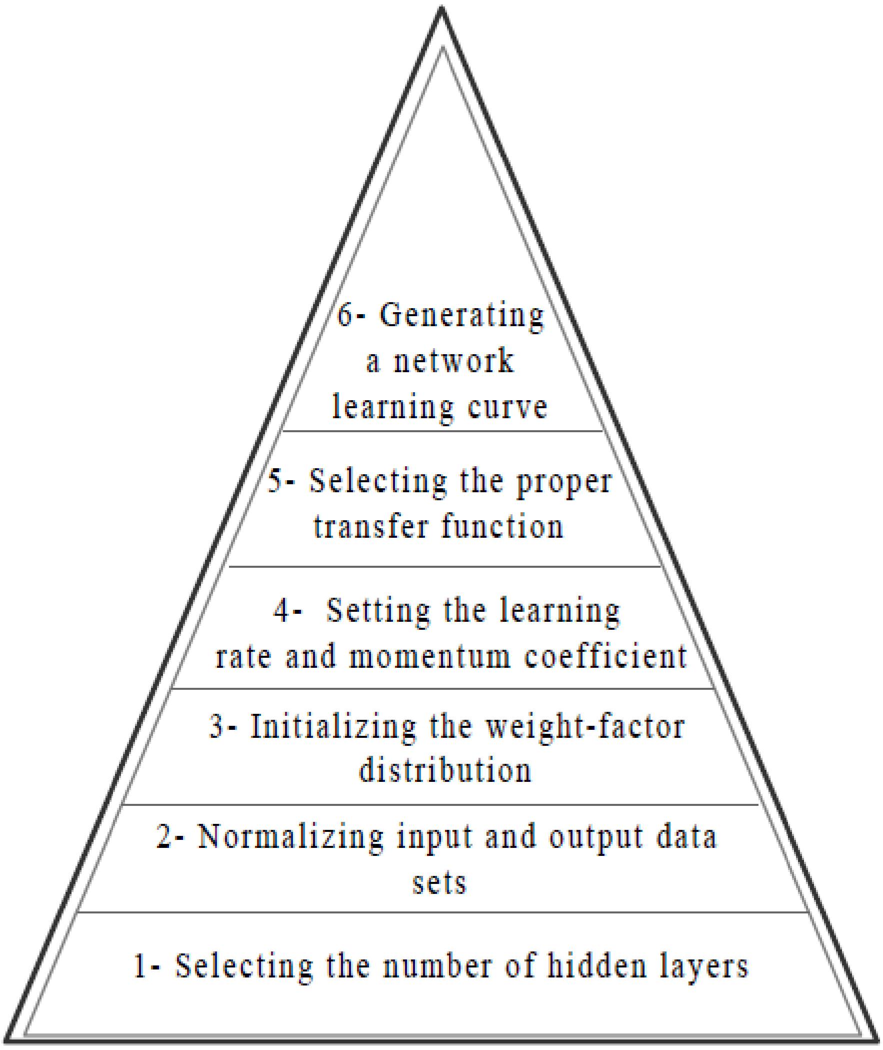

Figure 3.14: Neural network parameters that control the network's performance and prediction capability (Baugham and Liu,1995).

3.9.1 Number of hidden layers selection

The number of network inputs and outputs give rise to the number of input and output nodes (Gaurang, 2011). The choice of the number of hidden layers and the nodes in the hidden layer(s) depends on the network application. Determining the number of hidden layers is a critical part of designing a network and thus not straightforward as it is for input and output layers.

To obtain an optimal number of hidden layers and nodes in each layer, the network is trained using various configurations. The best configuration is selected when the combination of few layers and nodes yield a minimum root mean square error quickly and efficiently. Baugham and Liu (1995) found out that adding a second hidden layer significantly improves the network's prediction capability without having any detrimental effects on the generalisation of the testing data set. However, adding a third hidden layer yields prediction capabilities similar to those of 2-hidden layer networks, but requires longer training times due to the more complex structures. Baugham and Liu (1995) recommend a 30:15 hidden-layer configuration as the initial architecture for most networks but it may not always be the optimal configuration.

Although using a single hidden layer is sufficient for solving many functional approximation problems, some problems may be easier to solve with a two-hidden-layer configuration.

3.9.2 Normalisation

Neural networks require that their input and output data are normalized to have the same order of magnitude. Normalisation is very critical; if the input and the output variables are not of the same order of magnitude, some variables may appear to have more significance than they actually do. The training algorithm has to compensate for order-of- magnitude differences by adjusting the network weights, which is not very effective in many of the training algorithms. In addition, typical transfer functions, such as a sigmoid function, or a hyperbolic tangent function, cannot distinguish between two values of x_i when both are very large, because both yield identical threshold output values of 1.0.

To avoid such problems all input and output data have to be normalised. Often one can normalize input and output data in different ways for different runs. Figure 3.15 shows the three normalization methods.

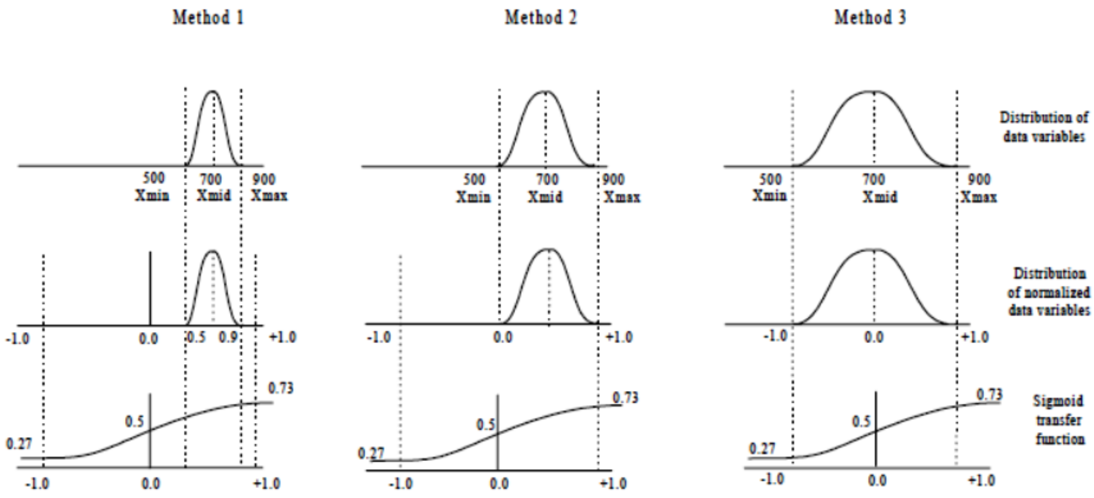

Figure 3.15: Three normalization techniques (Baugham and Liu,1995).

Method 1: Normalise each variable, x_i, in the data set to between *0* and *1*.The normalsed variable is calculated from Equation 3.18 (Baugham and Liu,1995):

$$X_{i,} = \frac{X_i}{X_{i,\max}} \tag{3.18}$$

One limitation of this method is that it does not utilize the entire range of transfer functions. Figure 3.15 shows that only a small portion of the transfer function corresponds to x_i values of *0.5* to *0.9* and *-0.5* to *-0.9*. The weight factors can broaden and shift this range to include a larger region of the transfer function. However, as the number of variables and weight factors increase, these adjustments become more difficult for training algorithms. As a result, this normalisation method is adequate for many simple networks, but problems can arise as the network architecture becomes more complex. We have chosen to use this normalization technique for most data sets and to interpret results without more complex data transformations.

Method 2: the normalisation is expanded so that the minimum value of the normalized variable, $x_{i,norm}$, is set at *0* and the maximum value, $x_{i,max}$ is set at one. The normalized variable $x_{i,norm}$ is defined by using the minimum and maximum values of the original variable, $x_{i,min}$ and $x_{i,max}$, respectively as seen in Equation 3.20 (Baugham and Liu,1995).

$$X_{i,norm} = \frac{X_i - X_{i,\min}}{X_{i,\max} - X_{i,\min}} \tag{3.20}$$

This method significantly improves on the first method by using the entire range of the transfer function, as Figure 3.15 illustrates. In this method every input variable in the data set has a similar distribution range, which improves training efficiency.

Method 3: The data set is normalised between limits of *-1* and *+1*, with the average value set to zero. This technique is called the zero-mean normalization and represent the normalisation variable, $x_{i,norm}$ as seen in Equation 3.21 (Baugham and Liu,1995):

$$X_{i,norm} = \frac{X_i - X_{i,avg}}{R_{i,\max}} \tag{3.21}$$

and

$$R_{i,\max} = Maximum\left[\left(X_{i,\max} - X_{i,avg}\right),\left(X_{i,avg} - X_{i,\min}\right)\right] \tag{3.22}$$

where x_i is an input or output variable, $x_{i,avg}$ is the average value of the variable over the data set, $x_{i,min}$ is the minimum value of the variable, $x_{i,max}$ is the maximum value of the variable, and $R_{i,max}$ is the maximum range between the average value and either the minimum or the maximum value.

The zero-mean normalisation method utilises the entire range of the transfer function, and every input variable in the data set has a similar distribution range. This allows the weight factors to follow a more standard distribution, without requiring them to shift and broaden the input variables to match their respective output variables. This method gives some meaning to the values of the normalized variable; *0* represents the normal states (average) of the variable; *-1* represents a very low level of the variable, and *+1* represents a very high level of variable. In addition, by setting all of the normal states of the variables to zero, the network will have a standard structure that makes training more efficient and consistent from one problem to the next. That is, all networks should normally predict output responses of approximately *0* (normal value) for a set of input variables at their normal values. Therefore, the network is essentially only training deviations in the output variable due to various deviations in the input variables. The zero mean normalisation technique was used in normalising the data range for this research.

3.10 CLOSURE

The artificial neural network approach has been discussed and various methods used in this type of approach discussed. There is no doubt that neural network design is of significance importance in order to be able to close to the desired result.

Chapter 4 METHODOLOGY

In this chapter, the following will be discussed; the desalting process and plant as pertains to the Saline Water Conversion Corporation (SWCC), how the experimental data was collected and finally how the collected experimental data was analysed in the context of Artificial neural network approach.

4.1 DESALINATION PRE-TREATMENT

The membrane is the heart of the RO plant and is made of special semipermeable thin polymeric film deposited on a relatively thick strong support material or made of a thin polymeric film of the same composition as its strong support material.

Membranes are characterized by their unique properties of high water permeation (flow), very low salt passage and dimensional and chemical stability. In spite of their small sizes and high solubilities in water, salts, even those with small molecular weights, do not pass through the membrane at a significant rate. Their passage is held to a very low level, for example., less than 1% using thin film composite (TFC) seawater membranes. Passage of the larger size colloidal and other suspended solid particles is not permitted at all through the membrane closed structure. This is also true of microorganism such as bacteria which, when present in the feed, will be trapped on the membrane surface causing it to foul Membrane fouling is also introduced by the presence in the feed of scaling and corrosion products. The presence of any of the above matters in the feed could cause membrane fouling and the lowering of the reverse osmosis plant efficiency, hence feed pre-treatment is required.

In water desalination by the reverse osmosis process feed water pre-treatment is essential in order to remove all the potential membrane foulants from the feed. The degree of pre-treatment, however, is dependent on the raw water quality, particularly its content of suspended and biological matter as well as on the membrane configuration. The Hollow fine fibre membrane configuration with tight fibre packing in the module requires maximum pre-treatment as compared to an intermediate, and modest degrees of pre-treatment for the spiral wound and plate & frame membrane configurations, respectively.

Pre-treatment of surface seawater, however, is rather more demanding than that of membrane treated feed. It may consist of disinfection, followed by coagulation-filtration and dosing of antiscalants. Feed chlorination/de-chlorination is also required when the feed is intended for chlorine sensitive membranes while antiscalant agents are added as needed.

An ideal pre-treatment is designed to cause a minimum or no membrane fouling at the lowest possible cost. This not only results in longer membrane life but also improves the overall plant efficiency and reduces the cost of fresh water production. Seawater feed derived from a well-designed requires minimum of pre-treatment by passing it only through cartridge filter, size 5 to 15 microns.

In this investigation an exhaustive, systematic study was carried out to optimise the coagulation-filtration SWRO pre-treatment for Gulf seawater taken from an open intake, Al-Jubail, Saudi Arabia, by investigating the effects of various pre-treatment variables on feed water quality.

4.2 EXPERIMENTAL WORK AND EQUIPMENT

The variables examined were as follows:

- Feed flow rate
- Sand filter layer thickness
- Ferric chloride coagulant
- The coagulant-aid, Polyelectrolyte with ferric chloride
- coagulant
- pH of seawater feed to the pre-treatment plant
- Chlorinated and non-chlorinated seawater
- feed

- Ultrafiltration.

A schematic flow diagram of the pilot plant is given in Figure 4.1. Basic components of the unit are: seawater feed line, destabilisation-agglomeration tanks, feed pumps, dual media and fine sand filters, followed by five 11m cartridge filter and a pre-treated feed holding tank. The unit was equipped with a filter backwash system to wash the filter as needed and a booster feed pump to boost feed pressure (up to 50 psi) supplied to the SWRO high pressure pump.

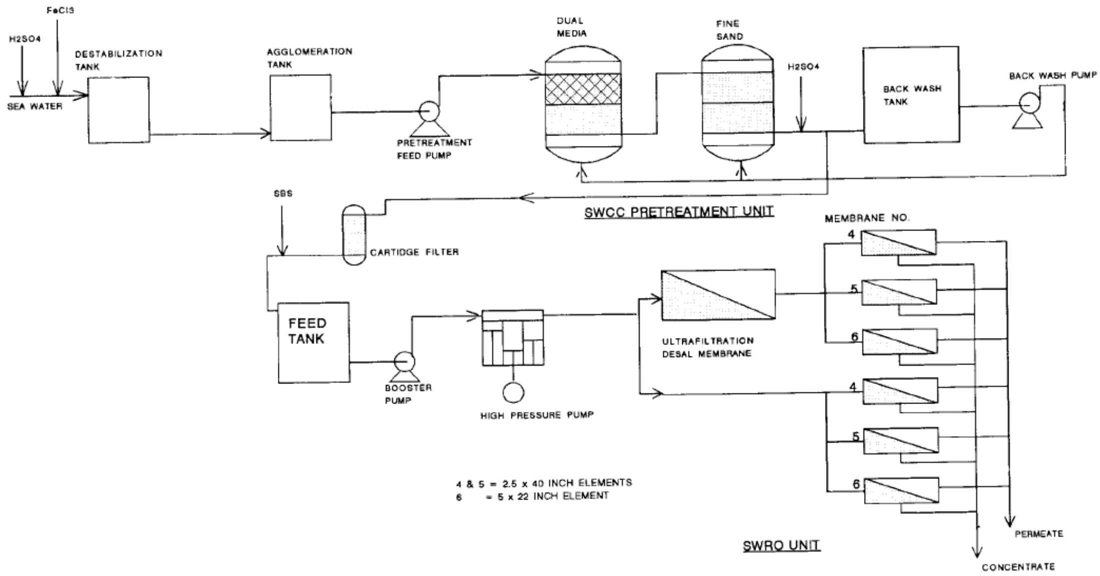

Figure 4.1: Schematic flow diagram of SWCC pre-treatment and SWRO pilot plant (Saline Water Conversion Corporation)

Chlorinated or non-chlorinated seawater was supplied to the unit by the feed pipeline at an adjustable flow rate. After its dosing with the coagulant agents, feed flows to the destabilization-agglomeration tanks where flocks formation takes place. Under low pressure the feed water pump supplies the water to the dual media (sand/anthracite) filter from which the filtrate flows into a second fine sand filter followed by the cartridge filter. Antiscalant acid and sodium bisulphite are introduced after the five 11m cartridge filter to condition the feed and to remove the chlorine from it prior to the feed entry into the SWRO feed tank.

4.3 DATA ACQUISITION

There are three parameters that will be studied in the course of this work. That is pressure, flow and conductivity, this will be studied in relation to the feed, permeate and retentate, with conductivity of the product as the target.

4.4 DATA FILTERING AND NORMALISATION

Wrong data leads to wrong fitting using fitting algorithms especially in data modelling. The reason for finding outliers in a data set is that they have a significant effect on estimating the model parameters which at last influence the output (caroni *et al* 2004). Outliers occur in a data set because of incorrect measurement resulted from malfunctioning or poorly calibrated instruments or human error in recording of data.

Even if data reflects the real system behaviour, the trained network may produce results with high error and one of the main reasons is either not normalizing the data set or normalising using the wrong method. For the case presented, the normalisation to the maximum method was chosen as the best method. The reason for this was that some data was fed to the neural network and using all the normalisation techniques in Figure 3.15 in Chapter 3, the normalisation to the maximum method gave the least error. The frequency of the normalised input data is viewed in Figures 4.2 to 4.4 with the rest seen in Appendix B

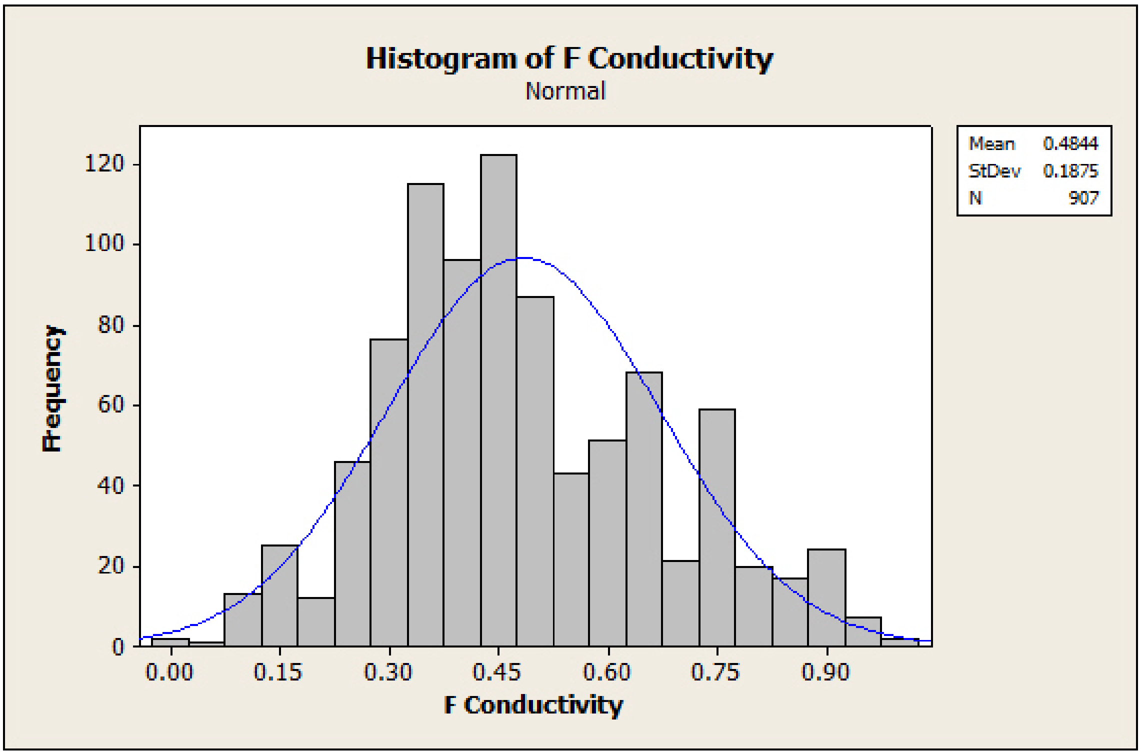

Figure 4.2: Normalised feed conductivity frequency.

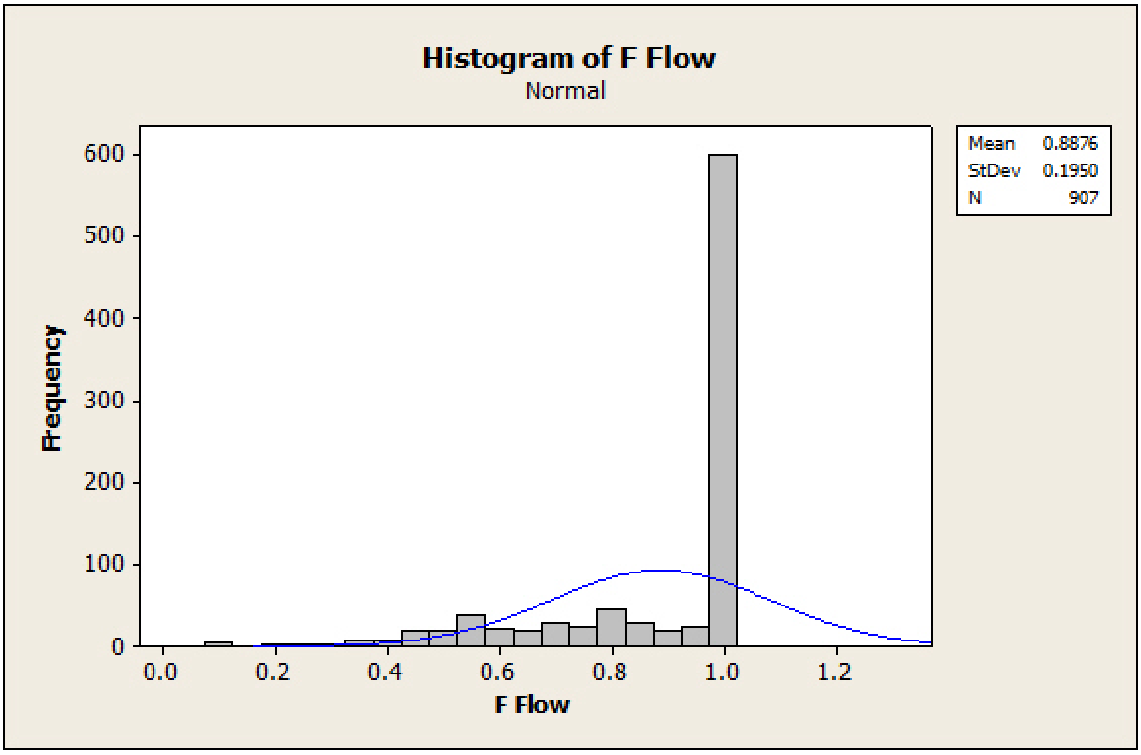

Figure 4.3: Normalised Feed flow frequency.

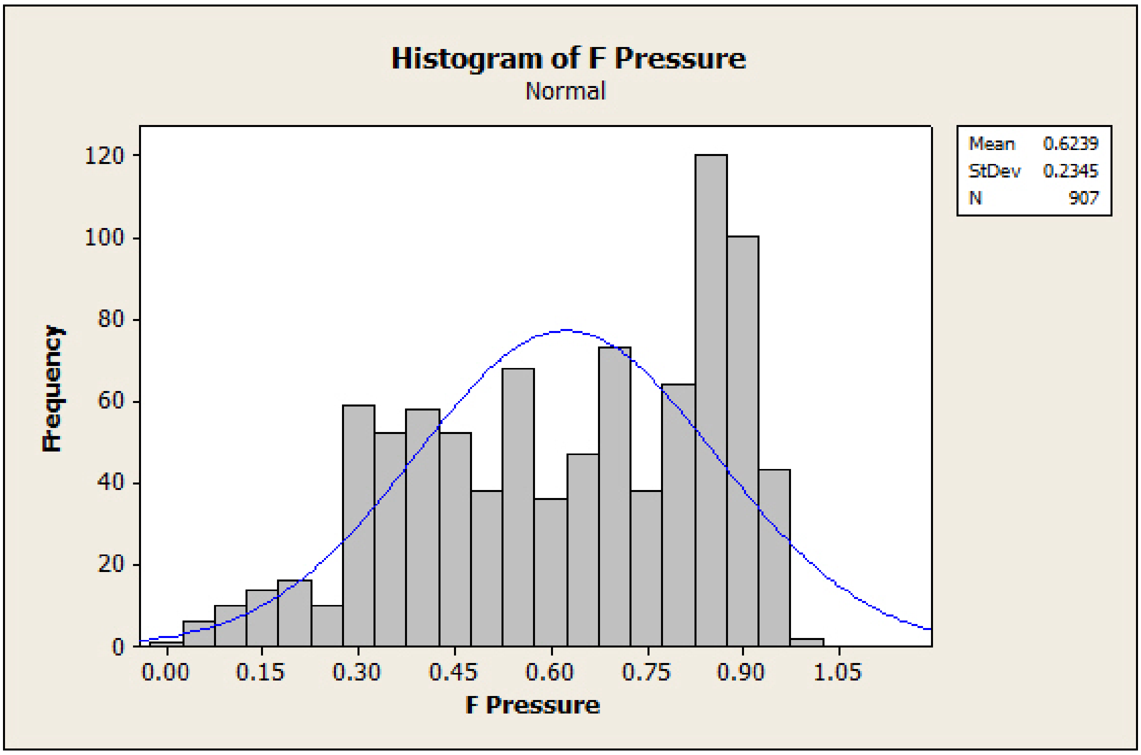

Figure 4.4: Normalised feed pressure frequency.

4.5 NEURAL NETWORK DESIGN

In the development of a neural network model the goal is always to obtain the least error between the actual and predicted values of the output variable. This gives rise to an important argument, what are the optimum design criteria for the selection of transfer function, number of hidden layers and number of neurons to be used in each layer.

4.5.1 Picking the best transfer function

The network output accuracy is highly affected by the selected transfer function. As shown in chapter 3, there are three main transfer functions normally used in neural network modelling. To determine the best combination of transfer functions in network with one and two hidden layers, different transfer functions were used in the developed network. The advantage of the written code was that one could choose any transfer function based on errors obtained as can be seen in the written code in Appendix A.

4.5.2 Number of layers

The selection of the numbers of hidden layer is critical for the network to predict the network output with less error. Usually the optimum number of hidden layers is decided through trial and error procedure and the lowest number of hidden layers with satisfactory generated error is selected. The reason for such selection is that as the number of hidden layers kept at an optimum low, the less time required for training the network.

The ability of neural network to learn complex mapping function is enhanced by the proper selection of the number of neurons in the hidden layers (Kamel, 1999). Neural networks are highly responsive to the number of neurons in the hidden layers. Using too few neurons will make the network not able to learn al1 often patterns accurately. In contrast, too many neurons will make the network tending to remember the patterns rather than learning to distinguish the global characteristics of the pattern.

4.5.3 Initialisation of weights

After the number of layers and neurons in each layer are decided and before training the network, network weight should be set otherwise the Matlab initializes weight to random values. The process of training neural network with Back propagation algorithm can be described as an optimization process in which the error is minimized through manipulating the network weights Back propagation follows the local optimization technique which works to reach the minimum error (Mercedes *et al*, 2001).

4.6 CLOSURE

The desalting process pertaining to the Saline Water Conversion Corporation has been explained along with how the experimental data was obtained and how it was analysed in order to get basic inputs for neural network design. The neural network procedure has been explained and in the proceeding chapter will be seen in more detail and the results obtained discussed in the context of the objectives that pertain to this research.

Chapter 5 ARTIFICIAL NEURAL NETWORK FOR THE MODELLING OF REVERSE OSMOSIS PLANT DATA

This chapter describes the application of neural networks specifically to predicting problems of large-scale reverse osmosis plants. We first introduce the desalting plant under study. We next demonstrate the use of neural-network predictors in conjunction with statistical techniques to identify the major independent variables to optimise the process performance.

5.1 REVERSE OSMOSIS PLANT DATA

ANN models can effectively describe membrane process performance with respect to the dynamics of both flux and separations performance. ANN models developed in previous studies were based on training the model with a certain fraction of experimental data through the complete dataset and including extreme values. As a result the models were successful for predicting an input variable range which the ANN model had been trained on. However this meant that it was impossible to predict performance for those occasions not covered by the training data set.

The desire to be able to predict membrane plant performance would make it possible to provide additional process control strategies and would be used for example in aiding membrane cleaning and adjusting process variables such as flow rate and pressure.

Although ANN approach is data-driven and therefore results in plant-specific application, it has the advantage of capturing unique aspects of the plant such as operational behaviour for example; pumps and control devices, processes elements and plant configuration as well as feed quality variations. With this in mind, an ANN model of RO plant performance was developed to predict the temporal changes in product flow. The experimental data used for building the ANN models was provided by the Institute of Research for desalination in Saudi Arabia, a government body.

Figure 5.1 illustrates the methodology used for developing a neural network model, based on the back propagation algorithm, for the prediction and optimisation of process performance variables of large-scale desalination plants.

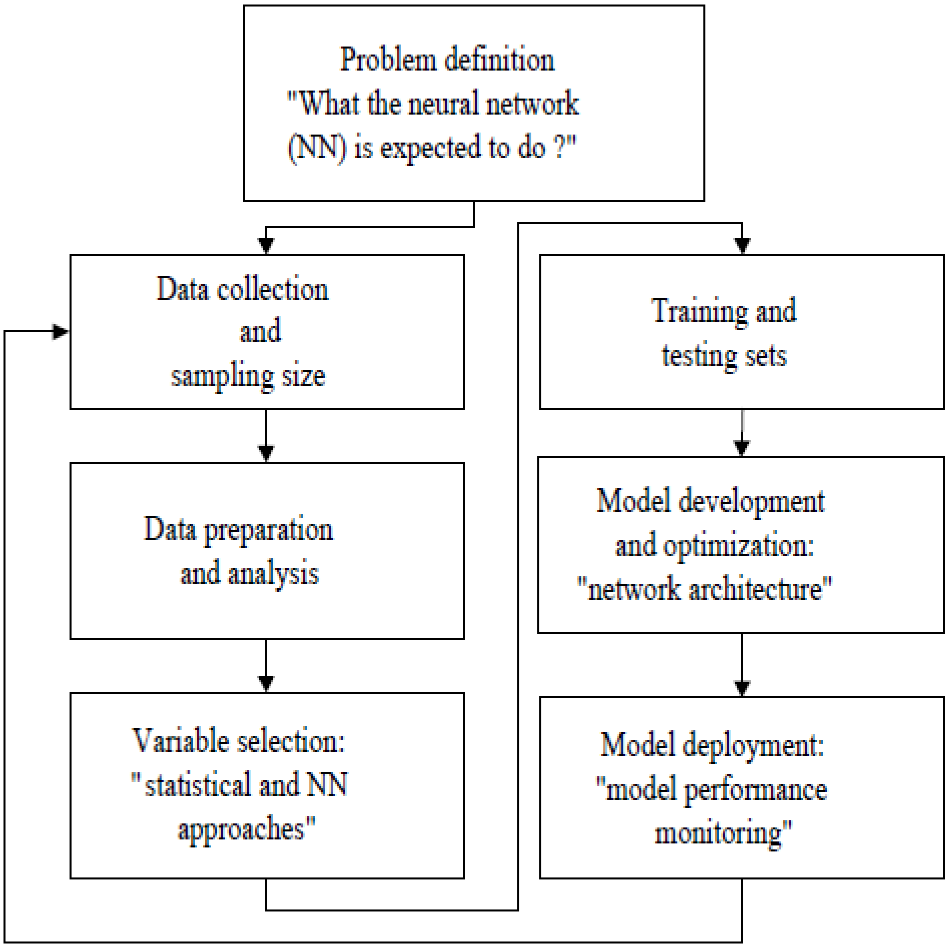

Figure 5.1: Methodology of neural network development
(Baughman and Liu, 1995)

This study demonstrates the use of neural-network predictors in conjunction with statistical techniques to determine the optimal operating conditions of commercial RO processes. This study also compares the neural network model and the statistical model in predicting the performance variables of desalination plants.

To accomplish this work, we use MATLAB neural networking tool as well as Microsoft excel for graphing and data analysis purposes.

5.2 DATA PREPARATION AND ANALYSIS

Real-life data obtained from the plant must be filtered to remove unmeasured noise, outliers, and fault-contaminated measurements. It often contains outliers, which are observations that do not reasonably fit within the pattern of the bulk of the data points and are not typical of the rest of data. Some outliers are the result of incorrect measurements and can be immediately rejected and removed from the data set. Other outliers are observations resulting from unusual process phenomena that are of vital interest. Data require careful inspection and examination in order to observe this distinction.

Outliers are given particular attention in a neural network and in a statistical analysis in order to determine the reasons behind large discrepancies between those points and the remainder of the data set. The inclusion of outliers in training data forces the network to consider a larger solution space, and can therefore reduce the overall precision of the resulting network. This is observed as occasional large differences between actual and predicted values of output variables. Removing outliers generally improves network performance.

One of the simplest techniques for detecting outliers is to examine the frequency histogram of the data, plotting the number of occurrence of the observed data within a specific range of a selected operating variable. Figures 5.2-5.8 illustrate the frequency distribution of the 5 operational variables after removing the outliers. The frequency distribution becomes to be continuous and normally distributed with a bell shape, with the exception of a few outliers that are observations of unusual phenomena.

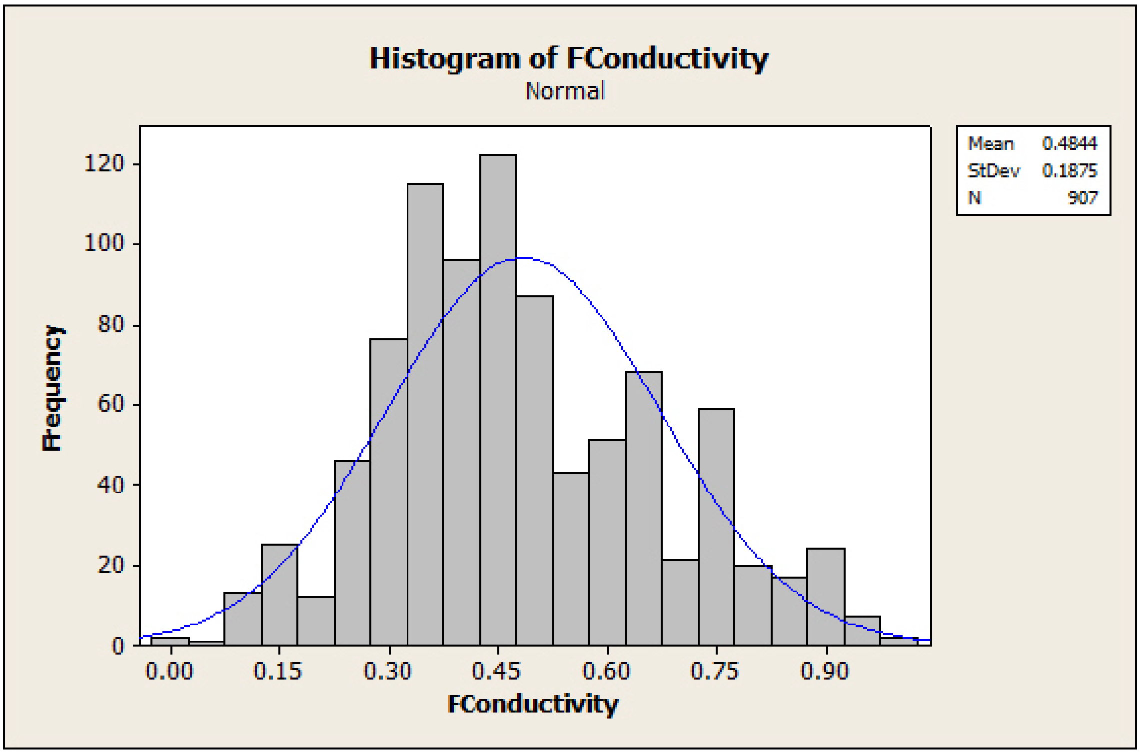

Figure 5.2:Feed conductivity

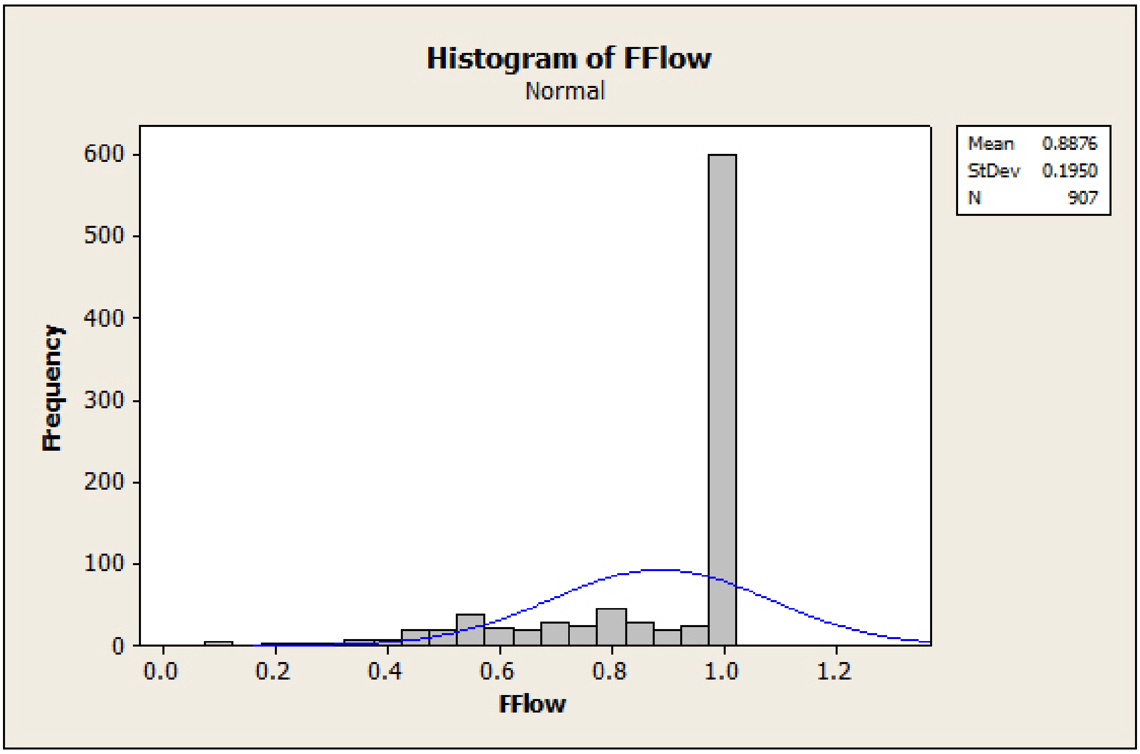

Figure 5.3: Feed flow

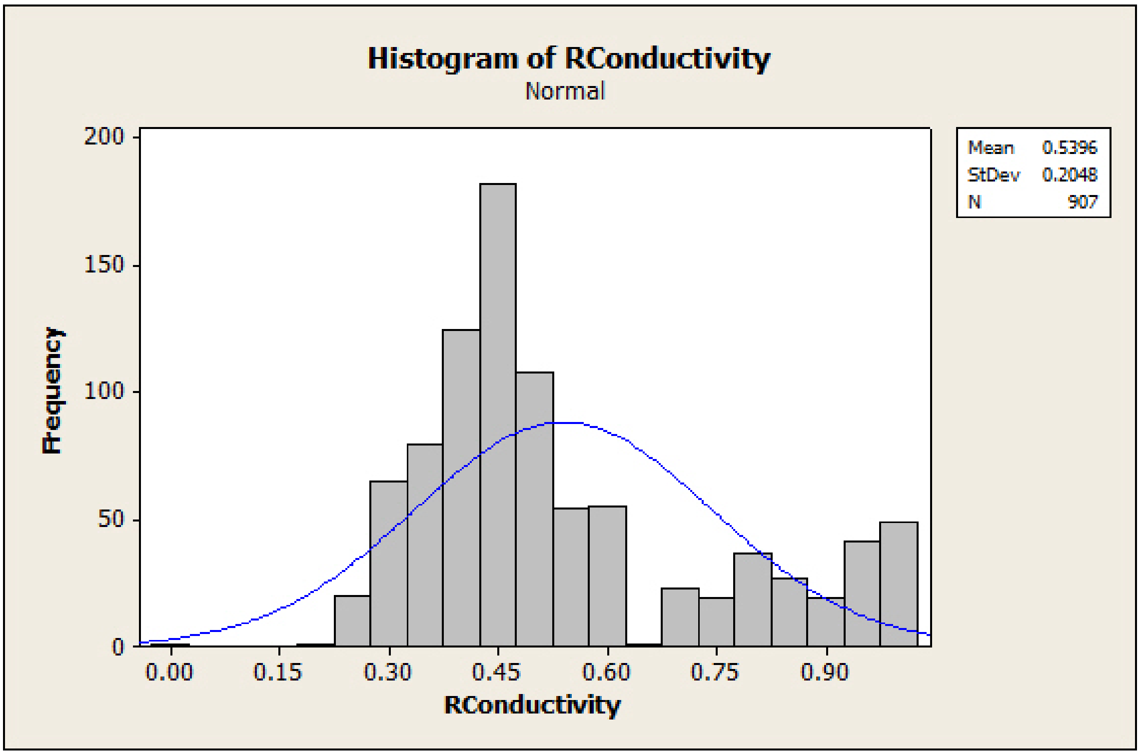

Figure 5.4: Retentate conductivity

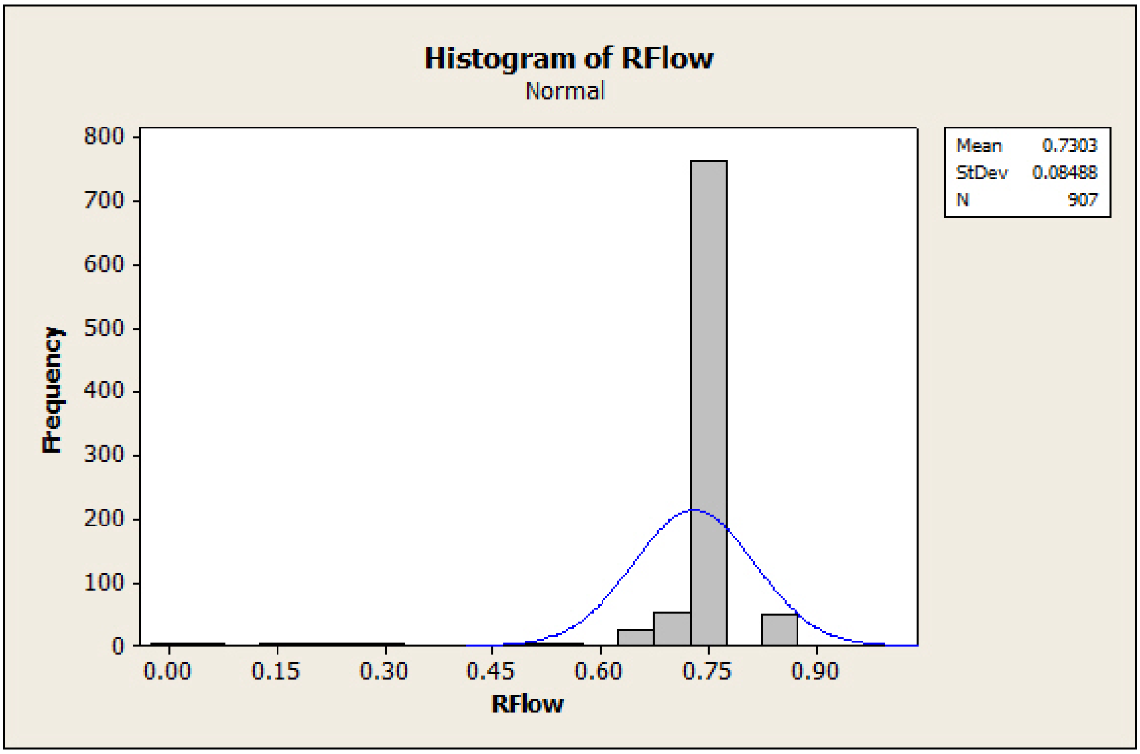

Figure 5.5: Retentate flow

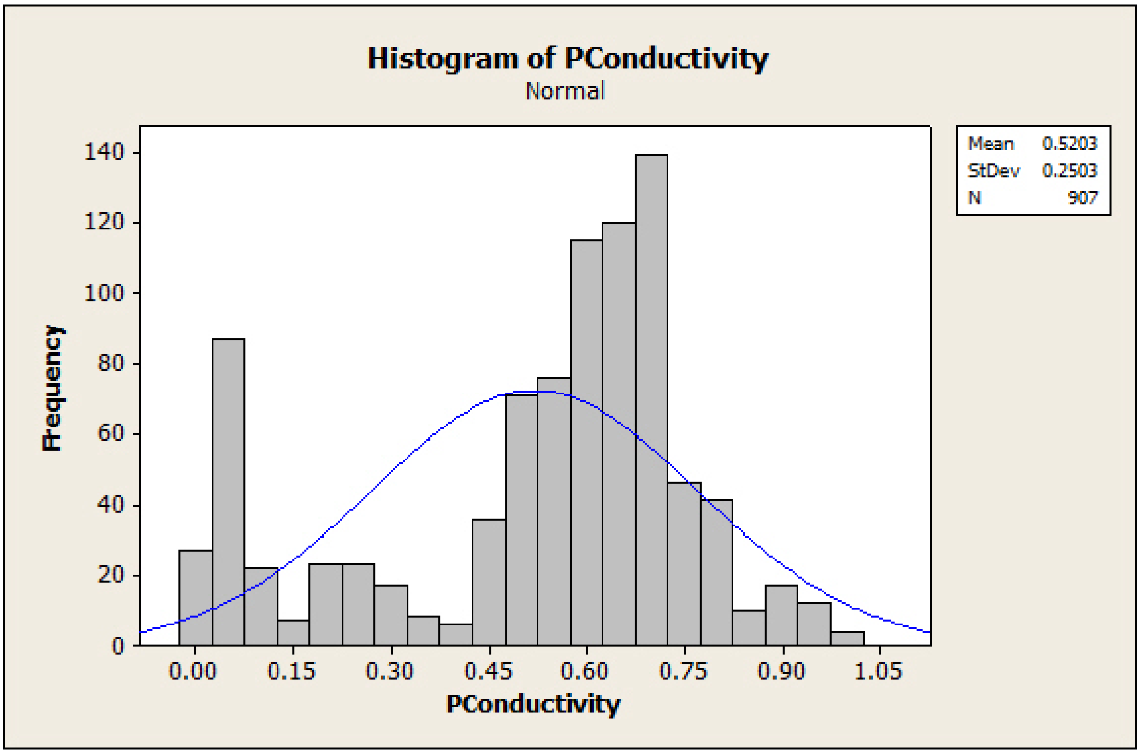

Figure 5.6: Product flow

The nature of the data meant that all the best fit equations were non-linear in type. The coefficient of regression, R^2, measures how a line fits, good or undetermined. However this does not mean that the model is good if R is huge as one may find that insignificant variables in the model contribute to the total R^2 . The various variables and there fits are shown in Figures 5.7-5.11.

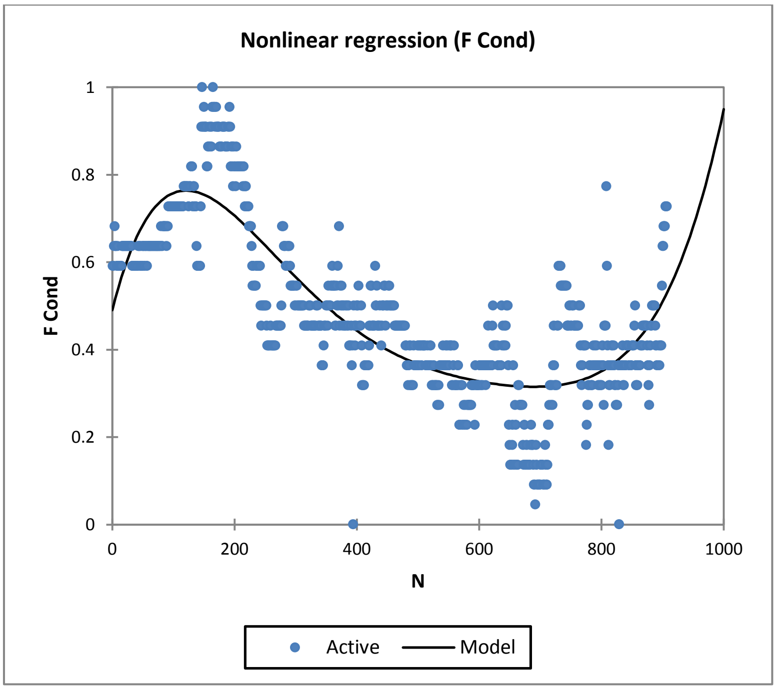

Figure 5.7: Nonlinear regression plot of feed conductivity

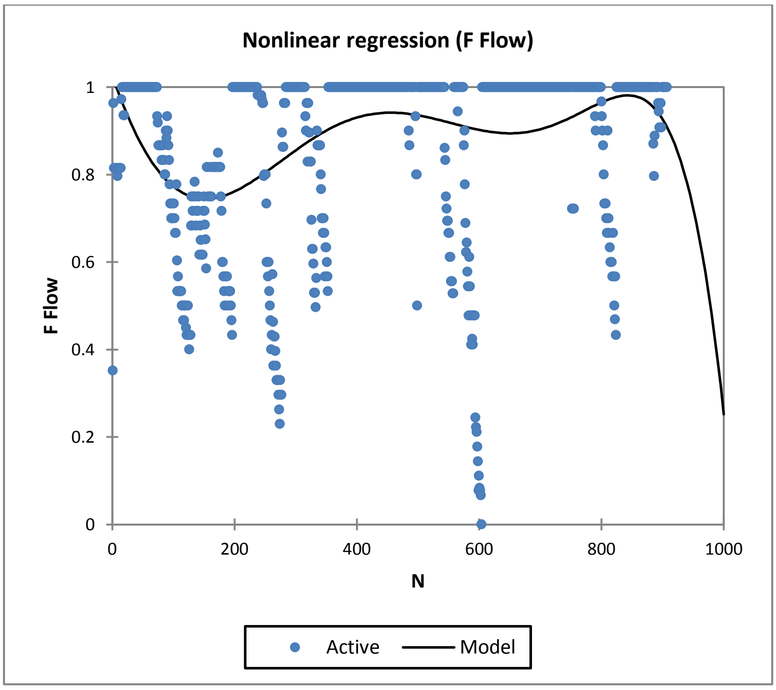

Figure 5.8: Nonlinear regression plot of feed flow

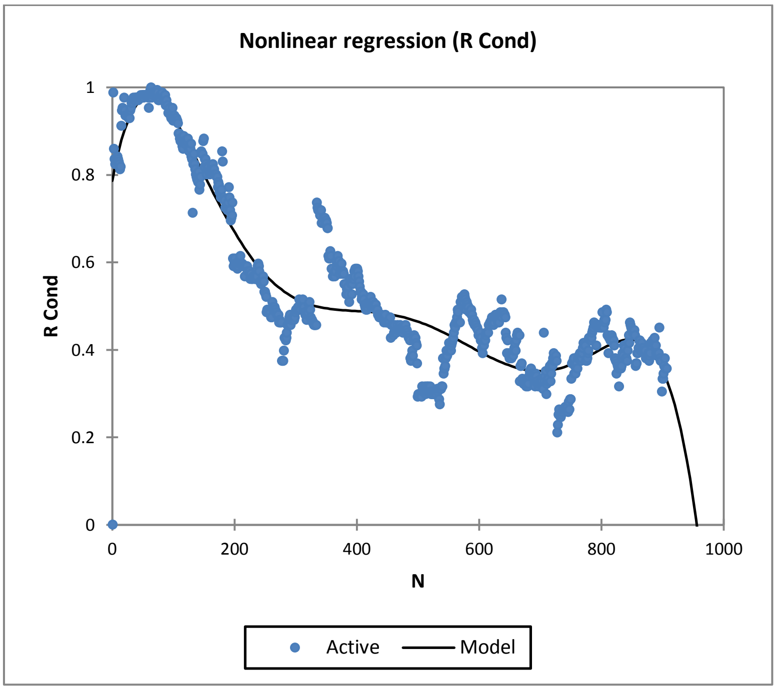

Figure 5.9: Nonlinear regression plot of retentate conductivity

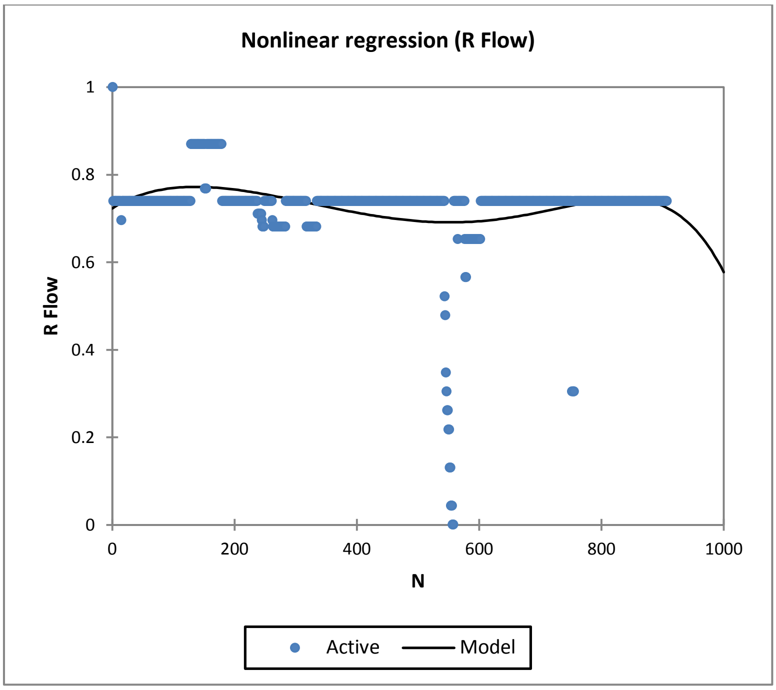

Figure 5.10: Nonlinear regression plot of retentate flow

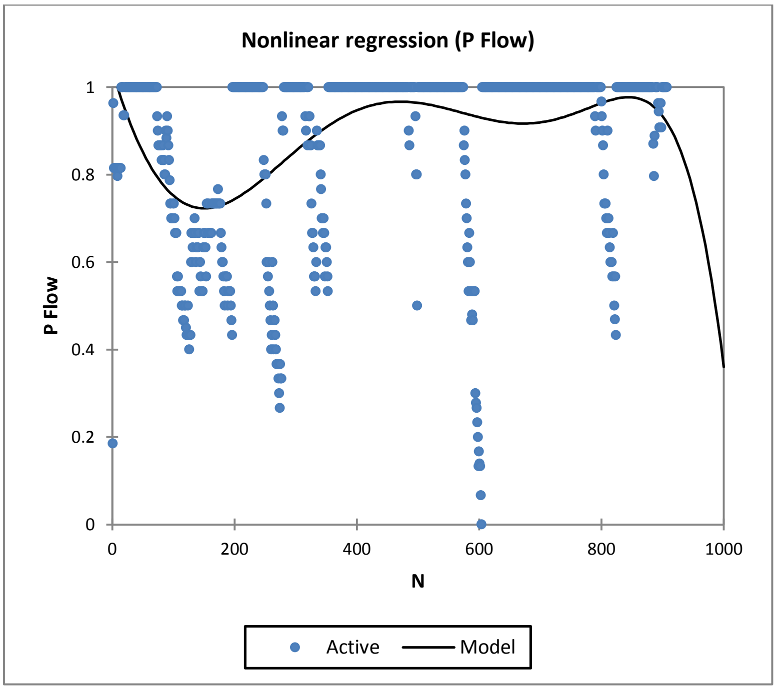

Figure 5.11: Nonlinear regression plot of permeate flow

As can be seen from the figures above, all the figures showed non linearity and their respective best fit equations as well as R^2 are shown in Table 5.1.

Table 5.1: Best fit equations and R^2 values after outlier removal

Variable	Best fit equation	R^2
Feed conductivity	$y = -6.5E-18X^6 + 4.77E-14X^5 - 9.5E-11X^4 + 8.41E-8X^3 - 3.52E-5X^2 + 5.45E-3X + 0.49$	0.694
Feed flow	$y = -6.86E-17X^6 + 1.52E-13X^5 - 1.01E-10X^4 + 5.93E-9X^3 + 1.54E-5X^2 - 4.06E-3X + 1.03$	0.932
Retentate conductivity	$y = -2.20E-16X^6 + 6.31E-13X^5 - 6.96E-10X^4 + 3.65E-7X^3 - 8.97E-5X^2 + 7.40E-3X + 0.79$	0.877
Retentate flow	$y = -7.55E-18X^6 + 1.70E-14X^5 - 1.68E-11X^4 + 1.13E-8X^3 - 4.93E-6X^2 + 8.60E-4X + 0.72$	0.097
Permeate flow	$y = -6.25E-17X^6 + 1.37E-13X^5 - 8.61E-11X^4 - 3.68E-9X^3 + 1.92E-5X^2 - 4.67E-3X + 1.04$	0.187

5.3 INPUT VARIABLE SELECTION

5.3.1 Principal component analysis

A number of multivariable statistical methods are available to reduce the data dimensionality and to extract useful information from process data involving large numbers of measured variables. Utojo and Bakshi (1995) give an excellent overview and comparison of multivariable statistical methods and neural networks for data processing.

Factor analysis is a technique of multivariate analysis that attempts to account for the covariation among a set of observable random variables (denoted as X) in term of a minimal number of unobservable or latent random variables called factors. These unobserved factors are assumed to be linear combinations of the variables which make up the set X. Thus, the objective becomes one of reducing the complexity of the set X into as few linear combinations of those variables within X as possible. There are numerous strategies for performing this reduction of the set X. One such approach is Principal Component Analysis (PCA) that reduces the complexity of the set X via a canonical analysis of the correlation matrix of X. The dominant eigenvectors of the matrix X are then taken to be the principal factors of X. The elements comprising the eigenvectors are then taken to be the weights which produce the linear combination of the set of variables within X. For instance, if we denote the first factor as F1, then F1 is simply a linear combination of the variables in X, where the weights are determined by the elements of the first (most dominant) eigenvector of the correlation matrix of X as seen in Equation 5.1 (Utojo and Bakshi, 1995).

$$F_1 = e_{11}x_1 + e_{21}x_2 + ...+ e_{p1}x_p \tag{5.1}$$

Where $e_1 = e_{11}e_{21}.....e_{p1}$ denotes the most dominant eigenvector of the correlation matrix of X. The elements of e_1 are known as factor loading for each of the p variables that comprise X. These factor loadings are always between -1.0 and 1.0, and a useful heuristic is that variables whose factor loadings have absolute value greater than 0.5 are related highly to the corresponding factor. The rotated principal component analysis generally involves the following steps (Herve, 2010):

a) Selecting the variables

b) Computing the matrix of correlations among the variables
c) Extracting the unrotated factors
d) Rotating the factors
e) Interpreting the rotating matrix

Current estimation and rotation methods require iterative calculations that must be done on a computer and XLSTAT software was used to carry out the factor analysis tests. The resulting factor loadings for the seven variables are summarised in Table 5.2

Table 5.2: Factor loadings for the seven operating variables

Variable	**PC_1**	**PC_2**	**PC_3**	**PC_4**	**PC_5**
Feed flow	0.640	0.763	-0.081	-0.026	-0.006
Feed conductivity	-0.724	0.346	-0.103	0.587	-0.019
Retentate flow	-0.237	0.550	0.799	-0.057	0.007
Retentate conductivity	-0.856	0.391	-0.283	-0.164	0.078
Permeate flow	0.721	0.621	-0.308	-0.010	-0.008

According to the preceding heuristic, the variables whose loading values are greater than 0.5 for a particular factor are taken to represent that factor. PC_1 has a high loading value for the variables permeate flow and much lower values for all the rest. PC_2 has a high loading factor for feed flow and much lower values for the rest of the variables. The factor columns in the matrix represent the input variables. In order to determine the relationship between significant input variables and output variables, each input variable must be matched to a factor column. To match an input variable to a factor column, an examination of the input variable’s row of loading values is carried out and the input variables determined. Specifically the largest loading value in that row is identified and the column in which this value is located indicates the appropriate factor match for that output variable. This process was repeated for each of the input variables, and if there are fewer input variables than columns, we discard the extraneous columns.

5.3.2 Engineering know how as input selection

Variable selection comprises decisions to include or exclude input variables and these decisions are necessarily made on only the specifications determined by the researcher. Often as an aid in this process, we use the factor analysis, R^2 test or some other statistical method to examine relationships between inputs and outputs, and to select input variables. In using these methods, there is always the risk that significant input variables may be excluded if we do not utilize the particular functional relationship in that testing method. Our emphasis is on selecting an appropriate subset of these variables for use in a final prediction model. Therefore, we investigated various specifications of the input variables, based on the plant design and engineering knowhow, and retained any that were deemed worthy of further study. Table 5.3 presents the input variables when using engineering know how approach we have twelve inputs as compared to principle component analysis which give seven.

Table 5.3: Factor loadings for the seven operating variables

Engineering knowhow	**Principal component analysis**
Feed conductivity	Feed conductivity
Feed pressure	Feed flow
Feed pH	Salt out
Feed flow	Retentate conductivity
Retentate conductivity	Retentate flow
Retentate pressure	Permeate flow
Retentate pH	
Retentate flow	
Permeate conductivity	
Permeate pressure	
Permeate pH	
Permeate flow	

Figures 5.12-5.13 compares the neural network performance of permeate flow prediction as an output based on principle component analysis and engineering knowhow variable selection. It is evident that the network with variables selected based on more variables, engineering knowhow, gave less reliable results than those based on factor analysis.

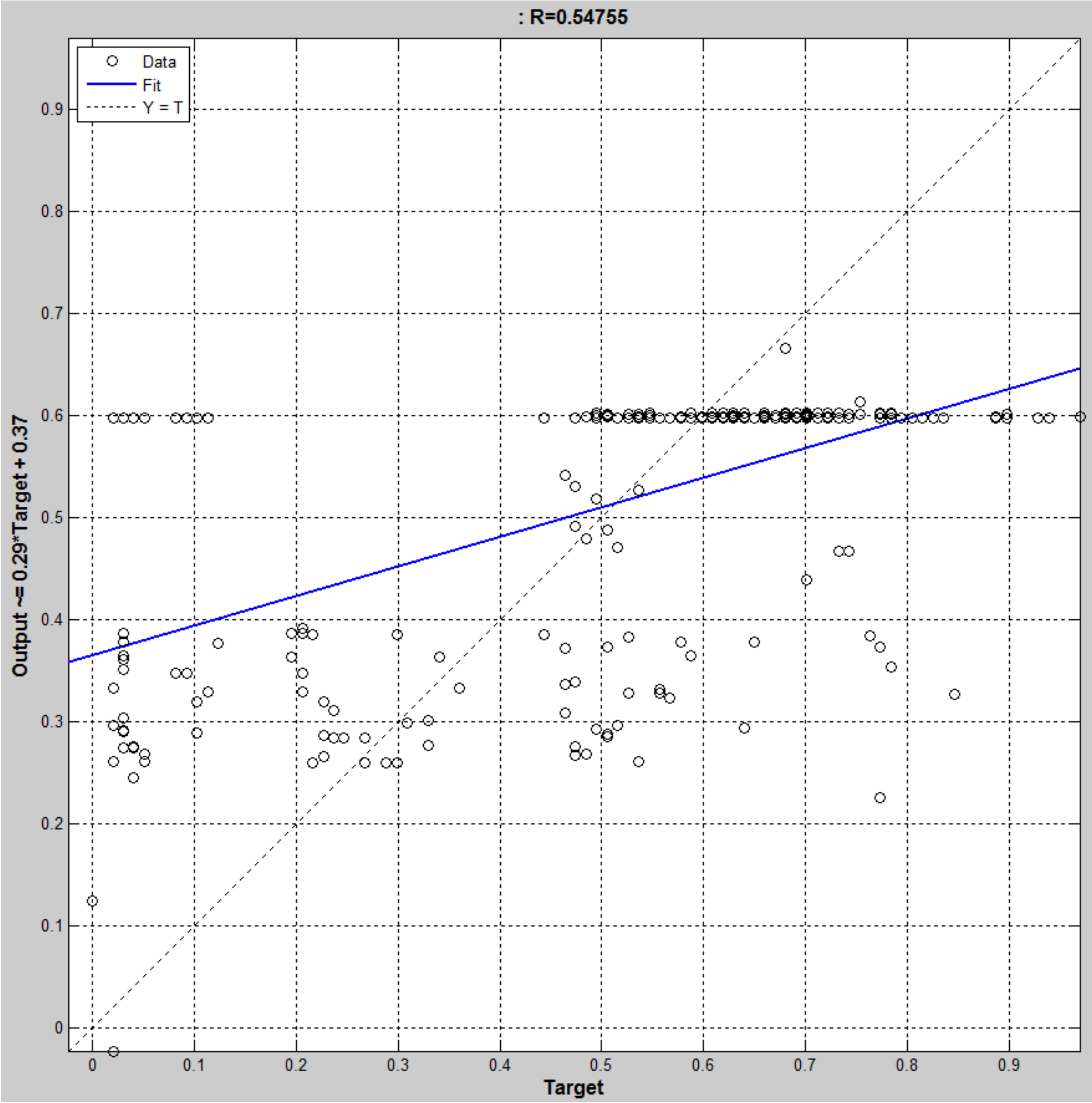

Figure 5.12: Actual and predicted output variables for permeate flow prediction by engineering knowhow

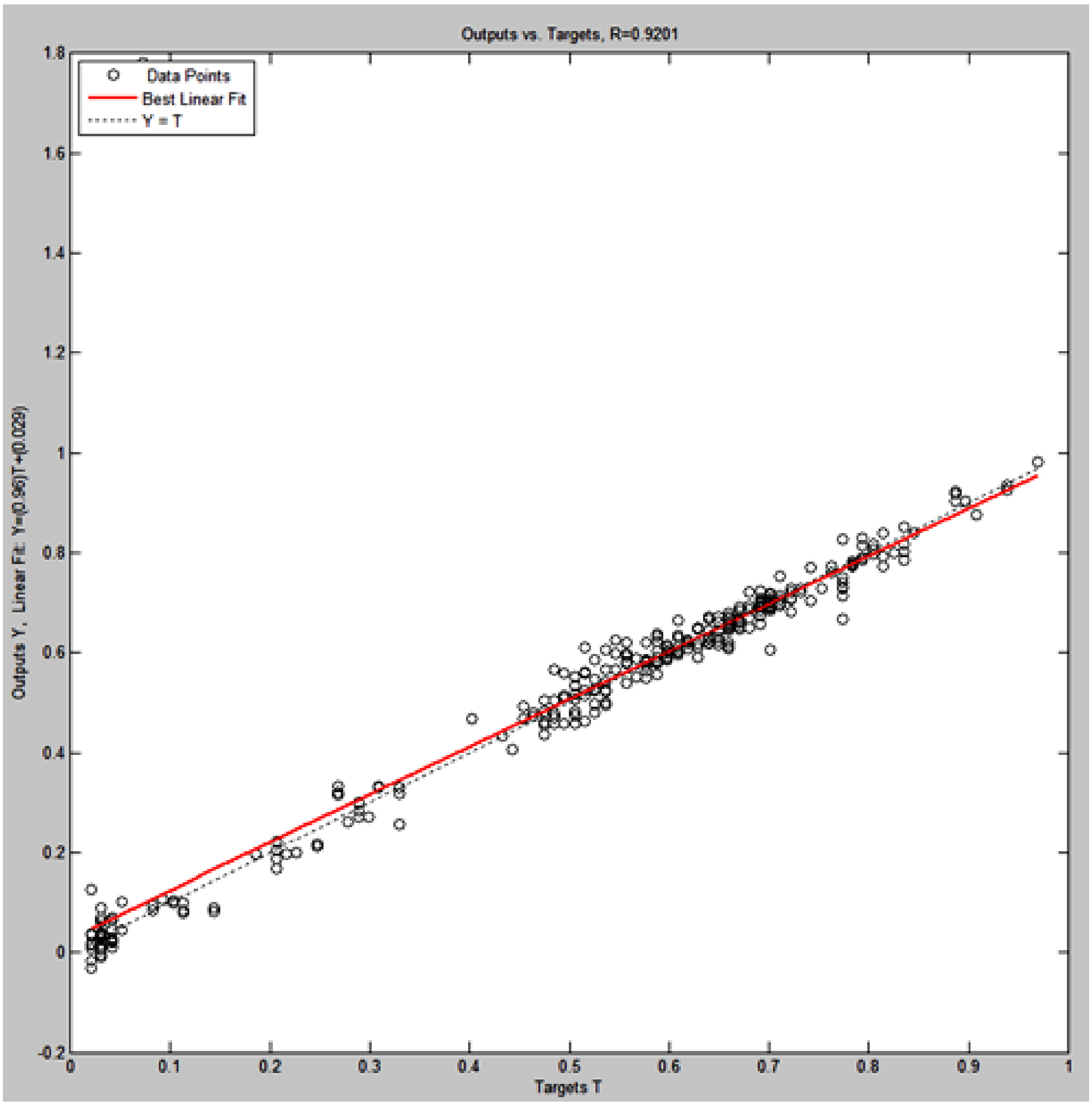

Figure 5.13: Actual and predicted output variables for permeate flow prediction by principal component analysis

The degree of success in variable selection greatly influences the resulting networks ability to predict the output. In general, statistical methods aid in the process of variable selection; however when it comes to accurate predictions it is better to use more mathematically proven concepts like principal component analysis.

5.4 ARTIFICIAL NEURAL NETWORK APPROACH

5.4.1 Training and testing sets

Two subsets of data were used to build a model; that is, a training set and a testing set. The training phase was needed to produce a neural network that was both stable and convergent. Therefore, the selection of what data to use for training a network was one of the most important steps in building the neural network model. Neural networks interpolate data very well, but they do not extrapolate. Therefore, the training set should be selected in such a way that it includes data from all regions of desirable operation.

An important aspect of developing neural networks is determining how well the network performs once training is complete. Checking the performance of a trained network involves two main criteria

1) how well the neural network recalls the predicted response from data sets used to train the network, the recall step

2) how well the network predicts responses from data sets that were not used in training, the generalisation step.

In the recall step, the network's performance in recalling (retrieving) specific initial input used in training is evaluated. Thus, we introduce a previously used input pattern to the trained network. A well-trained network should be able to produce an output that deviates very little from the desired value.

In the generalisation step, the network is feed with new input patterns to the trained network. The network is said to generalise well when it sensibly interpolates these new patterns. Generalisation is affected by three factors (Baughman and Liu, 1995):

i. the size and the efficiency of the training data set

ii. the architecture of the network

iii. the physical complexity of the problem.

To effectively visualize how well a network performs recall and generalization, we often generate a learning curve, which represents the average error for both the recall of training data sets and the generalization of the testing sets as a function of the number of examples in the training data set. The two main uses of a learning curve are (Baughman, and Liu, 1995):

- to find the number of training example required to achieve a fixed average error.
- to estimate the minimum average error attainable through adding data sets.

5.4.2 ANN Model development

In the development of the neural network model the objective was to try and maximise the performance of the model developed, which is the speed of convergence and accuracy of prediction. This was done through the investigation of the following network characteristics (Baughman and Liu, 1995):

- Normalisation of input data
- Weight initialisation
- Optimum network architecture
    - epoch size
    - transfer function
    - learning rate
    - number of nodes in the hidden layers
- Network configuration
- Comparison between statistical analysis and neural network approach

5.4.2.1 normalisation of input data

The raw data input was normalised by using the zero mean normalisation method, Equation 3.20, which was explained in great detail in Chapter 3, section 3.9.2. The real valued were scaled down to network ranges for representation to the network.

5.4.2.2 weight initialisation

The first step in neural computing, prior to training a neural network, is to initialize the weight factors between the nodes of the hidden layers. Since no prior information about the system being modelled is available, it was preferable to set all the free parameters of the network to random numbers that are uniformly distributed inside a small zero-mean range of values, say, between ± 0.5. optimal network architecture *epoch size*

The optimum epoch size should be determined for better training. An epoch is defined as a sequence of training data sets presented to the network between weight updates. The epoch size was chosen such that the total number of training patterns used for each run was constant. Setting the epoch size to the size of the training data set allows the RMS error graph to show the performance of the entire training data set. When using back propagation, the optimal epoch size is a function of the data. Therefore, determining the epoch size is important for better training. This can be done by setting the epoch size to different fractions of the total training set (1/10, 2/10, 9/10, full training set size) and testing the R^2 values of different networks. Select the epoch size produce the highest lowest R^2 value. This method is particularly successful on noisy data. A default epoch size of 100 was chosen for all network predictions.

choice of transfer function

Another factor governing a node's output is the transfer function. The most common transfer functions are the sigmoid, hyperbolic tangent, and radial-basis functions. The hyperbolic tangent transfer function performs well for the prediction networks, while the radial-basis-transfer function works best in classification problems (Baughman and Liu, 1995).

A multilayer prediction network trained with the back propagation algorithm will, in general, learn faster when the transfer function built into the network is symmetric (hyperbolic tangent, with output value between -1.0 and +1.0) rather than non-symmetric (sigmoid, with output value between 0.0 and 1.0), as previously described in Chapter 3. The hyperbolic tangent transfer function is used throughout this study.

setting the learning rate

The learning rate is an important parameter that controls the effectiveness of the training algorithm. The learning rate is a positive parameter that regulates the relative magnitude of weight changes during learning. However, a question one has to ask is how would a change in the learning rate change the performance of the algorithm? To understand the effect of the learning rate on the network training, let us consider the prediction network for the salt removal with 210 training examples. We use a back propagation network with the 30:15 hidden-layer configurations, the delta learning rule and the hyperbolic tangent transfer function.

Figure 5.14-5.16 compared the RMS error using a low learning rate of 0.01, a moderate learning rate of 0.3, and a high learning rate of 5.0. In general it was observed that a low learning rate resulted in slower convergence. When the learning rate was low (0.01), the network took a longer time, roughly 200 iterations to reach an RMS error of 3.24. This was due to the fact that the smaller the learning rate, the smaller the changes to the weights in the network from one iteration to the next, and the larger the number of update steps were needed to reach a minimum. However, when the learning rate was set at 0.3, the network reached an RMS error of 0.66 in a shorter time, about 66 iterations. When the learning rate was set to high values, greater than 4 error fluctuations increased and minimums were never attained thus it was deemed to give unstable results.

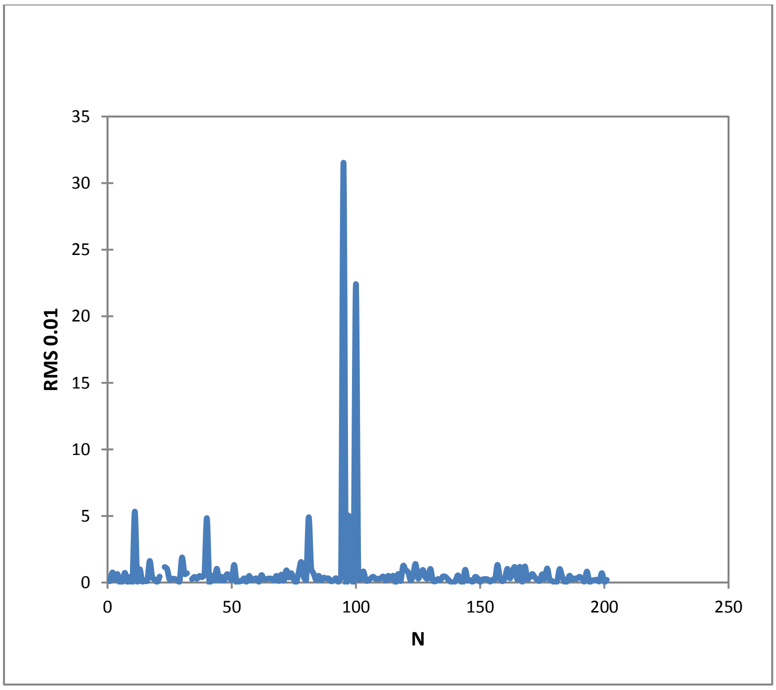

Figure 5.14: RMS error for permeate flow prediction by principal component analysis learning rate set at 0.01

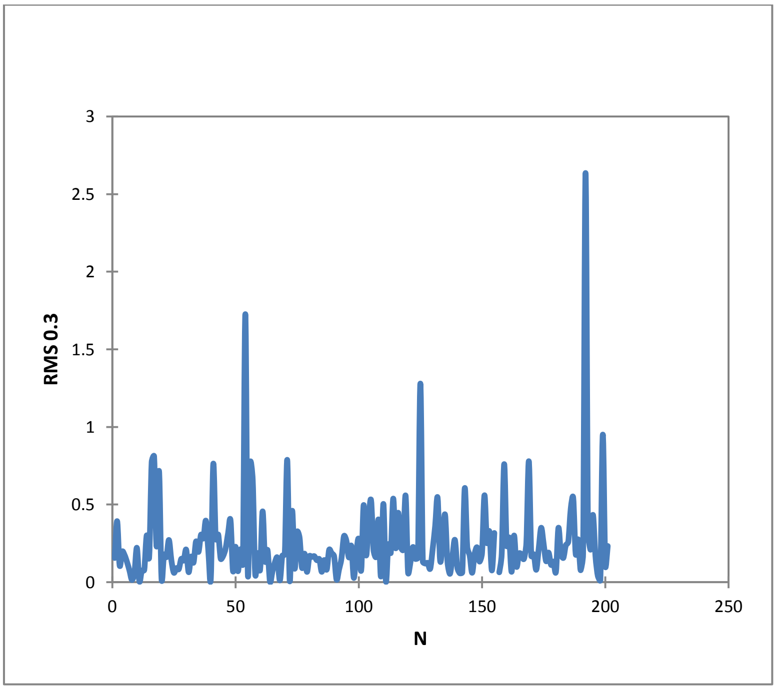

Figure 5.15: RMS error for permeate flow prediction by principal component analysis learning rate set at 0.3

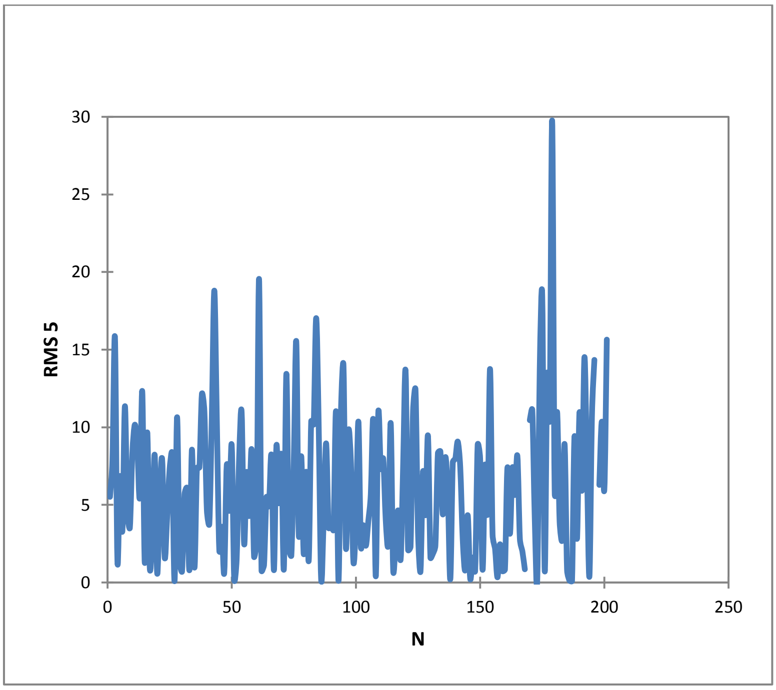

Figure 5.16: RMS error for permeate flow prediction by principal component analysis learning rate set at 5

Therefore, to avoid the danger of instability and improve convergence as we increased the learning rate, a momentum coefficient was introduced, which smoothed out the oscillations. The momentum coefficient is a constant, between 0 and 1, used to promote stability of weight adaptation in a learning rule, and it tends to accelerate descent in a steady downhill direction. In back propagation with momentum coefficient, the weight changes in a direction that is a combination of the current gradient and the previous gradient. This will help in moving the minimization routine out, if during training; it is trapped in a local minimum.

In general a smaller learning rate results in a slower convergence, thus the learning rate was set at 0.3 which agreed with what was recommended by Baugham and Liu (1995). The learning rate should be assigned a smaller value in the last layers than the front-end layers, because the last layers tend to have larger local gradients than the layers at the front-end of the network.

number of nodes in the hidden layers

The number of input and output nodes corresponds to the number of inputs into the network and the number of desired outputs of the network, respectively. The choice of the number of nodes in the hidden layer(s) depends on the network application. Although using a single hidden layer is sufficient in solving many functional approximation problems, some problems may be easier to solve with a two-hidden-layer configuration.

For the prediction of permeate specified in Tables 5.5, the network consisted of 5 input and 1 output variables. The back propagation network was used with hyperbolic transfer function and 0.3 learning rate. 607 data sets were used to train these configurations with 100 iterations. The network was tested with 1 and 2 hidden layer configuration with an increase in number of nodes in each hidden layer. Figures 5.17-5.18 illustrate the network response as the number of nodes in one and two hidden layer network increases. The results showed that the two hidden layer network performed significantly better. The optimal configuration in the two hidden layer network with less network error was found to be 25:10. Figures 5.19-5.20 showed that the trained network predicted the salt removal efficiency well.

Table 5.4: Format of data used for training salt removal efficiency network

Column number	Variable name	Variable type
1	Feed conductivity	Input
2	Feed flow	Input
4	Retentate conductivity	Input
5	Retentate flow	Input
6	Permeate flow	Output

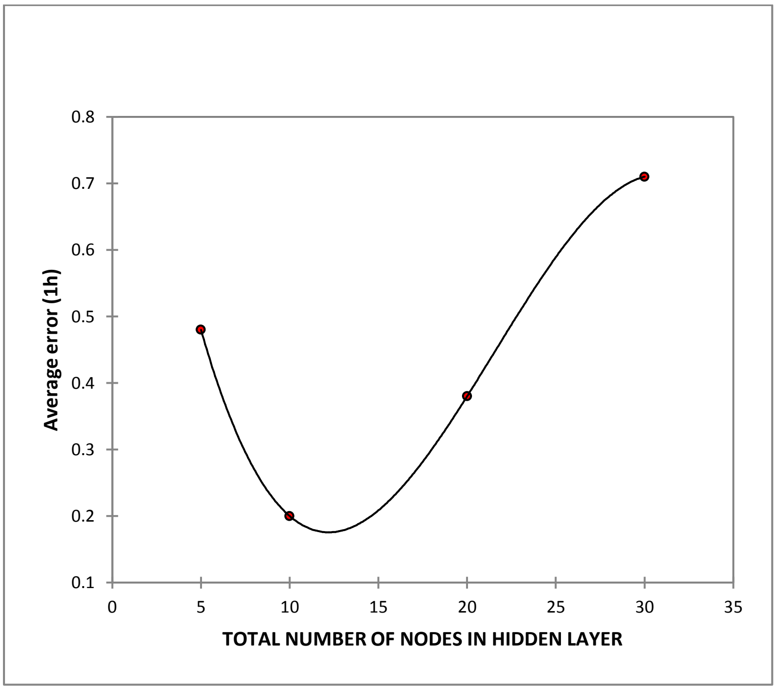

Figure 5.17: Average error trained with one hidden layer for prediction of permeate flow

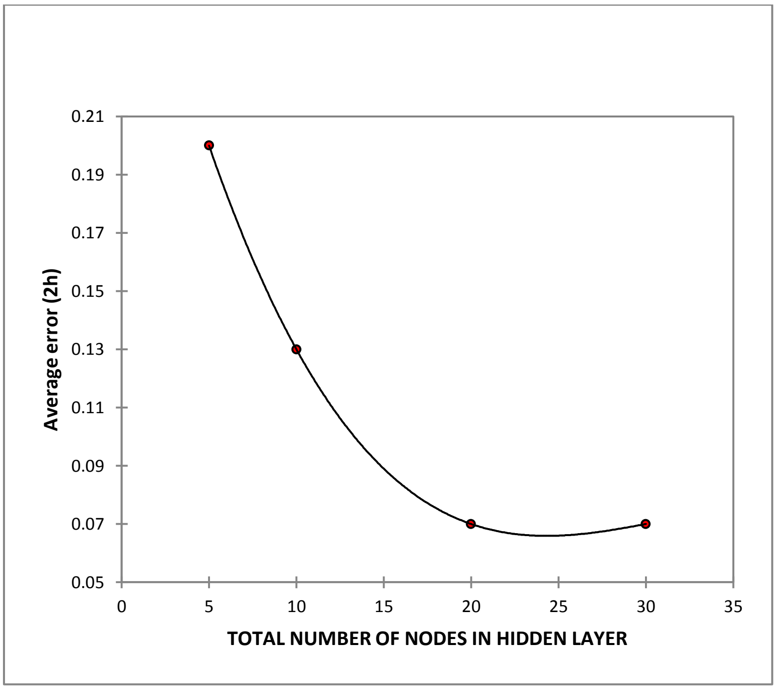

Figure 5.18: Average error trained with two hidden layers for prediction of permeate flow

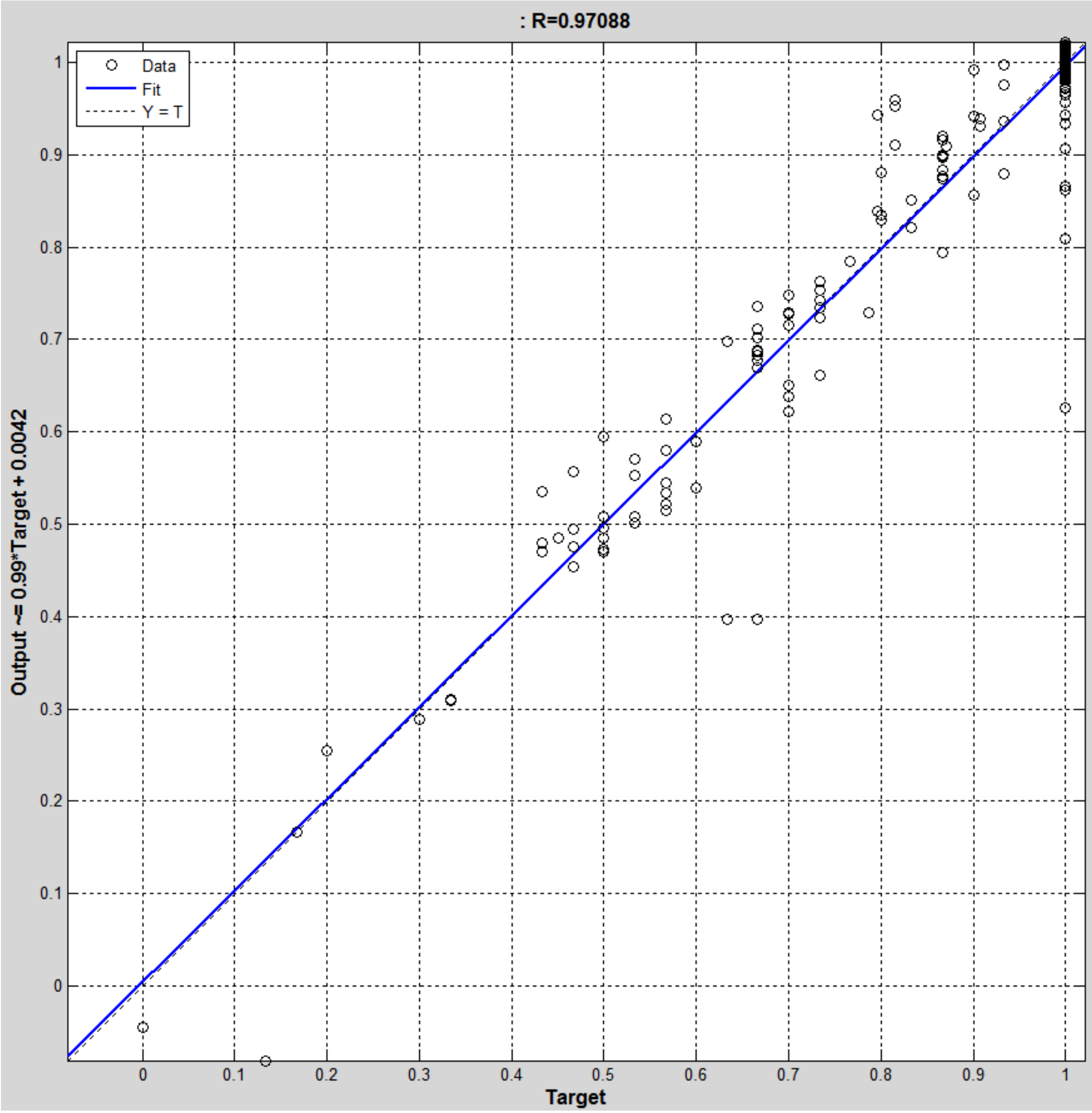

Figure 5.19: Actual and predicted permeate flow 25:10 hidden-layer configuration.

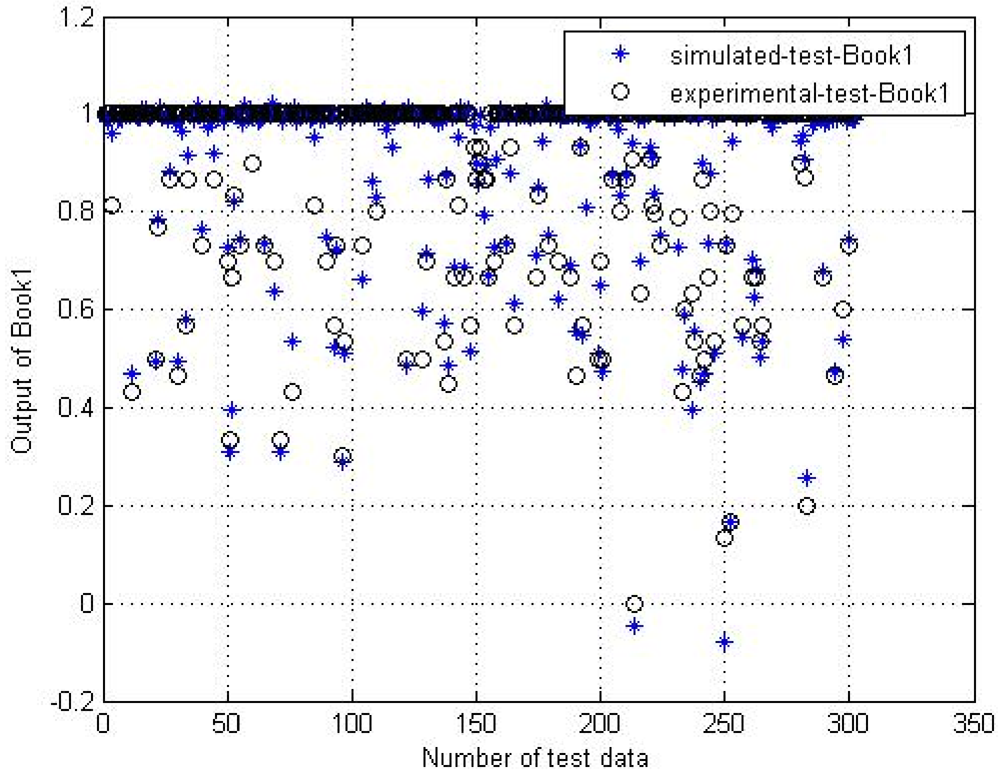

Figure 5.20: Actual and predicted permeate flow for 25:10 hidden-layer configurations.

Based on the above results, the optimal network architecture recommended for permeate flow prediction network is one based on a back propagation algorithm, using the delta learning rule, and the hyperbolic tangent transfer function. The learning rate is set to 0.3 and it decreases with increasing number of hidden layers, and with increasing
The two hidden layers have 25 and 10 nodes, respectively, whereas the maximum number of training iterations is 100 and the epoch size is fixed at 10 examples. The data are divided into 607 sets of data for training and 300 for testing.

5.5 NETWORK APPROACH VERSUS STATISTICAL APPROACH

Using the statistical approach and using R^2 as a determinant to the perfect fit, Table 5.6 shows the resulting polynomial fit equations and R^2 values. Figures 5.21 -5.22 shows the predicted output when using statistical analysis. It can be seen that using the statistical approach to predict salt removal efficiency proves rather difficult owing to the value of R^2 being low and the predicted model giving predictions that are not similar to the original salt removal efficiency data. It is also worthwhile noting that the statistical approach also does not take into account the interaction between the inputs and outputs whereas the neural network approach has been show to give near perfect predictions of salt removal efficiency

Table 5.5: Best fit equations and R^2 values for predicting permeate flow

Variable	Best fit equation	R^2
Permeate flow	$y = -6.25E-17X^6 + 1.37E-13X^5 - 8.61E-11X^4$ $-3.68E-9X^3 + 1.92E-5X^2 - 4.67E-3X + 1.04$	0.187

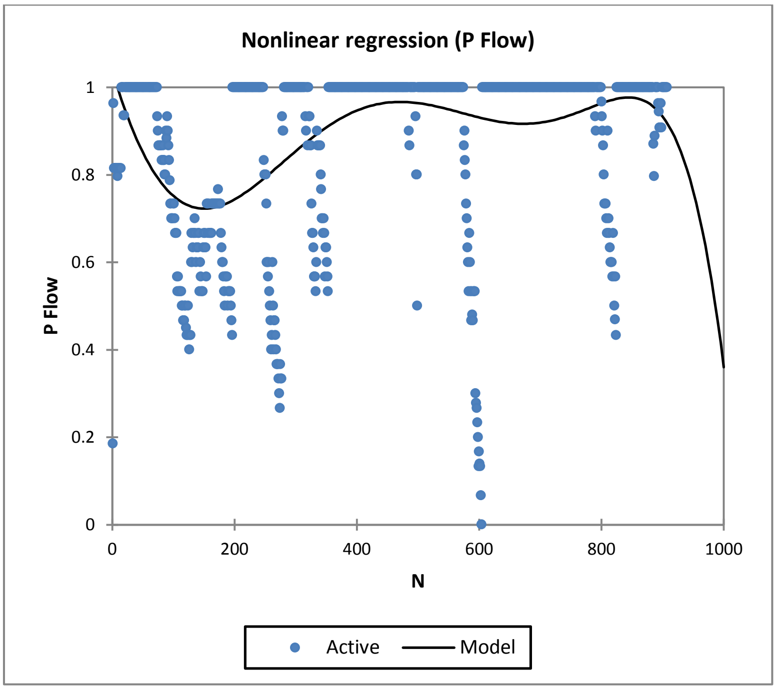

Figure 5.21: Nonlinear regression plot of permeate flow

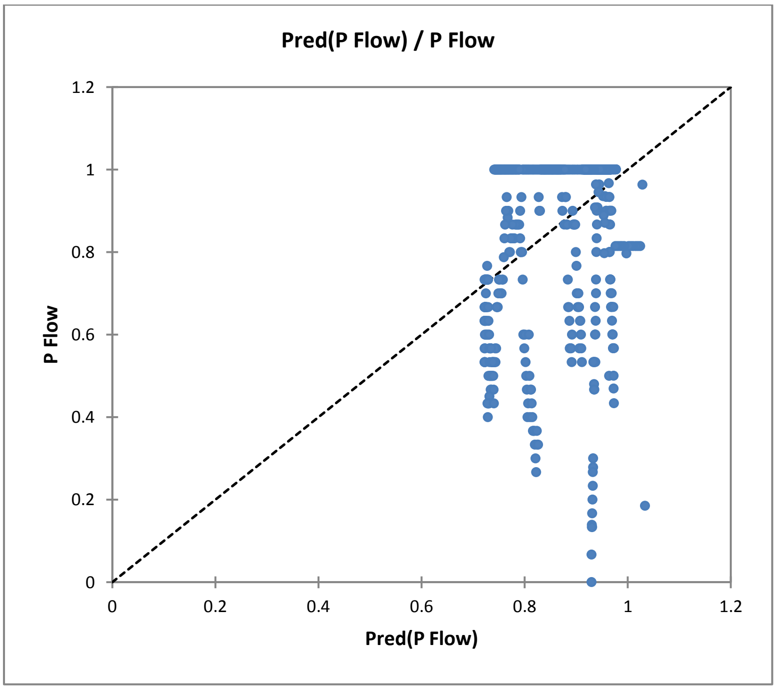

Figure 5.22: Predicted model output of permeate flow

5.6 CLOSURE

The RO membrane process operation was successfully modelled using ANN. The network was observed to be effective in predicting the performance variable and was capable of handling complex and nonlinear problems. A comparison between statistical and network predictions showed that the network outperformed the statistical in prediction.

Chapter 6 CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

The reverse osmosis data was successfully modelled by using ANN by analysing plant data. Careful data analysis revealed a significant amount of outliers present in the raw data. As discussed Chapter 4, these outliers make it hard for the prediction of pattern recognition using ANN and were evident in initial findings. Perhaps the methods of data collection need to be synchronised between human intervention and controller intervention thus anomalies are eliminated. Careful data analysis is also quite important in the preparation of data for use in ANN networks as was shown in Chapter 4. Many variables were obtained and choosing the right variables to use as input data would be quite difficult without the use of principal component analysis. This aided in the selection of the right inputs and led to the discarding of the least effective inputs. A total of five inputs were determined to be the most important in the prediction of salt removal efficiency.

The design of the optimum ANN network was done through trial and error, by adjusting various combinations of hidden layers and number of nodes in each layer, the best combination was found to be a network with two hidden layers with a 25 and 10 nodes in the hidden layers respectively. 1200 sets of data were used for each input variable, with 804 used for training and 396 used for testing and validation. What was quite clear from the onset was that the results obtained were poor with R^2 oscillating between -0.1 to 0.6. One of the contributing factors to this was that a lot of the data contained outliers and thus once these outliers were identified, the new data then consisted of 907 sets of data for each input variable, 607 were used for testing and 300 for testing and validation and the process was carried out again.

The ANN network model that was developed predicted the salt removal efficiency which could be described as perfect prediction based on the value of R^2 which was greater than 0.9, meaning it was a perfect fit. This would seem to suggest that for single output single input it was highly effective but this theory was not tested further due to unavailability of plant data. The use of plant data also severely limits the effectiveness of the model in trying to investigate different effects of input variables on the output.

This is also quite significant owing to the fact that the plant is highly optimised thus further optimisation of input variables cannot be carried out.

6.2 FUTURE WORK

It has been shown that using plant data severely compromises investigations on various effects of different variables thus reducing the understanding of better performance of the RO membrane. Possible suggestion to overcome this limitation would be;

1. To use an alternative approach such as Fuzzy logic which would be useful in forecasting the process performance parameters considered thus comparing between this approach and neural network approach
2. It would be interesting to model the RO membrane using Aspen Hysys and thus be able to use model predictive control algorithms to actually find the optimum input variable parameters and comparing these findings with those of the experimental stage and combining this with the results of ANN prediction in order to compare the three methods.

NOMENCLATURE

A Membrane area (m^2)

C_f Salt concentration in the feed (Kg/m^3)

C_P Salt concentration in the product (Kg/m^3)

J_1 Water flux ($m^3/m^2/sec$)

J_2 Salt flux ($Kg/m^2/sec$)

K_1 Pure water transport coefficient, i.e. the flux of water through the membrane per unit driving force, ($m^3/m^2/sec$ atm)

K_2 Salt transport coefficient (m/sec)

k_1 given by the membrane manufacturer or may be found by solving the equation at the standard test conditions.

K_w Membrane permeability coefficient for water.

M_i Molarity of the i^{th} ionic or non-ionic materials

Q_P Product flow (m^3/day)

Q_f Feed flow (m^3/day)

R Recovery rate

$R_{i,max}$ maximum range between the average value and either the minimum or the maximum value

T Feed water temperature (K)

$x_{i,avg}$ average value of the variable over the data set,

$x_{i,min}$ minimum value of the variable

$x_{i,max}$ maximum value of the variable

ΔP Hydraulic pressure differential across the membrane (atm)

$\Delta \pi$ Osmotic pressure differential across the membrane (atm)

τ Membrane thickness (m)

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APPENDIX A
ANN CODE

```
% %%__________________Book1 modeling using
ANN_________________________________
% MATLAB neural network back propagation code
% by Hakem AlShalan

%
% This code implements the basic backpropagation of
% error learning algorithm.

% %%_________________training
program________________________________________
close all
clear all
clc
format long
data = xlsread('hakout.xlsx');
%
%%---------------------train------------------------------------------
-----
inputs=data(:,1:2)';  %all inputs
outputs=data(:,10)'; %all outputs
%
[u1,us] = mapminmax(inputs);
[y1,ys] = mapminmax(outputs);

% % % random selection for inputs and outputs
N= 907; %number of data
w=randperm(N);
s=size(w);
intrn=u1(:,w(1:ceil(N*2/3))); %inputs
outtrn=y1(:,w(1:ceil(N*2/3))); %outputs
%
% % ------------ Create the network-----------------------------------
-----
%m=[10]
%m=round (2/3*(size(intrn,1))+size(outtrn,1)+sqrt(20)) %Number of
hidden neurons=2/3(inputs+outputs)+sqrt(number of training patterns)
%n=m;
%
%net = newff(intrn,outtrn,[30,15],{'tansig','tansig'}, 'trainBfg');
net = newff(intrn,outtrn,[10],{'tansig'}, 'trainlm');
%net = newff(intrn, outtrn,[30,15,10,5]);
%net.trainFcn = 'trainBFg'
%net.trainFcn = 'trainlm'
net.trainParam.epochs=50;
net.trainParam.show=10;
net.trainParam.lr = 0.3; % Learning rate
net.trainParam.goal=1e-6;
tolerance = 1e-3;
%net = newrb(intrn, outtrn,1e-6,1)
%net = newrbe(intrn, outtrn,110);
%net = newpnn(intrn, outtrn);
%net = newgrnn(intrn, outtrn);
net = init(net);


%
```

```
% %%----------- train the network-------------------------------------
------

%[net,tr] = train(net,intrn,outtrn);
[net, record] = train(net, intrn, outtrn);
X = getx(net);

%plotperform(tr);
%plottrainstate(tr);


%Training ANN
figure (1)
plot(record.epoch, record.perf);

xlabel('Epochs');
ylabel('Mean square error on train set');
hold on
%
% % % ---------- simulate the network --------------------------------
--------
ytrn = sim(net,intrn);
%
outtrn_again=mapminmax('reverse',outtrn,ys);
ytrn_again=mapminmax('reverse',ytrn,ys);
%
plotregression(outtrn,ytrn);grid on
 plotregression(outtrn_again,ytrn_again);grid on
 figure(1)
 [m1,b1,r1]=postreg(ytrn_again,outtrn_again)
%
 %save Book1train_bfg2
 %% ____________________testing program
___________________________________
%load Book1train_bfg22
close all
intst=u1(:,w(ceil(N*2/3)+1:s(2))) ; %inputs
outtst=y1(:,w(ceil(N*2/3)+1:s(2))); %outputs

ytst = sim(net,intst);

intst_again=mapminmax('reverse',intst,us) ;
ytst_again=mapminmax('reverse',ytst,ys)
outtst_again=mapminmax('reverse',outtst,ys)

figure(2)
plot(ytst_again', 'g')
hold on
plot(outtst_again', 'r'); grid on
legend('Testing data','real data')
xlabel('Data')
ylabel('Output')
hold off

err = ytst_again-outtst_again;
disp('Absolute error='); disp(err)
figure(3)
plot(err);grid on
title('Absolute error')
xlabel('Data')
ylabel('Absolute error (%)')
```

```
relerr = abs((ytst_again-outtst_again))./outtst_again*100;
disp('Relative error (%)='); disp(relerr)
figure(4)
plot(relerr);grid on
title('Relative error (%)')
xlabel('Data')
ylabel('Relative error (%)')

meanrelerr=mean(abs(relerr));% average on each raws
disp('mean of relative error (%)=') ; disp(meanrelerr)
 mse=mse(err)
mse2=sum((ytst_again-outtst_again).^2)/74
disp('Test MSE='); disp(mse2)
figure(5)
[m,b,r]=postreg(ytst_again,outtst_again)
plotregression(outtst,ytst);grid on
plotregression(outtst_again,ytst_again);grid on


%%%____________________________ ANN plot
_______________________________________________
figure(6)
plot(ytst_again(1,:),'*b');hold on ; plot(outtst_again(1,:),'ok');grid
on
%title('Book1','FontName','arial','color','k')
legend('simulated-test-Book1','experimental-test-Book1')
xlabel('Number of test data')
ylabel('Output of Book1')
%figure('NumberTitle','off','Name','Regression (plotregression)');



%save Book1test_bfg2
```

APPENDIX B
RAW DATA

Feed					Product			Reject				
Pressure (bar)	Flow (m^3/h)	pH	Temperature (^oC)	Conductivity (μS/cm)	Flow (m^3/h)	pH	Conductivity (μS/cm)	Pressure (bar)	Flow (m^3/h)	pH	Temperature (^oC)	Conductivity (μS/cm)
25	325	5.8	31.5	58300	190	5.64	48300	22.5	135	5.98		61300
30	358	5.8	31.5	58300	232	5.5	44300	26.25	126	5.88	32.2	78200
30	350	5.9	32.4	58400	224	5.7	44200	26.5	126	6	33.1	76000
30	350	5.8	31.7	58500	224	5.7	44400	26.5	126	5.95	33.3	75600
30	350	5.8	31.4	58400	224	5.6	44400	26.25	126	6	33.1	75400
30	350	6	30.6	58400	224	5.6	44400	26.25	126	6.1	32.5	75600
30	350	6	30.6	58400	224	5.6	44400	26.25	126	6.1	32.5	75600
30	350	6	30.2	58300	224	5.6	44600	26.25	126	6.1	32.2	75500
30	349	6	30.2	58400	223	5.6	44700	26.25	126	6.1	31.9	75700
30	350	6	30.3	58300	224	5.6	44500	26.5	126	6.1	32.2	75600
30	350	6	30.3	58300	224	5.6	44500	26.25	126	6.1	31.9	75500
30	350	6	30	58300	224	5.6	44500	26.25	126	6.1	31.9	75400
30	350	6	30	58300	224	5.6	44700	26.25	126	6.1	31.7	75200
30	350	6	30.8	58300	224	5.6	44800	26	126	6.1	32.8	75300
30	358.5	6	31.1	58300	234	5.6	45500	26.25	124.5	6.2	32.8	76900
31.2	360	6	31.1	58400	234	5.6	45600	27.5	126	6.2	32.8	77500
31.2	360	6	31.1	58400	234	5.6	45600	27.5	126	6.2	32.8	77600
31.2	360	6	30.6	58400	234	5.6	45500	27.5	126	6.1	32.5	77500
31.2	356.5	6	30	58400	230.5	5.6	45500	27.5	126	6.1	32.2	77500
31.2	356.5	6	30	58400	230.5	5.6	46000	27.5	126	6.1	32.2	78000
31.2	360	6	30.3	58400	234	5.6	45600	27.5	126	6.1	32.2	77500
31.2	360	6	30.3	58400	234	5.6	45300	27	126	6.1	32.2	77300
32.1	360	6	30	58400	234	5.6	45300	28	126	6.1	31.7	77300
32.1	360	6	30	58400	234	5.6	45300	27.75	126	6.1	31.4	77300
32.1	360	6	29.7	58400	234	5.6	45200	27.75	126	6.1	31.4	77300
32.4	360	6	30	58400	234	5.6	45200	28	126	6.1	31.7	77300
32.4	360	6	29.4	58400	234	5.6	45200	28.25	126	6.1	31.1	77200
33	360	6	29.7	58400	234	5.6	45100	28.75	126	6.1	31.4	77200
33	360	6	29.7	58400	234	5.6	45000	28.75	126	6.1	31.7	77200
33	360	6	30	58400	234	5.6	45000	29	126	6.1	31.7	77500
33.45	360	6	29.7	58400	234	5.6	45000	29.25	126	6.1	31.7	77600
32.7	360	6	29.7	58400	234	5.6	44900	29.5	126	6.1	31.7	77800
32.7	360	6	28.9	58300	234	5.6	44700	29.75	126	6.1	30.6	77800
32.7	360	6	28.6	58300	234	5.6	44600	30	126	6.1	30.6	77800
33	360	6	28.6	58300	234	5.6	44600	30	126	6.1	30.6	78000
32.7	360	6	28.6	58300	234	5.6	44600	30	126	6.1	30.6	77900
33	360	6	28.6	58300	234	5.6	44600	30	126	6.1	30.6	77900
33	360	6	28.3	58300	234	5.6	44500	30	126	6.1	30.8	78000
33	360	6	28.1	58300	234	5.6	44400	30.25	126	6.1	30.6	78000
33	360	6	28.3	58300	234	5.6	44400	30.25	126	6.1	30.8	78000
33	360	6	28.3	58300	234	5.6	44400	30.5	126	6.1	30.6	78000
33	360	6	28.3	58300	234	5.6	44400	30.25	126	6.1	30.3	78000
33	360	6	28.3	58400	234	5.6	44600	30.25	126	6.1	30.3	77900

33.3	360	6	28.3	58400	234	5.6	44600	30.5	126	6.1	30	78000
33.3	360	6	28.3	58400	234	5.6	44600	30.5	126	6.1	30	78000
33.6	360	6	28.1	58300	234	5.6	44500	30.5	126	6.1	30	78000
33.6	360	6	27.8	58400	234	5.6	44600	30.75	126	6.1	29.7	78100
33.9	360	6	27.5	58300	234	5.6	44500	31	126	6.1	29.1	78000
33.3	360	6	27.5	58300	234	5.6	44400	30.75	126	6.1	29.4	78000
33.6	360	6	27.8	58400	234	5.6	44600	30.5	126	6.1	30	78100
33.6	360	6	28.1	58400	234	5.6	44600	30.75	126	6.1	29.7	78100
33.6	360	6	27.8	58400	234	5.6	44600	30.75	126	6.1	30	78000
33.6	360	6	27.8	58300	234	5.6	44500	30.75	126	6.1	29.7	78100
33.6	360	6	27.8	58400	234	5.6	44500	30.75	126	6.1	29.7	78100
33.6	360	6	27.8	58400	234	5.6	44500	30.75	126	6.1	29.7	78100
33.6	360	6	27.8	58400	234	5.6	44500	30.75	126	6.1	29.7	78100
33.9	360	6	27.5	58300	234	5.6	44500	31	126	6.1	29.4	78100
33.9	360	6	27.5	58400	234	5.6	44600	31.25	126	6.1	29.8	78100
33.9	360	6	27.2	58400	234	5.6	44700	31	126	6.1	29.2	78000
33.9	360	6	27.2	58400	234	5.6	44600	31	126	6.1	29.2	77600
33.9	360	6	27.2	58400	234	5.6	44600	31	126	6.1	29.2	78000
33.9	360	6	27.2	58400	234	5.6	44500	31.25	126	6.1	29.2	78000
34.5	360	6	26.7	58400	234	5.6	44500	31.5	126	6.1	28.6	78300
34.5	360	6	26.7	58400	234	5.6	44500	31.5	126	6.1	28.6	78400
34.5	360	6	26.7	58400	234	5.6	44500	31.5	126	6.1	28	78000
34.8	360	6	26.7	58400	234	5.6	44400	31.75	126	6.1	28.9	78200
34.8	360	6	26.5	58400	234	5.6	44500	31.75	126	6.1	28.9	78100
34.8	360	6	26.45	58400	234	5.6	44400	31.75	126	6.1	28.9	78200
34.8	360	6	26.15	58400	234	5.6	44400	32	126	6.1	28.9	78200
34.8	360	6	26.4	58400	234	5.6	44500	32	126	6.1	28.6	78200
34.8	360	6	26.1	58400	234	5.64	44500	32	126	6.1	28.3	78200
34.8	360	6.05	25.8	58400	234	5.7	44500	32	126	6.15	28.1	78100
34.8	360	6	26.1	58400	234	5.6	44500	32	126	6.13	28	78100
35.1	356.4	6	26.1	58400	230.4	5.6	44500	32.25	126	6.13	28.05	78300
35.4	355.6	6.02	25.8	58400	228.6	5.64	44500	32.5	126	6.16	27.8	78200
35.4	352.8	6.01	25.6	58400	226.8	5.65	44400	32.5	126	6.17	27.5	77900
35.4	352.8	6	25.6	58400	226.8	5.61	44500	32.5	126	6.16	27.5	77900
35.4	352.8	6.01	25	58400	226.8	5.6	44400	32.5	126	6.12	27.2	78000
35.4	352.8	5.98	25	58400	226.8	5.66	44400	32.75	126	6.14	27.2	78100
35.4	352.8	6.01	25.3	58500	226.8	5.6	44500	32.75	126	6.12	27.3	78100
35.7	351	5.79	25	58400	225	5.71	44400	33	126	6.15	27.2	78100
35.7	351	6	25	58400	225	5.64	44400	33	126	6.16	27.2	78200
35.7	352.8	6.03	25	58500	226.8	5.6	44500	32.75	126	6.17	27.2	78000
35.4	351	5.94	25.2	58500	225	5.65	44500	32.75	126	6.13	26.9	78000
35.7	351	5.98	24.7	58500	225	5.62	44500	32.75	126	6.16	26.9	78000
35.7	349.2	6.02	24.7	58500	223.2	5.6	44500	32.75	126	6.18	26.9	78000

36	349.2	6.03	24.4	58500	223.2	5.6	44500	33	126	6.15	26.6	78100
35.4	354.6	6	25.5	58500	228.6	5.61	44700	32.5	126	6.12	27.5	77700
35.4	353.7	5.97	25.3	58400	227.7	5.62	44700	32.5	126	6.13	27.2	77900
35.7	356.4	5.99	25.5	58500	230.4	5.64	44700	33	126	6.12	27.5	77700
36	354.6	5.96	25.3	58500	228.6	5.09	44600	33	126	6.09	27.2	77700
35.7	352.8	5.97	24.3	58600	226.8	5.6	44600	33	126	6.1	27.5	77400
36	351	5.98	24.4	58600	225	5.6	44600	33	126	6.1	26.3	77400
36.3	348	5.98	23.9	58600	222.5	5.6	44500	33.5	126	6.1	26.1	77600
36.6	345.6	5.98	23.4	58600	219.6	5.6	44400	33.5	126	6.09	26.1	77400
36	345.6	5.97	23.8	58600	219.6	5.6	44500	33.25	126	6.1	25.8	77300
36	343.8	5.96	24.2	58600	217.8	5.6	44500	33.25	126	6.1	26.1	77200
36.3	343.8	5.98	24.2	58600	217.8	5.6	44500	33.5	126	6.1	26.4	77200
36.3	343.8	6	24.4	58600	217.8	5.6	44500	33.25	126	6.1	26.1	77600
36	345.6	5.98	24.7	58600	219.6	5.6	44600	33.25	126	6.1	26.7	77100
36.6	345.6	5.98	24.7	58600	219.6	5.6	44600	33.5	126	6.1	26.7	77200
36.9	343.8	5.97	24.4	58600	217.8	5.6	44500	34	126	6.1	26.4	77300
36.6	342	5.98	24.4	58600	216	5.6	44500	34	126	6.1	26.1	77200
36.6	342	5.95	23.9	58600	216	5.6	44500	34	126	6.1	26.1	77200
36.6	348	5.98	23.6	58600	216	5.6	44500	34	126	6.1	26.1	77200
36.6	338.6	6	23.3	58600	210.6	5.6	44500	34	126	6.1	25.6	77100
36.6	334.8	6	23.3	58600	208.8	5.6	44500	34	126	6.1	25.6	77100
36.9	336.6	5.98	23.3	58600	210.6	5.6	44500	34.25	126	6.1	25.6	77000
36.6	334.8	6	23.3	58600	208.8	5.6	44400	34	126	6.1	25.6	76600
36.6	334.8	6	23.3	58600	208.8	5.6	44400	34	126	6.1	25.6	76600
36.6	334.8	6	23.9	58600	208.8	5.6	44600	33.75	126	6.1	25.9	76400
36.6	334.8	5.97	23.6	58600	208.8	5.6	44600	34	126	6.1	25.8	76300
36.6	334.8	5.98	23.6	58600	208.8	5.6	44500	33.75	126	6.1	25.6	76300
36.6	333	5.98	23.3	58600	207	5.6	44500	34	126	6.1	25.6	76300
36.6	333	5.97	23.3	58600	207	5.6	44500	34	126	6.1	25.5	76100
36.6	331.2	5.98	23.3	58600	205.2	5.6	44400	34	126	6.1	25.5	76000
37.2	331.2	5.98	23.1	58700	205.2	5.6	44400	34.75	126	6.15	25.3	76500

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37.2	331.2	5.98	23.1	58700	205.2	5.6	44400	34.75	126	6.16	25.3	76300
37.2	333	6	23.6	58700	207	5.6	44600	34.5	126	6.14	25.8	76200
36.9	333	6	23.6	58700	207	5.6	44700	34.5	126	6.17	25.8	76200
37.32	330.3	6	23.3	58700	204.3	5.6	44600	34.9	126	6.16	25.6	76300
37.5	329.4	5.98	23.3	58700	203.4	5.6	44600	35	126	6.15	25.6	76300
37.5	329.4	5.98	23.1	58700	203.4	5.6	44600	35	126	6.14	25.3	76300
37.8	333	6	23.1	58700	207	5.6	44600	35.5	126	6.11	25.3	76400
37.8	329.4	6	23.3	58600	203.4	5.6	44400	35.5	126	6.15	25.6	76000
37.8	327.6	6	23.1	58700	201.6	5.6	44400	35.5	126	6.14	25	75900
38.1	329.4	5.98	23.1	58700	203.4	5.6	44500	35.75	126	6.1	25	76100
38.1	329.4	5.97	23.3	58700	203.4	5.6	44600	35.5	126	6.1	25	76000
37.2	342.9	5.97	23.9	58800	212.4	5.6	44700	34.5	130.5	6.1	25.8	76200
37.2	346.5		24.4	58800	216		44900	34.5	130.5		26.1	75700
36.9	342.9	6	24.4	58800	212.4	5.6	44800	34	130.5	6.2	26.4	75600
36.6	344.7		24.8	58600	214.2		44900	33.75	130.5		26.3	73500
36.3	346.5	6	25.3	58700	216	5.6	45200	33.75	130.5	6.2	27.2	75400
36.3	346.5	6.02	25.6	58700	216	5.65	45300	33.5	130.5	6.15	27.5	75800
36.6	348.3	6.01	25.6	58600	217.8	5.7	45200	33.75	130.5	6.16	27.5	75400
36.6	346.5	6.01	25.6	58600	216	5.64	45200	34	130.5	6.15	27.5	75200
36.6	342.9	6	25.6	58600	212.4	5.63	45200	33.75	130.5	6.13	27.5	75000
36.6	344.7	6	25.6	58400	214.2	5.64	45100	33.75	130.5	6.14	27.5	74900
36.6	344.7	6	25.6	58300	214.2	5.64	45000	33.75	130.5	6.15	27.5	74800
36.9	344.7	5.95	25.6	58300	214.2	5.6	45000	34	130.5	6.17	27.5	74800
36.9	346.5	6	26.1	58300	216	5.6	45200	34	130.5	6.1	28.1	74700
36.3	346.5	6	26.1	58300	216	5.6	45300	33.75	130.5	6.1	28.1	75100
36	339.3	6	26.4	58300	208.8	5.6	45300	34	130.5	6.1	28.3	74400
36.3	342.9	6	26.4	58300	212.4	5.6	45400	34	130.5	6.1	28.3	74600
36.6	341.1	6	26.4	58600	210.6	5.6	45600	34.25	130.5	6.1	28.3	74900
36.6	339.3	6	26.7	59000	208.8	5.65	46100	34	130.5	6.15	28.9	75900
36.6	339.3	6	26.7	59200	208.8	5.6	46100	34.25	130.5	6.11	28.9	75800
36.6	339.3	6	26.9	59000	208.8	5.6	46200	34.25	130.5	6.18	28.9	75800

36.6	344.7	6	27.8	59000	214.2	5.65	46200	34	130.5	6.15	30	76300
36.6	346.5	6	27.8	59100	216	5.64	46300	34	130.5	6.11	30.2	76400
36.3	344.7	6	28.1	59000	214.2	5.6	46200	34.25	130.5	6.16	30	75300
36.6	343	6	28.3	59000	216	5.7	46300	34	127	6.18	30.3	75600
36.9	341.2	6	28.3	59000	214.2	5.65	46200	34.25	127	6.18	30.3	75600
36.9	337.6	6	28.1	59000	210.6	5.6	46100	33.25	127	6.18	30	75400
36	350.1	6	27.2	58800	219.6	5.7	46200	33.75	130.5	6.2	29.2	75000
36.3	350.1	6	27.2	58800	219.6	5.7	46300	34	130.5	6.2	29.2	75300
36.3	346.5	6.01	27.2	58900	216	5.62	46400	34.25	130.5	6.2	29.2	75200
36.3	350.1	6	27.2	58900	219.6	5.65	46500	34	130.5	6.12	29.2	75300
36.3	346.5	6	27.2	59000	216	5.66	46400	34	130.5	6.15	29.2	75100
35.7	346.5	6	27.2	58900	216	5.7	46500	33.25	130.5	6.2	29.2	75000
36	346.5	6	27.2	59000	216	5.7	46500	34	130.5	6.2	29.2	75100
36	346.5	6	27.5	58900	216	5.75	46400	34	130.5	6.2	29.4	75200
36.9	350.1	6.02	27.5	59000	219.6	5.75	46400	34.75	130.5	6.18	29.4	75300
36.6	350.1	6.01	27.5	59100	219.6	5.7	46600	34.5	130.5	6.2	29.7	75300
36.6	350.1	6	27.5	59200	219.6	5.71	46800	34.5	130.5	6.16	30	75400
36.3	350.1	6.01	28.3	59100	219.6	5.73	46800	34.25	130.5	6.18	30.3	75200
36.6	350.1	6	28.3	59100	219.6	5.75	46900	34.25	130.5	6.19	30.3	75200
36.6	350.1	6.01	28.1	59100	219.6	5.75	46800	34.25	130.5	6.16	30	75000
36.3	350.1	6	28.1	59000	219.6	5.71	46900	34.25	130.5	6.16	30	75000
36.3	350.1	6	28.3	59100	219.6	5.75	46900	34.25	130.5	6.17	30.3	75000
36.3	350.1	6.02	28.6	59000	219.6	5.75	47000	34	130.5	6.2	30.6	74900
36.6	350.1	6	28.6	59000	219.6	5.7	47000	34.25	130.5	6.18	30.6	74900
36.6	351.9	6	28.9	59000	221.4	5.65	47000	34.25	130.5	6.13	30.6	74500
36.3	350.1	6	28.9	59000	219.6	5.69	47000	34.25	130.5	6.16	30.6	74700
36.6	350.1	6	29.2	59000	219.6	5.65	47000	34.25	130.5	6.12	30.8	74600
36.6	350.1	6	29.2	58900	219.6	5.66	47100	34.25	130.5	6.08	30.8	74300
36.7	350.1	6	29.2	58900	219.6	5.64	47000	34.5	130.5	6.15	30.8	74300
36.9	346.5	6	29.2	58900	216	5.7	46900	34.25	130.5	6.14	30.8	74100
36.6	344.7	6	29.2	58900	214.2	5.68	46800	34.25	130.5	6.11	30.8	74400

37.2	338.4	6	29.2	59000	212.4	5.68	47100	35	126	6.1	30.8	75900
37.5	338.4	6	28.6	59000	212.4	5.65	47100	35.25	126	6.08	30.8	75500
38.36	336.6	6	28.6	59000	210.6	5.7	46800	35.5	126	6.1	30.3	74100
37.5	334.8	6	28.4	59000	208.8	5.71	46800	35.5	126	6.08	30.3	74000
37.5	333	6	28.6	59000	207	5.7	46800	35.5	126	6.07	30.6	74000
37.5	336.6	6	29.7	58900	210.6	5.65	47200	35.25	126	6.14	31.4	73700
37.8	336.6	6	29.7	58900	210.6	5.65	47100	35	126	6.15	31.4	73700
37.5	336.6	6	30	58900	210.6	5.65	47500	35.5	126	6.16	31.9	73700
37.5	336.6	6	30	58900	210.6	5.65	47200	35.25	126	6.17	31.9	73700
37.8	333	6	30	58900	207	5.65	47200	35.5	126	6.15	31.9	73600
37.8	334.8	6	30.3	59000	208.8	5.7	47500	35.5	126	6.13	32.2	73900
37.5	334.8	6	30.3	59000	208.8	5.65	47500	35.5	126	6.11	31.9	74500
37.5	334.8	6	30.3	59100	208.8	5.7	47700	35.5	126	6.14	31.9	74100
37.5	334.8	6.02	30.3	59000	208.8	5.68	47700	35.5	126	6.15	31.9	73600
37.8	333	6.01	30.3	58800	207	5.69	47400	35.75	126	6.19	32.2	73200
37.8	331.2	6	30.3	58900	205.2	5.65	47400	35.75	126	6.19	32.2	73300
37.8	329.4	6.1	30.6	58800	203.4	5.68	47400	35.5	126	6.13	32.8	73400
26.1	360	6	30.6	58900	234	5.8	49900	23.25	126	6.16	32.8	73900
26.7	360	5.98	31.4	58700	234	5.75	49800	24	126	6.17	33.1	71700
25.8	360	5.98	31.9	58900	234	5.74	50100	23.25	126	6.12	33.9	71400
26.4	360	6	31.4	58800	234	5.8	50000	23.75	126	6.17	33.1	71600
26.4	360	6.02	31.9	58800	234	5.75	50000	23.75	126	6.18	33.9	71700
26.4	360	6	31.9	58700	234	5.75	49900	23.75	126	6.16	33.9	71500
26.4	360	6	32.2	58900	234	5.78	50200	23.75	126	6.18	34.2	71400
26.4	360	6	32.7	58800	234	5.8	50200	24	126	6.1	34.4	71400
26.1	360	6	32.8	58800	234	5.8	49900	23.5	126	6.15	34.4	71300
26.4	360	6	32.8	58800	234	5.76	49900	24	126	6.2	34.4	71400
26.4	360	6	32.8	58800	234	5.75	49900	24	126	6.18	34.4	71600
26.4	360	6.02	32.8	58800	234	5.76	50000	24	126	6.15	34.4	71500
26.7	360	6.02	32.8	58800	234	5.75	50000	24.25	126	6.19	34.4	71600
26.7	360	6.02	33.1	58800	234	5.76	50000	24.25	126	6.17	35	71800
26.4	360	6	33.3	58800	234	5.8	50000	24.25	126	6.1	36.1	71500

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26.7	360	6.02	33.3	58800	234	5.74	50000	24.25	126	6.17	35.3	71500
26.7	360	6.02	33.3	58800	234	5.74	50100	24.25	126	6.17	35.3	71500
26.7	360	6	33.3	58700	234	5.74	50000	24.25	126	6.19	35.3	71400
27.3	360	6.04	33.3	58800	234	5.76	50100	24.5	126	6.17	35.3	71400
27.9	360	6.05	33	58700	234	5.78	49900	25	126	6.18	35.5	71400
27.6	360	5.96	33.6	58600	234	5.75	49900	25	126	6.14	35.5	71000
27.9	360	6	33.6	58700	234	5.79	49800	25	126	6.2	35.5	71400
28	360	6	33.6	58700	234	5.75	49800	25	126	6.2	35.5	71400
28.8	360	6	33.6	58600	234	5.73	49900	25.5	126	6.12	35.3	71400
28.8	360	5.94	33.4	58600	234	5.71	49700	25.75	126	6.1	35.3	71400
28.8	360	5.97	33.6	58600	234	5.7	49800	25.75	126	6.12	35.3	71200
29.1	360	5.98	33.6	58600	234	5.78	49800	26.25	126	6.17	35.4	71200
29.4	360	5.96	33.6	58500	234	5.71	49700	26.75	126	6.16	35.5	71200
29.4	360	5.97	33.6	58500	234	5.74	49700	26.5	126	6.15	35.5	71200
29.4	360	5.97	34.1	58500	234	5.73	49700	26.5	126	6.18	36.1	70900
29.1	360	5.95	34.4	58500	234	5.73	49800	26.5	126	6.11	36.4	71100
30.3	360	6.05	33.9	58400	234	5.85	49500	27.5	126	6.22	35.8	70900
30.3	360	6.04	33.9	58300	234	5.6	49500	27.5	126	6.22	35.8	70900
30.9	360	6	34.4	58200	234	5.78	49200	28	126	6.2	36.1	70900
31.2	360	6.04	34.1	58300	234	5.77	49400	28	126	6.21	35.8	71000
31.5	360	6	33.9	58200	234	5.7	49400	28.5	126	6.09	35.8	71000
31.8	360	5.97	33.9	58200	234	5.76	49400	29	126	6.12	35.8	70900
32.4	360	6.02	33.9	58200	234	5.76	49300	29.5	126	6.14	35.8	70900
32.4	360	6.04	33.9	58200	234	5.8	49400	29.75	126	6.15	35.8	70900
33	360	6.02	33.9	58300	234	5.8	49400	30	126	6.19	35.8	71000
32.7	360	6.01	33.9	58300	234	5.8	49400	30	126	6.16	35.8	71000
33.9	359	6.01	34.2	58300	234	5.83	49400	31.25	125	6.16	36.1	71400
33.6	359	6.04	34.4	58300	234	5.8	49400	31	125	6.19	36.4	71500
34.4	359	6.04	34.4	58300	234	5.8	49400	32	125	6.18	36.4	71400
34.8	359	6.01	34.25	58300	234	5.8	49400	31.5	125	6.2	36.1	71200
31.8	359	6	34.25	58300	234	5.8	49400	28.5	125	6.1	36.1	70800

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33.9	359	6.04	34.2	58100	234	5.8	49200	30.5	125	6.16	36.1	70800
34.5	359	6.01	33.9	58000	234	5.78	49000	31.25	125	6.25	35.8	70700
33.3	358.5	6.02	34.1	58100	234	5.85	49300	30.25	124.5	6.23	36.1	70800
34.5	358	6.04	33.65	58100	234	5.83	49100	31.5	124	6.16	35.6	70900
35.4	358	6.04	33.35	58100	234	5.81	49100	32.5	124	6.15	35.6	71000
35.7	349	6.01	33.1	58100	225	5.8	49000	33	124	6.14	35	70800
36	349.2	6.02	32.8	58100	223.2	5.84	49000	33	126	6.18	35	70400
36	349.2	6	32.8	58100	223.2	5.8	49000	33	126	6.18	35	70400
36.3	349.2	6.02	33.05	58100	223.2	5.81	49000	33.25	126	6.16	35	70300
36.3	345.6	6.04	33.1	58100	219.6	5.8	49000	33	126	6.2	35	70200
36.9	338.4	6	32.3	58000	212.4	5.76	48500	33.75	126	6.14	34.4	69600
36.9	338.4	6.01	32.2	57900	212.4	5.8	48600	34	126	6.12	34.4	69700
36.9	336.6	6.02	32.2	57900	210.6	5.8	48600	33.5	126	6.13	34.4	69600
36.6	338.4	6	32.2	57900	212.4	5.82	48600	33	126	6.13	34.4	69700
36.6	334.8	6.04	32.2	57900	208.8	5.81	48700	33.25	126	6.14	34.4	69700
37.2	333	6.04	32.2	57900	207	5.83	48700	33.5	126	6.15	34.4	69700
36.9	331.2	5.97	32.2	58000	205.2	5.78	48800	33.5	126	6.11	34.4	69600
37.2	327.6	6.01	32.2	57900	201.6	5.76	48700	33.75	126	6.1	34.4	69400
37.2	329.4	6.03	32.2	57900	203.4	5.8	48600	33.9	126	6.14	34	69400
37.5	336.9	6.03	31.85	57900	212.4	5.8	48700	33.9	124.5	6.13	34	70000
37.8	331	6	31.7	57900	207	5.8	48700	34.5	124	6.15	33.9	69800
38.1	325.6	6	31.7	57900	201.6	5.8	48700	34.5	124	6.18	33.9	69700
37.8	329.2	6.03	31.4	57900	205.2	5.8	48800	34.5	124	6.16	33.3	69700
38.1	329.2	6.03	31.1	57900	205.2	5.78	48700	34.5	124	6.12	33.3	69800
38.1	327.4	6	31.4	57900	203.4	5.8	48700	34.75	124	6.12	33.3	69700
38.4	325.6	6	31.7	58000	201.6	5.8	48800	35	124	6.1	33.9	69600
38.4	323.8	5.98	31.7	58000	199.8	5.8	48800	35	124	6.13	33.9	69600
38.7	323.8	6	31.7	58000	199.8	5.8	48800	35.25	124	6.12	33.9	69500
38.7	323.8	6	31.7	58000	199.8	5.8	48800	35	124	6.15	33.9	69500
38.7	322	6	31.7	58000	198	5.8	48800	35.25	124	6.1	33.4	69500
38.7	320.2	6	31.9	58000	196.2	5.8	48900	35.75	124	6.08	33.4	69200

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39.6	318.4	6	31.7	58000	194.4	5.8	48800	36.25	124	6.12	33.9	69300
39	323.8	6	31.4	58000	199.8	5.8	48800	36	124	6.09	33.3	69200
39	322	6.02	31.1	58000	198	5.8	48700	35.75	124	6.1	33.3	69200
39	322	6.03	31.1	58100	198	5.8	48700	36	124	6.12	33.3	69200
23.1	354.4	6	31.4	58500	230.4	5.8	52100	19.25	124	6.06	33.6	67700
23.4	352.6	5.98	31.1	58500	228.6	5.82	51900	20	124	6.08	33.1	67700
23.88	352.6	6	30.8	58500	228.6	5.83	51700	20.25	124	6.1	32.8	67700
26.4	358	6	31.1	58400	234	5.81	51400	22.75	124	6.12	32.8	68100
26.7	358	6	31.1	58400	234	5.82	51400	23	124	6.16	32.8	68600
27	358	6	30.8	58400	234	5.8	51300	23.5	124	6.15	32.8	68600
27.3	360	6	31.1	58300	234	5.8	51200	23.5	126	6.13	32.8	68500
27.72	360	6	30.8	58300	234	5.8	51100	23.75	126	6.14	32.8	68600
29.1	360	6	30	58300	234	5.85	50900	25	126	6.1	31.9	68800
26.4	360	6.02	30	58400	234	5.83	51000	23	126	6.14	31.7	69100
27	360	6	30	58400	234	5.85	51000	23.5	126	6.15	31.7	69100
27.3	360	6	30	58400	234	5.85	51000	23.75	126	6.13	31.7	69100
27.9	360	6	30	58400	234	5.85	51000	24.25	126	6.14	31.7	69400
28.2	360	6	29.7	58300	234	5.85	51000	24.75	126	6.15	31.4	69500
28.5	360	6	29.4	58200	234	5.86	50500	25	126	6.14	31.1	69100
29.1	360	6	29.4	58200	234	5.85	50500	25.5	126	6.14	31.1	69300
29.1	360	6	29.2	58200	234	5.85	50500	25.75	126	6.16	31.1	69300
30	360	6	29.2	58200	234	5.81	50600	26.25	126	6.13	31.1	69400
29.7	360	6.02	29.2	58200	234	5.85	50400	26.25	126	6.13	31.1	69300
30	360	6	29.2	58200	234	5.85	50400	26.5	126	6.12	31.1	69400
30.3	360	6	29.2	58200	234	5.85	50400	26.75	126	6.12	31.1	69300
30.9	360	6	28.9	58100	234	5.84	50300	27.25	126	6.14	30.6	69400
31.5	360	6	28.9	58100	234	5.86	50200	27.75	126	6.17	30.6	69600
31.8	360	6	28.25	58200	234	5.85	50200	28.25	126	6.17	30.6	69700
32.4	360	6	28.3	58200	234	5.84	50200	28.5	126	6.15	30.3	69700
32.4	360	6	28.3	58100	234	5.86	50100	29	126	6.15	30	69700
33	360	6	28.3	58100	234	5.85	50100	29.5	126	6.14	30	69800

33.3	360	6	28.3	58100	234	5.84	50000	29.5	126	6.13	30	69800
33.9	360	6	28.1	58100	234	5.83	49900	30.25	126	6.13	30	70100
34.2	360	6	28.1	58100	234	5.85	49900	30.5	126	6.14	30	69700
34.2	360	6	27.8	58100	234	5.83	49800	30.5	126	6.14	29.4	69700
35.4	360	6	27.5	58100	234	5.82	49800	31.25	126	6.12	29.4	70000
35.4	360	6.02	27.2	58100	234	5.86	49800	31.75	126	6.16	29.2	70000
36	360	6.03	27.2	58100	234	5.86	49800	32.25	126	6.18	29.2	70000
36	360	6.02	27.2	58100	234	5.85	49800	32.25	126	6.18	29.2	70100
36	360	6	27.2	58100	234	5.85	49600	32.5	126	6.15	29.2	69700
36	360	6	27.2	58000	234	5.85	49700	32.25	126	6.15	29.2	69800
36	360	6	27.2	58000	234	5.8	49700	32	126	6.14	29.2	69600
36.3	356.4	6	26.7	58000	230.4	5.81	49600	32.5	126	6.12	28.9	69500
36.3	354.6	6	26.7	58000	228.6	5.85	49600	32.5	126	6.12	28.9	69500
35.7	358	6	27.2	58000	234	5.86	49700	32	124	6.13	29.2	69300
36	358	6	26.4	58000	234	5.83	49500	32.25	124	6.12	28.3	69500
36.6	350.8	6	25.8	58000	226.8	5.84	49500	32.75	124	6.11	27.8	69500
35.7	358	6	25.8	58000	234	5.85	49501	31.75	124	6.14	27.8	69600
36	354.4	6	25.8	58100	230.4	5.86	49700	32	124	6.12	27.8	69900
36.3	354.4	6	25.8	58100	230.4	5.8	49700	32.5	124	6.15	27.8	70000
36.9	350.8	6	25.8	58100	226.8	5.82	49600	33.25	124	6.13	27.8	69700
36.9	350.8	6	25.55	58000	226.8	5.8	49400	33.25	124	6.11	27.8	69400
37.2	343.6	6	25.6	58000	219.6	5.85	49300	34	124	6.1	27.5	69300
36.9	340	6	25.6	58000	216	5.85	49400	33.75	124	6.1	27.5	69300
36.9	340	6	25.6	58000	216	5.85	49300	34.25	124	6.12	27.5	69200
36.9	338.2	6	25	58000	214.2	5.85	49300	34.5	124	6.1	27.2	69200
36.9	334.6	6	25	58000	210.6	5.85	49300	34.5	124	6.09	27	69100
36.9	334.6	6	25.3	58000	210.6	5.85	49300	34.25	124	6.09	27.2	69100
36.9	334.6	6	25.3	58000	210.6	5.84	49400	34.5	124	6.09	27.5	69100
36.9	332.8	6	25.3	58000	208.8	5.81	49400	34.5	124	6.07	27.5	69100
36.9	336.4	6	26.7	58100	212.4	5.8	49500	34.25	124	6.12	28.3	69100
36	354.6	6	26.1	58100	228.6	5.75	46800	33.25	126	6.12	28.1	73900

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36	352.8	6	26.1	58100	226.8	5.75	46800	33.5	126	6.09	28.1	73700
36.6	352.8	6	25.8	58000	226.8	5.8	46600	33.5	126	6.16	27.8	73600
36.6	352.8	6	25.6	58000	226.8	5.76	46600	33.75	126	6.08	27.5	73600
36.9	352.8	6	25.6	58000	226.8	5.74	46600	34	126	6.12	27.5	73600
37.2	352.8	6	25.3	58000	226.8	5.75	46500	34	126	6.09	27.2	73400
37.2	349.2	6	24.7	58000	223.2	5.76	46400	34	126	6.1	26.7	73600
37.5	347.4	6	24.4	58000	221.4	5.74	46200	34.5	126	6.07	26.4	73600
37.8	343.8	6	24.2	57800	217.8	5.84	45900	34.75	126	6.14	25.6	73100
37.8	343.8	6	23.9	57800	217.8	5.8	46000	35	126	6.09	25.6	73100
37.8	342	6	23.9	57800	216	5.8	46100	35	126	6	25.6	73100
37.8	343.8	6	23.9	57900	217.8	5.82	46100	35	126	6	25.8	73300
37.8	342	6	23.8	58000	216	5.78	46200	35	126	6	25.8	73300
37.8	336.6	6	23.3	58000	210.6	5.8	46200	35	126	6	25.6	73300
37.5	340.2	6	23.3	58000	214.2	5.84	46300	35	126	6	25.3	73100
37.8	340.2	6	23.3	58100	214.2	5.84	46400	35	126	6	25.3	73200
37.8	338.4	6	23.3	58100	212.4	5.81	46300	35	126	6	25.3	73100
37.8	336.6	6	23.1	58000	210.6	5.8	46000	35	126	6.15	25	72900
38.1	334.8	5.98	23.3	58100	208.8	5.77	46200	35.5	126	6.16	25.6	72900
30	360	5.96	24.2	58200	234	5.77	48700	26.75	126	6.1	26.1	71800
30	360	5.99	23.3	58100	234	5.79	48500	26.75	126	6.18	25.3	71700
30	360	5.98	23.3	58100	234	5.78	48400	27.25	126	6.15	25.3	71700
30.3	360	5.98	23.9	58100	234	5.81	48500	27.25	126	6.12	25.8	72000
25.8	360	5.98	23.3	58200	234	5.78	48800	22.75	126	6.1	25.8	71800
25.5	360	6	23.9	58200	234	5.82	48800	22.75	126	6.15	25.8	71300
25.5	360	6	23.9	58300	234	5.78	48900	22.5	126	6.11	25.8	71300
24.9	360	5.98	26.1	58200	234	5.72	49100	22	126	6.11	27.2	71000
24.9	360	6.05	25	58200	234	5.83	49100	21.75	126	6.13	26.9	71000
24.9	360	6.04	25.6	58200	234	5.85	49300	21.75	126	6.15	27.2	71100
25.2	360	6.02	25	58200	234	5.72	48900	22	126	6.13	26.7	71000
25.2	360	6	24.65	58000	234	5.8	48900	22.25	126	6.07	26.2	71200
25.5	360	6	25	58000	234	5.74	48900	22.5	126	5.98	25	71200
25.8	360	5.9	27	58200	234	5.6	49000	22.5	126	6.0	26.9	71600

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25.8	360	5.91	24.25	58100	234	5.7	48800	22.5	126	6.02	25	71400
25.8	360	5.92	26.5	58300	234	5.75	49100	22.5	126	6.06	27	71800
25.2	360	5.91	24.95	58100	234	5.81	49000	22.4	126	6.03	26	71500
25.2	360	5.92	25.8	58500	234	5.81	49500	22	126	6.03	25.9	71600
24.9	360	5.92	26	58000	234	5.82	49100	21.5	126	6.02	26	71100
25.5	360	5.94	26	58200	234	5.92	49200	22	126	6.03	26	71400
25.8	360	5.95	25	58100	234	5.97	49100	22	126	6.04	25.1	71200
25	360	5.96	25	58200	234	5.86	49200	22.25	126	6.05	26.7	71500
25	360	6.04	25	58100	234	5.88	49000	22.5	126	6.22	26.7	71200
25	360	6	25.3	58000	234	5.85	49100	22.25	126	6.12	27.2	71100
25	360	5.9	25.6	58100	234	5.85	48300	22	126	6.1	27.2	71200
25	360	5.98	25.6	58100	234	5.98	48100	22	126	6.18	27.8	71100
25	360	5.98	26.1	58000	234	5.98	48000	21.75	126	6.1	28.1	70700
24	360	5.8	26.1	58000	234	5.96	49300	21.75	126	6.1	28.05	70700
24	360	5.98	26.4	58100	234	5.98	49300	21.75	126	6.1	28.05	70700
24.3	360	5.98	26.4	58100	234	5.98	49300	21.25	126	6.12	28.3	70300
24.6	360	6	26.4	58000	234	6	49200	21.25	126	6.09	28.3	70500
24.6	360	6.03	26.1	58100	234	5.85	49000	21.5	126	6.2	28.1	70300
24	360	6.04	26.1	58000	234	5.8	49100	21.25	126	6.15	28.1	70600
22.8	360	6	26.7	58100	234	5.9	49200	21	126	6.2	28.3	70300
24	360	6.03	25.6	57900	234	5.87	49000	21.5	126	6.22	27.2	70000
24	360	6.04	25.8	57900	234	5.87	49100	21.75	126	6.2	27.2	70900
23.4	360	6.02	25.8	57900	234	5.82	49100	21.25	126	6.23	27.5	70900
23.7	360	6.04	26.1	58000	234	5.81	49300	21.25	126	6.15	28.1	70700
24	360	6.03	26.1	57800	234	5.8	48900	21.5	126	6.11	27.5	70300
24.9	360	5.97	25.8	57900	234	5.8	48900	22.5	126	6.14	27.2	70700
24.6	360	6	25	57000	234	5.82	48900	22.25	126	6.11	26.9	70900
24.6	360	6.02	26.1	58100	234	5.8	49400	22	126	6.13	27.8	70900
24.9	360	6.01	25.6	58000	234	5.82	49200	22.25	126	6.08	27.8	71200
25.5	360	5.98	25	57900	234	5.8	49000	22.75	126	6.12	26.9	71000
25.5	360	5.97	25.3	58000	234	5.8	49000	23	126	6.12	27.2	71300

25.2	360	6	25.3	58000	234	5.8	49100	23	126	6.13	29.2	71300
25.2	360	5.98	26.7	58100	234	5.9	48100	22.75	126	6.15	27.8	71300
25.2	360	6	25.8	58100	234	5.8	48100	23	126	6.15	27.5	71300
25.2	360	6	26.4	58100	234	5.85	49300	22.75	126	6.17	28.1	71200
24.6	360	6	27.2	58200	234	5.85	49600	22.5	126	6.16	28.9	71000
24.6	360	6.04	27.2	58000	234	5.86	49400	22.25	126	6.15	28.9	70800
24.3	360	6	27.2	58000	234	5.86	49400	22	126	6.18	29.2	70600
24	360	6	28.1	58000	234	5.88	49600	21.75	126	6.19	30	70400
23.4	360	6	28.3	58100	234	5.84	49800	21.5	126	6.19	30.3	70400
24.6	360	6.02	27.2	57900	234	5.85	49100	22.25	126	6.2	29.2	70100
24.9	360	6.01	26.9	57700	234	5.85	49100	22.25	126	6.24	28.9	70200
24.9	360	6	26.9	57700	234	5.84	49100	22.25	126	6.17	28.9	70300
25.5	360	6.03	26.9	57700	234	5.84	49100	22.5	126	6.11	28.9	70300
24.6	360	6	26.9	57700	234	5.85	49100	22.25	126	6.15	28.9	70100
24	360	6.01	27.8	57800	234	5.83	49400	21.5	126	6.15	29.4	69900
24	360	6	27.8	57800	234	5.84	49400	21.5	126	6.15	29.4	69800
24	360	6.02	27.8	57800	234	5.86	49400	21.5	126	6.2	29.4	69700
24	360	6.02	27.8	57800	234	5.82	49400	21.5	126	6.17	29.4	69700
24	360	5.98	27.8	57800	234	5.82	49400	21.5	126	6.1	29.4	69700
24.3	360	6	27.8	57800	234	5.8	49400	21.75	126	6.12	29.7	69800
24.3	360	5.98	27.8	57800	234	5.8	49400	22	126	6.11	29.7	70000
24	360	6	27.8	57900	234	5.8	49500	22	126	6.1	29.7	69900
24.3	360	6	28.1	58000	234	5.8	49600	22	126	6.11	30	69900
24.3	360	6	28.1	58000	234	5.8	49600	21.75	126	6.1	30	69900
24	360	6	29.2	58200	234	5.82	49800	21.75	126	6.08	31.1	70200
24.3	360	6	28.9	58200	234	5.8	49800	21.75	126	6.11	30.8	69800
24.3	360	6	28.9	58000	234	5.82	49700	22	126	6.12	30.8	69800
24.6	360	6	28.3	58000	234	5.98	49600	22.25	126	6.09	30.3	70000
24.6	360	6	28.6	58000	234	5.8	49700	22.25	126	6.12	30.6	70000
25.8	360	6	28.3	58000	234	5.8	49800	23.25	126	6.08	31.1	69800
25.8	360	6	28.3	58000	234	5.8	49800	23.25	126	6.1	30	69900
25.8	360	6	28.1	58300	234	5.8	50100	23.25	126	6.1	30.6	69800
26.1	360	6	28.3	58100	234	5.8	49900	23.75	126	6.07	30.3	69900

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26.1	360	6	29.4	58100	234	5.8	50100	23.5	126	6.11	31.4	69700
24	360	6	29.4	58200	234	5.8	50200	22.25	126	6.07	31.4	69700
25.5	360	6	28.9	58000	234	5.82	50000	23	126	6.1	31.1	69700
25.8	360	6	29.4	58000	234	5.8	50000	23.25	126	6.09	31.1	69500
25.8	360	6	29.4	58000	234	5.78	50100	23	126	6.07	31.1	69500
26.1	360	5.98	30	58000	234	5.8	50200	23.5	126	6.12	31.7	69400
26.4	360	6	30	58100	234	5.8	50200	23.5	126	6.12	31.7	69400
26.7	360	5.98	29.7	58000	234	5.82	50200	24	126	6.1	31.7	69400
27	360	5.97	29.7	57900	234	5.84	50200	24.5	126	6.12	31.7	69400
27.6	360	6.02	29.4	58000	234	5.82	50100	25	126	6.12	31.4	69500
27.9	360	5.89	30	58100	234	5.85	50200	25	126	6.07	31.4	69400
27.3	360	6.01	30.6	58100	234	5.85	50200	24.75	126	6.15	32.2	69400
27.9	360	5.98	30.6	58100	234	5.86	50200	25.5	126	6.1	32.2	69400
27.9	360	5.98	30.8	58200	234	5.87	50300	25.25	126	6.19	32.8	69200
27.9	360	6	31.1	58200	234	5.88	50300	25.25	126	6.19	32.8	69400
28.8	360	6	31.1	58000	234	5.88	50200	26.5	126	6.14	32.8	69500
24.3	360	6	31.1	58100	234	5.86	50700	21.75	126	6.16	33.1	69200
24.6	360	6	31.1	58100	234	5.8	50700	22	126	6.14	33.1	69200
25.2	360	6.02	31.1	58100	234	5.8	50600	22.75	126	6.07	32.8	69200
25.5	360	5.96	31.1	58100	234	5.85	50600	22.75	126	6.05	32.8	69200
25.8	360	5.96	31.4	58200	234	5.8	50700	22.75	126	6.08	33.3	69200
25.8	360	6.03	31.1	58200	234	5.82	50700	23	126	6.08	33.3	69200
26.4	360	6.04	31.1	58100	234	5.82	50600	23.5	126	6.08	33.3	69200
27	360	6.03	31.1	58100	234	5.84	50600	24	126	6.07	33.3	69400
24.6	360	5.96	31.7	58100	234	5.83	50900	21.75	126	6.05	33.4	68600
26.4	360	5.97	32.2	58100	234	5.84	50900	23.5	126	6.08	33.9	69100
26.7	360	6	32.2	58100	234	5.85	50800	24	126	6.06	33.9	69100
26.7	360	5.98	32.2	58100	234	5.81	50800	24	126	6.07	33.9	69100
27	360	5.98	32.2	58100	234	5.8	50800	24.25	126	6.12	33.9	68700
27.9	360	5.98	32.2	58100	234	5.8	50800	25.25	126	6.06	33.9	68800
28.2	360	5.98	32.2	58000	234	5.8	50700	25.25	126	6.07	33.9	69100

27	360	5.97	32.2	58000	234	5.78	50700	24.25	126	6.06	33.9	68800
27	360	6	32.8	58000	234	5.8	50800	24.25	126	6.07	34.4	68800
27	360	6	32.8	58000	234	5.8	50700	24.75	126	6.07	34.4	68800
27.9	360	5.98	32.8	58000	234	5.8	50800	25.5	126	6.1	34.4	68900
28.8	360	5.97	32.8	58000	234	5.8	50700	26	126	6.09	34.4	69100
28.8	360	5.98	32.8	58000	234	5.85	50700	26.5	126	6.14	34.4	68900
29.1	360	5.97	33.1	58000	234	5.84	50700	26.75	126	6.14	34.7	68900
30	360	5.96	33.1	58000	234	5.84	50700	27.5	126	6.06	35	69000
30	360	5.96	33.1	58000	234	5.81	50700	27.5	126	6.05	35	69100
30	360	5.96	33.1	58000	234	5.8	50700	27.5	126	6.05	35	68900
30.6	360	5.97	33.1	58000	234	5.8	50700	28	126	6.07	35	69000
30.6	360	5.98	33.1	58000	234	5.82	50600	28.6	126	6.06	35	68900
31.8	360	5.97	33.1	58000	234	5.78	50500	29.5	126	6.06	35	68900
32.4	360	5.96	33.1	58000	234	5.84	50500	29.75	126	6.05	35	68800
32.4	360	5.96	33.1	58000	234	5.8	50500	29.5	126	6.1	35	69000
32.4	360	5.98	33.3	58000	234	5.78	50500	29.75	126	6.08	35	68900
32.4	360	5.97	33.6	58000	234	5.8	50500	29.5	126	6.06	35.3	69000
34.2	360	6.04	33.6	57900	234	5.85	50400	31.5	126	6.11	35.6	69100
34.8	360	6.02	33.6	57900	234	5.82	50200	32	126	6.14	35.6	68900
35.1	360	6.02	33.6	57800	234	5.84	50200	32	126	6.12	35.6	68900
35.1	360	5.98	33.3	57800	234	5.85	50100	32.5	126	6.05	35.3	68800
35.4	360	5.95	33	57700	234	5.8	50000	32.5	126	6.04	35	68700
35.7	354.6	6.04	33.5	57800	228.6	5.94	50200	33	126	6.21	35.5	68600
35.4	352.8	6.02	33	57900	226.8	5.85	50200	32.5	126	6.15	35	68600
33.9	360	5.97	33	57700	234	5.86	50300	31.5	126	6.1	35	68500
26.1	360	5.96	33.3	57900	234	5.9	51000	23.5	126	6.14	35	67800
28.8	360	6.04	33	57700	234	5.92	50800	26	126	6.17	35	67700
29.7	360	6.05	33	57700	234	5.9	50700	27	126	6.19	34.5	67900
30	360	6.05	33	57700	234	5.9	50600	27.25	126	6.2	34.5	68100
28.8	360	6.04	33.3	57700	234	5.89	50800	26.5	126	6.19	34.7	67900
31.2	360	6.05	33	57900	234	5.92	50900	28.5	126	6.2	34.5	68500

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35.1	360	6.02	33	57800	234	5.85	50500	32.5	126	6.14	34.5	68700
35.4	360	5.96	33	57800	234	5.8	50500	33	126	6.12	34.5	68600
36	356.4	6	33	57800	230.4	5.85	50500	33.25	126	6.1	34.5	68600
36	349.2	5.98	33	57800	223.2	5.84	50500	33.5	126	6.12	34.5	68400
36.3	349.2	6	32.5	57800	223.2	5.85	50500	33.75	126	6.12	34	68300
36.9	333	5.98	32.5	57800	207	5.87	50400	34	126	6.11	34	67600
18.9	360	5.98	32	57900	234	6.06	52700	16	126	6.06	34	66300
19.2	360	5.97	32	57900	234	5.87	52600	16.25	126	6.1	34	66400
19.8	360	5.98	31.5	57800	234	5.87	52300	17.25	126	6.07	33.5	66400
20.4	360	6	31.5	57900	234	5.88	52300	17.5	126	6.07	33	66400
20.4	360	6.01	31	57900	234	5.86	52300	17.5	126	6.11	33	66400
20.7	360	5.97	31	57900	234	5.82	52300	18	126	6.06	33	66400
20.7	360	6.04	31	57800	234	5.85	52200	18	126	6.1	33	66300
21	360	6	31	57900	234	5.88	52200	18.5	126	6.07	32.5	66700
21.3	360	5.98	31	57900	234	5.87	52100	18.75	126	6.08	32.5	66500
21.3	360	6	31	57900	234	5.85	52100	18.75	126	6.07	32.5	66600
21.6	360	5.97	31	57900	234	5.84	52100	19	126	6.05	32.5	66600
21.6	360	6.01	31	57900	234	5.88	52100	19	126	6.05	32.5	66600
22.8	360	6.02	31	57900	234	5.87	52000	20	126	6.05	32.5	66700
21.9	360	6	30.5	57800	234	5.9	51800	19	126	6.15	32	66400
22.5	360	6	30.5	57800	234	5.86	51800	20	126	6.17	32	66500
22.5	360	6.05	30.5	57800	234	5.89	51800	19.5	126	6.07	32	66700
22.2	360	6	30.5	57900	234	5.84	51900	19.75	126	6.06	32	66500
22.2	360	6.04	31	57800	234	5.86	51900	19.25	126	6.07	32.5	66700
22.5	360	6.05	30.5	57800	234	5.87	51900	19.5	126	6.07	32	66500
22.8	360	5.98	31	57800	234	5.8	52000	19.5	126	6.05	33	66500
22.8	360	5.98	31	57900	234	5.78	52000	19.75	126	6.04	33	66700
22.5	360	6	31	57900	234	5.8	52000	19.25	126	6.05	33	66500
23.1	360	6	32	57800	234	5.82	52000	19.75	126	6.07	33.5	66400
23.4	360	5.98	31	57700	234	5.82	51900	20	126	6.05	33.5	66400
23.4	360	5.97	31	57700	234	5.82	51900	20	126	6.04	32.5	66500

24	360	6	31	57700	234	5.84	51900	20.25	126	6.04	32.5	66400
24.9	360	5.96	32.15	57800	234	5.81	51800	21.5	126	6.07	33.5	66400
25.2	360	5.97	32.5	57700	234	5.82	51700	21.75	126	6.06	32.5	66400
25.2	360	6.03	31	57700	234	5.85	51800	21.5	126	6.17	32.5	66400
25.2	360	6.04	31	57700	234	5.86	51800	21.5	126	6.14	32.5	66400
25.8	360	6.04	31	57700	234	5.9	51800	22	126	6.16	32.5	66400
27.3	360	6.05	30.5	57700	234	5.92	51600	23.5	126	6.16	32	66600
28.2	360	6.02	30.5	57600	234	5.89	51500	24.25	126	6.18	32	66600
28.8	360	6.04	30.5	57600	234	5.93	51500	24.75	126	6.14	32	66500
22.8	360	6	31	57700	234	5.9	51800	19	126	6.15	32.5	66600
23.4	360	6.04	30.5	57600	234	5.9	51800	19.5	126	6.12	32	66200
25.2	360	6.04	30	57800	234	5.9	51800	21.25	126	6.18	32	66000
25.5	360	6.05	30	57800	234	5.91	51800	21.75	126	6.12	32	66600
26.1	360	6.03	30	57800	234	5.88	51800	22.25	126	6.15	32	66600
26.4	360	6.04	30	57800	234	5.9	51800	22	126	6.17	32	66700
26.7	360	6.05	30.5	57800	234	5.92	51800	22.75	126	6.15	32.5	66700
28.2	360	5.96	30	57900	234	5.89	51700	24.25	126	6.08	32.5	67800
28.8	360	5.96	30	57800	234	5.85	51700	24.75	126	6.06	32	67200
29.4	360	5.96	30	57800	234	5.82	51700	25.25	126	6.08	32	67400
29.7	352.5	5.96	30	57800	234	5.8	51700	25.75	118.5	6.05	32	67400
30	351	5.95	30	57800	234	5.8	51600	26.75	117	6.06	32	67500
32.4	346.5	6	29.5	57900	234	5.8	51600	28.5	112.5	6.1	31.5	67800
32.7	345	5.96	29.5	57900	234	5.81	51700	29	111	6.1	31.5	68100
33.3	343.5	5.97	29.5	57800	234	5.8	51600	29.5	109.5	6.07	31.5	67900
33.6	343.5	6.01	29.5	57900	234	5.8	51700	29.75	109.5	6.11	31.5	68100
34.5	342	5.96	29	57800	234	5.84	51600	31	108	6.07	31	68100
36.6	342	5.95	29	57800	234	5.8	51600	33.5	108	6.06	31	68400
36.9	339	5.97	29	57900	234	5.87	51600	33.5	105	6.08	31	68400
30	339	5.95	29	57900	234	5.84	51900	26.25	105	6.05	31	68100
30.6	336	6	29	57900	234	5.85	51800	27	102	6.05	31	68100
33	336	5.95	28.5	57900	234	5.85	51800	29.75	102	6.07	30.5	68300

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34.2	336	5.96	28	57700	234	5.82	51600	31	102	6.05	30	68400
35.4	334.5	6	28	57700	234	5.8	51600	32	100.5	6.07	30	68500
36	334.5	5.98	28	57800	234	5.83	51600	33.25	100.5	6.12	30	68600
29.1	360	6	28.5	57900	234	5.83	50300	26	126	6.1	30.5	68800
30	360	5.97	27.5	57700	234	5.82	50100	27	126	6.07	29.5	69100
30	360	5.95	27.5	57700	234	5.8	50200	26.75	126	6.07	29.5	69000
30.3	360	5.97	27.5	57700	234	5.8	50100	27	126	6.06	29	69200
30.6	360	5.97	27.5	57700	234	5.8	50100	27.5	126	6.05	29	69200
31.5	360	5.96	27.5	57700	234	5.84	50000	28	126	6.06	29	69400
32.4	357	5.96	27	57800	234	5.8	49900	29	123	6.04	29	69700
32.4	360	5.96	27	57800	234	5.8	49800	29.25	126	6.04	29	69600
31.8	360	5.96	27.5	57700	234	5.83	49800	28.5	126	6.05	29	69200
32.4	360	5.97	27	57500	234	5.83	49500	29.25	126	6.08	28.5	69200
33.6	360	5.95	27	57500	234	5.82	49500	30.25	126	6.07	29	69200
34.8	360	6	26.5	57700	234	5.8	49400	31.5	126	6.14	28	70000
35.4	360	6	26.5	57700	234	5.82	49400	32	126	6.14	28	70000
35.7	360	6	26	57700	234	5.82	49200	33	126	6.13	27.5	70200
36	360	6	26	57500	234	5.85	49200	33.25	126	6.14	27.5	70200
35.1	360	6.03	26	57500	234	5.86	49300	31.75	126	6.13	27.5	69900
36.3	352.8	6	25.5	57600	226.8	5.8	49200	33.25	126	6.14	27	70000
36.3	354.6	5.96	25	57500	228.6	5.78	49100	33.25	126	6.08	27	70300
36.6	348	6	25	57500	225	5.85	49100	33.5	123	6.11	27	70200
36.9	343.2	6	25	57600	223.2	5.84	49100	33.75	120	6.14	27	70100
36.6	339.6	5.97	25.5	57500	219.6	5.75	49100	33.25	120	6.14	27.5	69700
37.2	340.8	6.05	24.5	57500	217.8	5.86	48900	34.25	123	6.12	27	70000
37.8	337.2	5.98	24.5	57600	214.2	5.8	48900	34.75	123	6.1	26.5	69900
37.8	335.4	6.04	24.5	57600	212.4	5.78	48800	35	123	6.15	26	69800
37.8	331.8	5.98	24.5	57600	208.8	5.82	48800	35	123	6.11	26	69800
37.5	339	6.03	24.5	57600	216	5.8	48800	34.5	123	6.1	26	69600
37.8	335.4	5.97	24	57600	212.4	5.8	48800	35	123	6.08	26	69600
38.4	331.8	5.98	24	57600	208.8	5.82	48800	35	123	6.07	26	69600

38.1	328.2	5.91	24	57600	205.2	5.8	48900	35	123	6.07	26	69700
38.1	331.8	5.96	24	57700	208.8	5.82	49000	35	123	6.14	26	69500
38.1	328.9	6	24	57700	205.9	5.81	49000	34.75	123	6.08	26	69500
38.1	328.2	6.03	25	57700	205.2	5.92	50400	35	123	6.09	26.6	69300
37.8	331.8	5.97	25	57700	208.8	5.97	49200	35	123	6.12	27	69200
37.8	331.8	6.05	25	57700	208.8	5.88	49200	35	123	6.09	27	69300
37.8	331.8	6.02	25.5	57500	208.8	5.86	49100	34.75	123	6.12	27	69100
38.7	319.2	6	24	57800	196.2	5.94	49100	35.75	123	6.09	26	69200
39	318	6.07	24.5	57700	195	5.87	49200	35.5	123	6.12	26.5	69100
39	317.4	5.96	24	57700	194.4	5.84	49000	35.5	123	6.07	26	69000
38.7	315.6	6	24	57700	192.6	5.84	49200	35.5	123	6.07	26	69000
38.7	313.8	6.1	24	57700	190.8	5.94	48900	35.5	123	6.16	25.5	68900
39	310.2	6.22	23	57700	187.2	6.22	49100	35.75	123	6.22	25	68700
39	312	6.03	23	57700	189	5.96	49200	35.75	123	6.12	25	68700
39	310.5	6.01	25.2	57800	187.5	5.9	49200	35.75	123	6.1	26	68700
39	310.2	5.95	23	57800	187.2	5.81	48900	35.5	123	5.98	25	68800
38.1	309.6	6.01	23.5	57700	183.6	5.9	49000	35.25	126	6.03	25	68500
37.8	306	6	23	57700	180	5.82	49200	34.75	126	6.02	25	68600
25.8	360	6.12	23	57800	234	5.82	51400	22.5	126	6.14	25	68200
26.4	360	6.02	22	57700	234	5.84	51100	23.25	126	6.18	24	68000
27.6	360	6.06	22	57800	234	5.85	50900	25	126	6.13	24	68300
28.2	360	6.05	22	57800	234	5.83	50900	25.5	126	6.13	24	68300
28.5	360	6.05	22	57800	234	5.93	50800	25.5	126	6.13	23.5	68500
28.8	360	6.03	22	57800	234	5.89	50700	25.75	126	6.13	23.5	68500
30	360	5.97	22	57700	234	5.84	50400	27	126	6.11	24	68700
30.3	360	6.02	22	57800	234	5.85	50400	27.5	126	6.07	24	68800
30.45	360	6	22	57800	234	5.85	50400	27.75	126	6.08	24.3	68800
30.3	360	6.05	22	57800	234	5.84	50400	27.5	126	6.14	24	68800
29.4	360	6	23	58000	234	5.81	50900	26.25	126	6.14	25	68800
31.2	360	5.98	22	57800	234	5.85	50400	28.25	126	6.12	24	69100
30.9	360	6	22	57800	234	5.82	50300	28.5	126	6.08	24	69100

31.8	360	6	22	57800	234	5.85	50300	28.75	126	6.09	24	69200
31.5	360	5.98	22	57800	234	5.86	50200	29.25	126	6.12	23.5	69200
32.4	360	5.98	21.5	57800	234	5.83	50200	29.25	126	6.12	23.5	69300
33	360	6	21.5	57800	234	5.81	50100	30	126	6.13	23	69400
31.2	360	6.04	21.5	58000	234	5.85	50600	28	126	6.16	23	69200
30.9	360	6	22.5	58100	234	5.82	50700	28	126	6.14	24	69200
31.8	360	6	22	57900	234	5.85	50400	29	126	6.17	24	69100
31.8	360	6.02	22	57900	234	5.86	50300	29	126	6.18	24	69200
32.7	360	6.05	22	57900	234	5.86	50300	30	126	6.19	24	69400
33	360	6.05	22	57900	234	5.89	50400	30	126	6.2	24	69500
33.15	360	6.04	22	57900	234	5.84	50200	30.5	126	6.2	24	69500
33.6	360	6.05	22	57900	234	5.86	50100	31	126	6.17	24	69400
33.6	360	6.03	23	57900	234	5.88	50300	30.75	126	6.17	25	69300
33.9	360	6.05	23	57800	234	5.9	50200	31	126	6.22	25	69200
34.2	360	6.05	23	57800	234	5.9	50100	31.5	126	6.18	25	69300
34.2	360	6.05	23	57800	234	5.9	50200	31.5	126	6.2	25	69200
35.7	360	6.05	22	57800	234	5.9	49900	33	126	6.19	24	69500
35.7	360	5.98	22	57800	234	5.84	50000	33.25	126	6.16	24	69600
36	360	5.96	22	57800	234	5.8	50000	33.25	126	6.15	24	69500
36	360	5.98	22.5	58100	234	5.8	50100	34	126	6.09	24.5	70100
31.2	360	6	21.5	57900	234	5.82	50400	29.25	126	6.11	23.5	69400
33.6	360	6	22	58000	234	5.83	50300	30.1	126	6.1	24	69600
33.75	360	6	22	57900	234	5.8	50300	30.75	126	6.1	24	69600
33.6	360	5.98	22	57900	234	5.81	50200	30.5	126	6.11	24	69500
33.6	360	6	22	58000	234	5.82	50200	30.5	126	6.13	24	69500
33.6	360	6.02	22.5	57900	234	5.85	50200	30.5	126	6.12	24.5	69400
30.6	360	6.04	25	58000	234	5.86	50800	27.75	126	6.06	27	68800
27.6	360	6	26	58100	234	5.86	50900	25.25	126	6.15	27.5	68600
28.5	360	5.95	26.5	58100	234	5.81	51100	25.5	126	6.11	28.2	68000
28.2	360	6.04	26	58100	234	5.8	51400	26	126	6.19	25.75	68500
27.9	360	6	26	57800	234	5	50100	25.5	126	6.17	28	68000
28.8	360	5.9	25.5	57500	234	5.8	50400	25.5	126	6.1	27.5	67900

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28.8	360	5.84	25.5	57400	234	5.84	50400	25.75	126	6.16	27.5	67800
29.1	360	6	26	57300	234	5.8	50300	26	126	6.11	28	67800
29.7	360	6.02	26	57300	234	5.83	50300	26	126	6.11	27.5	67800
29.4	360	6.04	26	57300	234	5.84	50300	26	126	6.1	27	67800
29.4	360	6.01	26.5	57400	234	5.8	50800	26.25	126	6.09	28.5	68000
29.4	360	6	26	57500	234	5.8	50600	26.25	126	6.1	28.5	68000
30.6	360	5.98	26	57800	234	5.82	50300	27.75	126	6.07	28.5	67900
31.2	360	6	25.5	57300	234	5.83	50200	28	126	6.06	27.5	68100
31.2	360	5.98	25	57300	234	5.8	50100	28.5	126	6.09	27	68200
30.9	360	5.98	28	57600	234	5.85	50600	28.25	126	6.07	28	68400
31	360	6	26	57500	234	5.82	50300	28.75	126	6.07	27.5	68100
32.4	360	6	25	57300	234	5.82	50100	29.5	126	6.09	27	68500
33.6	360	5.97	25	57300	234	5.8	50000	30.25	126	6.07	27	68700
33.6	360	6.02	25	57300	234	5.8	50000	30.5	126	6.1	27	68800
33.6	360	5.96	25.5	57700	234	5.76	50200	31	126	6.12	27.5	68700
33.6	360	6	26	57700	234	5.81	50200	30.75	126	6.1	28	68700
33.6	360	6.03	26	57600	234	5.76	50300	31	126	6.1	28	68700
27	360	5.98	27	57600	234	5.8	50600	24.25	126	6.1	29	66900
27	360	5.98	27	57600	234	5.8	50900	25	126	6.12	29	67500
27.3	360	6.04	28	57600	234	5.8	50900	25	126	6.12	30	67500
27.6	360	6.04	28	57600	234	5.8	51000	25	126	6.12	30	67600
25.2	360	5.98	29	57600	234	5.85	51200	23	126	6.15	30.5	67000
26.1	360	6.04	29	57400	234	5.87	51000	23.75	126	6.13	31	66900
25.2	360	5.96	29	57300	234	5.84	51000	23	126	6.07	31	66800
25.2	360	6	29	57500	234	5.8	51300	23	126	6.07	31	66800
24.9	360	5.96	29	57300	234	5.83	51000	20	126	6.14	31	66800
25.2	360	6	29	57300	234	5.86	51100	20	126	6.1	31	66800
25.8	360	5.97	29	57300	234	5.82	50900	20	126	6.06	31	66700
25.8	360	6.04	30	57400	234	5.89	51000	22.75	126	6.13	32	66900
25.2	360	5.96	29	57300	234	5.8	51200	22	126	6.06	31	66800
26.4	360	6.05	29	57300	234	5.9	51000	23.25	126	6.16	31	66700

26.7	360	5.96	29	57300	234	5.8	50800	23.75	126	6.07	31	66800
27	360	5.85	29	57300	234	5.85	50700	24	126	6.1	31	67100
27.6	360	6.05	29	57300	234	5.9	50800	24.75	126	6.14	31	67300
27.6	360	5.96	29	57400	234	5.86	50900	24.75	126	6.07	31	67200
27.9	360	5.96	29	57500	234	5.85	51000	25	126	6.08	31	67400
28.1	360	5.96	29	57400	234	5.86	50800	25.25	126	6.06	31	67200
28.2	360	6	29	57400	234	5.86	50800	25.25	126	6.1	31	67100
28.2	360	6	29.5	57400	234	5.84	51000	25	126	6.1	31.5	67200
28.2	360	5.95	29.5	57300	234	5.8	50900	25.25	126	6.12	31.5	67100
28.5	360	5.96	29.5	57200	234	5.86	50700	25.5	126	6.06	31.5	67200
28.8	360	5.97	29.5	57200	234	5.86	50500	25.75	126	6.14	31.5	66800
28.8	360	5.96	29.5	57100	234	5.82	50500	25.75	126	6.12	31.5	66700
29.1	360	6.05	30	57400	234	5.87	50800	26	126	6.07	32	67200
29.4	360	5.95	30	57300	234	5.84	50700	26.25	126	6.07	32	67100
29.4	360	5.97	30	57200	234	5.83	50600	26.25	126	6.07	32	66900
27	360	6	30	57200	234	5.83	50700	24.5	126	6.07	32	66800
27.6	360	6.04	30	57200	234	5.88	50900	25	126	6.11	32	66700
28.05	360	6	30	57200	234	5.85	50900	25.75	126	6.07	32	66800
28.2	360	6.05	30	57200	234	5.87	51000	25.75	126	6.1	32	66800
28.2	360	5.97	30.5	57200	234	5.83	50900	26	126	6.06	32.5	66800
28.2	360	5.96	31	57300	234	5.89	51000	26	126	6.05	33	66800
29.1	360	6.01	31	57300	234	5.88	50900	26.75	126	6.05	33	67000
28.8	360	6	31.5	57300	234	5.87	51000	26.75	126	6.05	33.5	66900
29.1	360	6.02	31.5	57300	234	5.87	50900	26.75	126	6.06	33.5	66700
29.1	360	6	31.5	57200	234	5.9	50900	27	126	6.09	33.5	66600
30	360	6	31.5	57200	234	5.82	50800	27.5	126	6.06	33.5	68800
30.6	360	6.02	31.5	57200	234	5.84	50900	28	126	6.09	33.5	66900
30.6	360	5.95	31.5	57400	234	5.82	51000	28	126	6.05	33.5	67100
30.9	360	6	31.5	57300	234	5.88	50900	28.5	126	6.12	33.5	67300
27.75	360	6.05	31.5	57200	234	5.89	51000	25.13	126	6.18	33.5	66400
29.4	360	5.96	31	57200	234	5.96	51000	26.5	126	6.06	33	66800

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30	360	6	31	57300	234	5.86	51000	27	126	6.09	33	66900
30	360	5.95	31.5	57500	234	5.83	51100	27.25	126	6.04	33.5	67000
30.3	360	5.96	31.5	57500	234	5.8	51200	27.75	126	6.03	33.5	67000
30	360	5.96	31.5	57600	234	5.84	51400	27.5	126	6.04	33.5	67400
31.8	360	5.95	31.5	57700	234	5.8	51300	29	126	6.02	33.5	67500
31.8	360	5.95	31.5	57700	234	5.81	51300	29	126	6.03	33.5	66900
31.5	360	6.05	32	57600	234	5.88	51100	28.75	126	6.12	33.5	67200
32.7	360	6.05	32	57700	234	5.9	51100	30	126	6.11	33.5	67600
33	360	6	32	57600	234	5.9	51000	30.75	126	6.12	33.5	67500
33.9	360	6.05	32	57800	234	5.9	51200	31.25	126	6.15	34	67800
34.5	360	6.01	32	58000	234	5.9	51300	31.75	126	6.1	34	68000
34.8	360	5.98	31.5	57800	234	5.82	51100	31.75	126	6.06	33.5	67700
35.4	360	6.04	31.5	57700	234	5.86	51000	32.25	126	6.08	33.5	67800
35.4	360	6	32	57700	234	6	51000	32	126	6.08	34	67800
36	360	6.01	32	57700	234	5.88	51000	32.75	126	6.07	34	67900
36	360	6.02	32	57700	234	5.88	50900	32.75	126	6.05	34	67700
18	360	5.96	32.5	58000	234	5.84	53900	14.5	126	6.06	34.5	64900
18.9	360	5.95	32.5	58000	234	5.88	53800	15.75	126	6.05	34.5	65200
19.2	360	6.04	33	58300	234	5.9	53700	16.13	126	6.08	35	65600
19.5	360	5.93	33	58300	234	5.88	53600	16.5	126	6.04	35	65800
19.5	360	6	33	58300	234	5.85	53600	16.5	126	6.05	35	65600
19.8	360	6	33	58300	234	5.84	53600	16.5	126	6.06	35	65500
19.8	360	6	32.5	58200	234	5.85	53500	17.25	126	6.05	34	65500
20.1	360	5.96	32.5	58200	234	5.96	53800	17.25	126	6.04	34	65600
20.1	360	6	32.5	58200	234	6.06	53400	17.25	126	6.06	34	65700
20.1	360	5.98	32	58200	234	6.05	53400	17.25	126	6.05	34	65700
20.4	360	6	32	58200	234	5.86	53300	17.5	126	6.06	34	65800
20.7	360	5.96	32	58200	234	5.96	53300	17.75	126	6.04	34	65800
20.7	360	5.96	32	58200	234	5.86	53300	17.75	126	6.04	34	65800
20.85	360	6	32	58200	234	5.88	53300	17.75	126	6.05	34	65900
21	360	5.96	32	58200	234	5.87	53300	18	126	6.03	34	65900

21	360	5.98	32	58200	234	5.98	53200	18	126	6.04	34	65900
20.4	360	5.96	31	58000	234	5.86	53000	19.25	126	6.03	33	65800
21	360	6	31	58000	234	5.85	53000	19.25	126	6.04	33	65900
21.6	360	5.98	31	58000	234	5.88	52900	19.25	126	6.03	33	65700
21.9	360	5.97	31	58000	234	5.88	52800	19	126	6.04	33	66100
22.2	360	6.04	31.5	58100	234	5.86	52900	19.25	126	6.07	33.5	65800
22.5	360	5.98	31	58100	234	5.98	52900	19	126	6.04	33	66200
22.2	360	5.98	31	58000	234	6.04	52800	19.25	126	6.04	33	66200
24	360	5.95	30.5	58000	234	5.8	52300	20.5	126	6.02	32.5	67000
25.2	345	5.95	30.5	58100	234	5.8	52300	22	111	6.02	32.5	67600
25.2	360	5.96	30.5	58100	234	5.86	52300	22.25	126	6.03	32.5	67600
25.8	345	5.98	30.5	58100	234	5.86	52400	22.5	111	6.04	32.5	67700
26.1	345	5.98	30	58000	234	5.88	52300	22.5	111	6.03	32	67800
24	360	5.97	30	58000	234	5.86	52100	21	126	6.03	32	67200
24.9	360	5.96	30	58000	234	5.8	52100	21.75	126	6.01	32	67500
24.9	360	5.95	30	58000	234	5.95	52000	22	126	6.01	32	67200
25.5	360	5.97	30	58000	234	5.97	51900	22.5	126	6.02	32	67500
25.8	360	5.97	30	58000	234	5.8	51900	22.75	126	6.02	32	67600
26.88	360	5.96	29.5	58000	234	5.84	51700	24	126	6.03	31.5	67400
27	360	5.95	29.5	58000	234	5.8	51700	24.25	126	6.02	31.5	67800
27.3	360	6.01	29.5	58100	234	5.83	51700	25	126	6.05	31.5	67900
27.3	360	5.97	30	58100	234	5.87	51600	25	126	6.08	32	67900
27.3	360	6.03	30	58100	234	5.86	51700	25	126	6.1	32	68000
28.2	360	5.96	29.5	57900	234	5.9	51400	25.75	126	6.04	31.5	67800
28.5	360	5.97	29	57800	234	5.82	51200	26	126	6.04	31	67700
28.8	360	6.04	29	57700	234	5.9	51000	26.25	126	6.1	31	67800
29.1	360	5.98	29	57800	234	5.89	51100	26.75	126	6.05	31	68000
29.4	360	6.04	29	57900	234	5.9	51100	26.75	126	6.06	31	68200
29.4	360	6.04	29	57900	234	5.87	51200	27.5	126	6.07	31	68400
29.4	360	6	29	57900	234	5.85	51200	27	126	6.06	31	68400
30	360	6	29	57900	234	5.86	51100	28	126	6.04	31	68300

29.88	360	5.98	29	57900	234	5.87	51100	27.75	126	6.04	31	68300
30	360	6	29.5	57400	234	5.83	50600	28	126	6.05	31.5	67700
30	360	5.98	29.5	57500	234	5.82	50700	28.25	126	6.1	31.5	67700
30.3	360	6	30	57600	234	5.8	50800	28.5	126	6.09	32	67800
30.6	360	6	30	57600	234	5.8	50700	28.75	126	6.06	32	68000
31.2	360	5.97	29.5	57700	234	5.8	50700	29	126	6.07	31.5	68100
32.1	360	6.04	29	57700	234	5.8	50800	30	126	6.1	31	68600
32.4	360	5.97	29.5	57800	234	5.75	50900	30	126	6.07	31.5	68600
32.7	360	5.96	29.5	57800	234	5.76	50800	30	126	6.06	31.5	68500
33	360	5.96	29.5	57700	234	5.77	50700	30.5	126	6.1	31.5	68500
33	360	5.97	29	57700	234	5.84	50700	30.75	126	6.1	31	68600
33.9	360	5.96	29	57700	234	5.96	50700	31.25	126	6.12	31	68800
34.2	360	6.05	29	57800	234	5.8	50600	31.5	126	6.1	31	68900
34.8	360	6.01	29	57900	234	5.83	50600	32.25	126	6.08	31	69000
35.4	360	5.95	29	57800	234	5.78	50500	33	126	6.04	31	69200
36	360	5.96	29	57800	234	5.81	50500	34.25	126	6.05	31	69100
36.6	356.4	5.85	29.5	57900	230.4	5.65	50500	34.5	126	5.93	31.55	69100
36.3	354.6	6.05	29.5	57800	228.6	5.81	50500	34.5	126	6.1	31.55	69100
30.3	360	5.7	28	57900	234	5.68	50800	28.25	126	5.88	29.5	68300
31.2	360	5.85	29.52	57800	234	5.81	50500	29.25	126	5.9	30.2	69100
31.8	360	5.96	29.5	57800	234	5.77	50600	29.5	126	6.1	31.5	69100
32.7	360	5.9	28.7	57700	234	5.8	50600	30.5	126	6.1	29.5	69100
33	360	6.01	29	57700	234	5.81	50600	31	126	6.08	30.1	69000
33.3	360	6.01	30.1	57800	234	5.82	50600	31.25	126	6.07	30.05	69100
34.8	360	6.02	30.15	57700	234	5.82	50600	32.5	126	6.1	30.81	69100
35.7	360	6.01	30.12	57700	234	5.81	50500	33.25	126	6.06	30.05	69000
36.6	358.2	6.04	29	57700	232.2	5.82	50500	33.75	126	6.1	30	69000
36.6	356.4	6.15	28.1	57800	230.4	5.9	50000	33.5	126	6.15	29.3	69000
36.9	354.6	6.1	29.5	57900	228.6	5.84	50100	33.25	126	6.16	30	69600
36.9	352.8	6.12	29.5	57800	226.8	5.85	50100	33.25	126	6.17	30	69100
37.2	349.2	6.12	28.5	57600	223.2	5.85	50200	33.5	126	6.15	29	69000
37.5	345.	6.0	27.01	58000	219.	5.8	49900	33	126	6.1	28	69300

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	6	2			6	2				2		
37.2	345.6	6.1	26	58000	219.6	6	50000	33	126	6.15	26.5	69200
37.8	345.6	6.01	27	58000	219.6	5.83	49900	33	126	6.12	28	69300
37.5	343.8	6.08	28.16	58700	217.8	5.95	50400	32.5	126	6.16	29	69700
37.8	342	5.98	29	58300	216	5.81	50500	33	126	6.23	29.5	69600
36.9	354.6	6.1	29	57900	228.6	5.85	49900	31.25	126	6.19	30	68700
37.8	342	5.95	25	57800	216	5.8	49900	32	126	6.03	27	68700
38.7	343.8	5.95	25	57400	217.8	5.79	49600	32.25	126	6.03	27	68000
38.7	342	5.95	25	57700	216	5.8	49600	32.75	126	6.04	27	68600
39	340.2	5.96	25	57700	214.2	5.98	49700	33	126	6.04	27	68600
39	338.4	5.96	25	57800	212.4	5.8	49800	33.5	126	6.06	27	68500
39	338.4	5.9	24	57800	212.4	5.75	49900	33.5	126	6.02	26	68500
39	338.4	5.96	24	57900	212.4	5.77	49900	34	126	6.04	26	68700
39	336.6	5.97	24	57900	210.6	5.8	49900	33.75	126	6.08	26	68600
39	342	5.95	25	57800	216	5.75	49900	33.5	126	6.02	27	68500
38.7	336.6	6	25	57900	210.6	5.83	50000	34	126	6.09	27	68500
39	333	6.04	24.5	57800	207	5.85	49800	34	126	6.14	26.5	68300
39	331.3	6.05	24	57700	205.3	5.86	49700	34	126	6.15	26	67800
39	336.6	6.08	26.5	57700	210.6	5.8	49800	34.5	126	6.08	26.5	67800
39.3	329.4	6.04	24.5	57600	203.4	5.86	49600	34.5	126	6.11	26.5	67700
26.6	360	6.05	23.5	57600	234	5.88	51700	23.83	126	6.14	25.5	67200
27.19	360	6.05	23	57600	234	5.84	51700	24.2	126	6.15	25	67600
26.51	360	6.05	23	57700	234	5.9	51700	23.52	126	6.16	25	67500
27.17	360	6.04	23	57800	234	5.9	51700	24.19	126	6.17	25	67400
26.02	360	6.05	23	57000	234	5.9	51700	23.48	126	6.18	25	66700
28.39	360	6.1	22.5	57800	234	5.9	51500	25.15	126	6.18	24.5	67400
27.26	360	6.1	22.5	57800	234	5.93	51500	24.65	126	6.18	24.5	67400
27.99	360	6.06	22.5	57800	234	5.9	51400	25.1	126	6.16	24.5	67400
28.68	360	6.05	22.5	57800	234	5.9	51200	25.75	126	6.17	24.5	67500
30.03	360	6.05	22.5	57800	234	5.87	51100	27.08	126	6.12	24.5	67800
31	360	6	22	57900	234	5.86	51100	28	126	6.07	24	68000
31.51	360	6.0	22	57700	234	5.8	50800	28.59	126	6.1	24	67900

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32.83	360	6.03	22	57700	234	5.87	50700	29.82	126	6.14	24	68300
32.88	360	6.03	22	57800	234	5.9	50800	29.98	126	6.16	24	68300
32.66	360	6.02	22	57800	234	5.87	50800	29.83	126	6.1	24	68200
29.88	360	6.02	22.5	57800	234	5.89	51200	27.07	126	6.09	24.5	67800
29.8	360	6.05	23	57900	234	5.9	51300	27	126	6.13	25	67800
30.97	360	6.05	23	57900	234	5.9	50900	28.13	126	6.16	25	67700
32.33	360	6.02	23	57900	234	5.89	50900	29.4	126	6.14	25	68100
33.75	360	6	21.5	57900	234	5.86	50700	30.83	126	6.12	23.5	68400
34.9	360	5.97	22	57800	234	5.86	50500	32.07	126	6.1	24	68700
34.4	360	5.98	22	57800	234	5.85	50400	31.5	126	6.09	24	68400
36.7	360	5.96	22	57800	234	5.8	50400	33.88	126	6.07	24	69200
36.93	360	6	22	57800	234	5.87	50400	34.16	126	6.06	24	69100
37.18	360	6	22	57800	234	5.8	50300	34.42	126	6.12	24	69000
36.79	360	6.04	22	57900	234	5.85	50400	34	126	6.12	24	68900
35.5	360	5.98	22	57900	234	5.84	50400	32.8	126	6.11	24	68900
36.32	360	6	22.5	57900	234	5.82	50500	33.56	126	6.08	24.5	68800
36.41	360	6	22.5	57900	234	5.83	50600	33.71	126	6.09	24.5	68800
36.02	360	6	23	58000	234	5.81	50700	33.16	126	6.07	25	68900
34.76	360	6.01	24	58100	234	5.8	50800	32.07	126	6.06	26	68700
29.77	360	6	24	57800	234	5.8	51300	26.97	126	6.09	26	67500
30.59	360	5.98	24	57700	234	5.87	51100	27.98	126	6.07	26	67600
32.19	360	6.04	24	57700	234	5.89	50900	29.33	126	6.08	26	67600
32.97	360	6.05	24	57700	234	5.84	50800	30.11	126	6.09	26	68000
32.57	360	6.05	24	57800	234	5.84	50900	29.75	126	6.09	26	68000
33.32	360	6.05	24	57800	234	5.86	50800	30.45	126	6.12	26	68200
34.91	360	6.05	23.5	57800	234	5.87	50700	32.07	126	6.1	25.5	68500
35.42	360	6.05	23.5	57800	234	5.83	50700	32.65	126	6.09	25.5	68500
32.41	360	6.05	23	57900	234	5.88	50800	29.54	126	6.14	25	68100
33.45	360	6	23	57900	234	5.88	50900	30.63	126	6.11	25	68200
33.85	360	6.05	23	57900	234	5.83	50800	31.11	126	6.12	25	68400
32.22	360	6	23.5	58000	234	5.8	51000	29.51	126	6.1	25	68200

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33.28	360	6.03	24	57900	234	5.88	51000	30.4	126	6.11	26	68200
32.33	360	5.96	24.5	58000	234	5.81	51000	29.51	126	6.08	26.5	68200
32.53	360	6.01	25	58000	234	5.88	51200	29.69	126	6.08	27	68100
32.81	360	6	25	58000	234	5.87	51200	29.98	126	6.11	27	68100
33.25	360	6.03	25	58000	234	5.82	51100	30.38	126	6.1	27	68100
31.96	360	6.05	26	58000	234	5.85	51200	29.18	126	6.08	28	67800
32.5	360	6.05	26	58000	234	5.88	51200	29.75	126	6.11	28	67800
33.45	360	6.01	25.5	57900	234	5.87	51000	30.61	126	6.12	27.5	67800
33.85	360	6.01	25.5	57800	234	5.85	50900	31.02	126	6.09	27.5	67900
34.9	360	6.04	25	57700	234	5.88	50600	32	126	6.12	27	68000
33.07	360	5.97	25	57600	234	5.76	50800	30.32	126	6.04	27	67700
33.66	360	6	25	57800	234	5.84	50900	31.02	126	6.12	27	67900
34.3	360	6.05	25	57900	234	5.88	51000	31.7	126	6.14	27	68000
35.83	360	6	25	58000	234	5.85	51000	33.09	126	6.1	27	68400
36.28	360	5.98	25	58000	234	5.86	51000	33.51	126	6.14	27	68300
34.24	360	6.02	25.5	58100	234	5.9	51200	31.42	126	6.12	27.5	68400
36.98	360	6.04	25	58100	234	5.85	51000	34.09	126	6.11	27	68500
37.1	353	6.02	25	58100	227	5.86	51000	34.39	126	6.11	27	68500
35.94	349	5.98	25	58100	223	5.86	50900	33.23	126	6.1	27	68400
37.02	354	6.04	25	58100	228	5.87	50900	34.1	126	6.11	27	68600
34.7	360	6.02	25	58000	234	5.83	51000	31.86	126	6.1	27	68300
35.43	360	6	25	57900	234	5.84	51000	32.73	126	6.07	27	68300
35.36	360	5.97	26	57900	234	5.8	51000	32.55	126	6.05	28	68000
35.33	360	5.98	26	57800	234	5.8	51000	32.57	126	6.06	28	67900
36.13	360	5.97	26	57800	234	5.84	51000	33.38	126	6.12	28	68000
36.84	358	5.96	26	57800	232	5.85	51000	34.1	126	6.12	28	68000
36.22	357	6.03	26.5	57900	231	5.87	51000	33.84	126	6.12	28.5	68000
36.09	355	6.05	27	57800	229	5.85	51000	33.51	126	6.1	29	69000
35.83	355	6.04	28	57900	229	5.87	51100	33.14	126	6.12	30	67800
36.4	358	5.98	28	57900	232	5.85	51100	33.5	126	6.06	30	67700
36.18	355	6	28	57900	229	5.8	51100	33.59	126	6.1	30	67700

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24.65	360	5.95	27.5	58200	234	5.79	53100	21.79	126	6.05	29.5	66500
26.02	360	5.96	27.5	58400	234	5.82	52900	23.15	126	6.05	29.5	67000
26.6	360	5.97	27.5	58400	234	5.81	52800	23.76	126	6.03	29.5	67000
27	360	5.97	27.5	58500	234	5.82	52800	24.12	126	6.02	29.5	67200
27.1	360	6.01	27.5	58500	234	5.82	52800	24.2	126	6.07	29.5	67500
27.26	360	5.97	27.5	58500	234	5.81	52800	24.36	126	6.04	29.5	67800
27.88	360	6.02	27	58600	234	5.81	52800	25	126	6.05	29	67400
28.19	360	5.98	27	58600	234	5.8	52800	25.38	126	6.04	29	67400
28.66	360	5.98	27	58600	234	5.86	52800	25.64	126	6.06	29	67400