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Title:

Pressure Exchanger Alarm Prediction Using KNN in Desalination Station

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Abstract

The desalination process removes dissolved salts from water, and this can include seawater, water from inland seas, mineralized groundwater, and municipal waste water, where the aim is to convert sea water into fresh water that's safe for drinking, irrigation, and other uses to help for solving the water crisis. The process involves separating salt from water molecules from water, that several desalination methods can accomplish. For example, membrane processes are a class of water treatment technologies that use permeable membranes to separate salts and other impurities from water as it passes through a two main types of membrane processes are reverse osmosis and electrodialysis. This type of technique contain an Energy Recovery Device called Pressure Exchange (PX) which is a flow based operating meaning that the flows of the process are the only factors affecting its operation when having good pre-treatment plant .where its alarms are not easily detected by the SCADA stuff due to codependency of the process flows from every plant equipments, such that there are percentages of one flow to the other that should be respected to avoid alarm cases from the domination of one on another resulting in unbalanced state. We propose in this project, an alarm prediction model that use standardization scalers for pre-processing and machine learning algorithms to investigate and compare the supervised ML binary classifiers choosing the top three. Experimental evaluation yields the best performance using Min-Max scaler as feature scaling technique, and K-Nearest Neighbors as a classifier, with an accuracy of 99.13%.

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Introduction

Introduction

In the recent years, desalination stations have been playing a significant role in solving lack of drinkable water problem. Algeria has been working on producing pure water using this technology from the year2000 and Fouka is one of this project stations .The later working on by the end of 2024 to get 3.7 million cubic meter daily covering 42% of the Algerians needs , aiming to reach 5.6 million cubic meter daily by the year 2030 with investing already a 2.1 billion dollar and another 2.4 billion dollar later for the second part of this project that already built a 5 large station from the year 2022-2024 each of 300 thousand cubic meter daily ; while preparing for the years2025 to 2030 in completing another seven stations in order to increase the covered needs from 42% to 60%.

This project done in Fouka station that produce a120 thousand cubic meter daily using Seawater Reverse Osmosis that is a technique depends on membrane salt rejection in removing the seawater salinity giving low permeate salinity water that goes through another post-treatment making it drinkable ,this process need high pressure flow fed to the membranes meaning for large amount of feed seawater we need larger high-pressure pump; but lately the pressure exchanger (PX)technology improve dramatically the consumed energy by decreasing the size of high-pressure pumps to only 45% of the total seawater ,but since PXs are flow driven equipments making its alarm prediction almost impossible for the fast changing process flows.

We present in this project a pressure exchanger alarm prediction model, which uses the RO process numerical values in classifying the sample to an alarm or non-alarm then identifying its source. We study and compare the different supervised classification algorithms and remove the false negative cases such that with the experimental evaluation we upend with a very encouraging result of 99.13% accuracy 100% sensitivity.

I. Introduction:

Approximately 97.5 % of the water on our planet is located in the oceans and therefore is classified as seawater. Of the 2.5 % of the planet's freshwater, approximately 70 % is in the form of polar ice and snow and 30 percent is groundwater, river and lake water, and air moisture. So even though the volume of the earth's water is vast, less than 35 million km3 of the 1386 million km3 (8.4 million of the 333 million) of water on the planet is of low salinity and is suitable for use after applying conventional water treatment only (Black and King, 2009). Desalination provides a means for tapping the world's main water resource the ocean. Over the past 30 years, desalination has made great strides in many arid regions of the world, such as the Middle East and the Mediterranean. Technological advances and the associated decrease in water production costs over the past decade have expanded its use in areas traditionally supplied with freshwater resources.

At present, desalination plants operate in more than 120 countries worldwide; some desert states, such as Saudi Arabia and the United Arab Emirates, rely on desalinated water for over 70 percent of their water supply. According to the 2011–2012 IDA Desalination Yearbook [Global Water Intelligence (GWI) and International Desalination Association (IDA), 2012], by the end of 2011 worldwide there were approximately 16,000 desalination plants, with a total installed production capacity of 71.9 million m3/day [19,000 million gal/day (mgd)].
While currently desalination provides only 1.5 % of the water supply worldwide, it is expected that in the next decade the construction of new desalination plants will grow exponentially due to the ever-changing climate patterns triggered by global warming combined with population growth pressures, limited availability of new and inexpensive terrestrial water sources, and dramatic advances in membrane technology, which are projected to further reduce the cost and energy use of desalination.

The brackish water quantity on the planet is fairly limited (0.5 %), and most of the large and easily accessible brackish water aquifers worldwide are already in use. A significant portion of the new capacity growth is expected to come from the development of seawater desalination plants. While brackish water sources, especially brackish aquifers, are finite in terms of capacity and rate of recharging, the ocean has two unique and distinctive features as a water supply source it is drought proof and practically limitless. Over 50 % of the world's population lives in urban centers bordering the ocean. In many arid parts of the world, such as the Middle East, Australia, North Africa, and Southern California, the population concentration along the coast exceeds 75 %. Usually coastal zones are also the highest population growth hot spots. Therefore, seawater desalination provides the logical solution for a sustainable, long-term management of the growing water demand pressures in coastal areas. Brackish desalination is also expected to increase in capacity, especially in inland areas with still untapped brackish water aquifers.

A clear recent trend in seawater desalination is the construction of larger-capacity plants, which deliver an increasingly greater portion of the freshwater supply of coastal cities around the globe. While most of the large desalination plants built between 2000 and 2005 were typically designed to supply only 5 to 10 % of the drinking water of large coastal urban centers, today most regional or national desalination project programs in countries such as Spain, Australia, Israel, Algeria, and Singapore aim to fill 20 to 25 percent of their long-term drinking water needs with desalinated seawater. Increased reliance on seawater desalination is often paralleled with ongoing programs for enhanced water reuse and conservation, with a long-term target of achieving near even contributions of conventional water supply sources, seawater desalination, water reuse, and conservation to the total water portfolio of large coastal communities [1].

There are three major desalination process kinds with two different types each ,and our studying process is the membrane desalination with reverse osmosis as shown in the following schema :

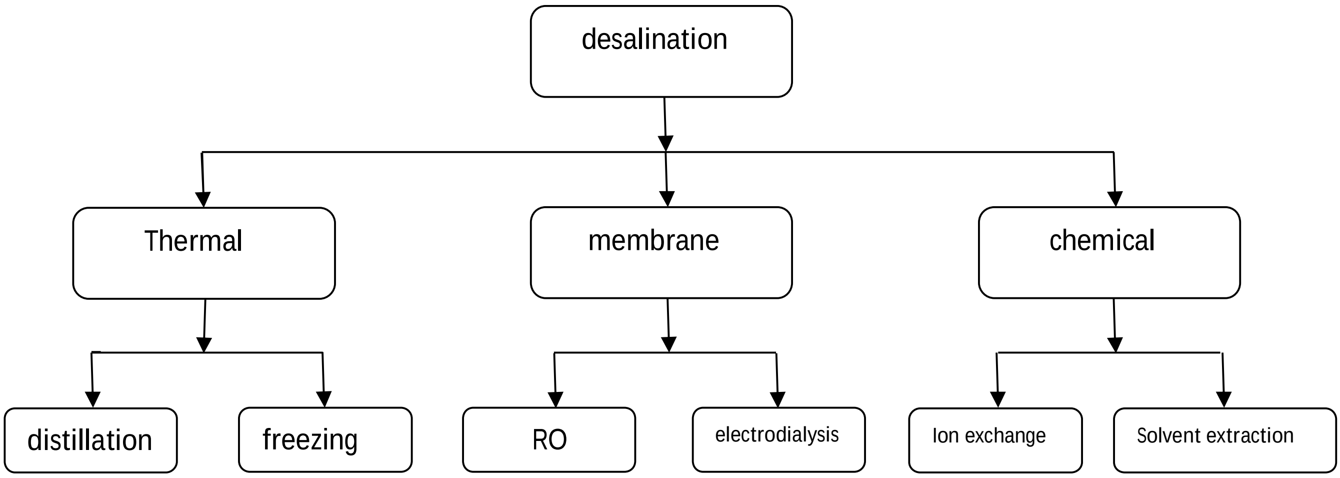


Figure 1.1 desalination types schema [1].

As shown in figure 1.1 among the different types of RO membranes when using sea water as product source the SWRO membrane are the most suitable type for handling its salinity:

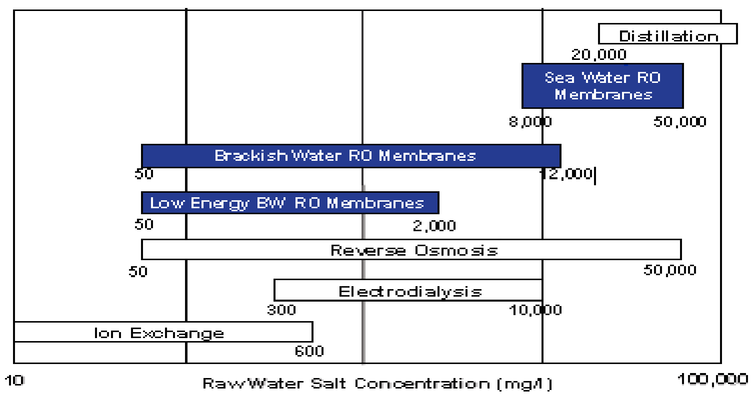


Figure 1.2 Major desalination processes [1].

I.1 Historical Background

Since the development of reverse osmosis (RO) and ultrafiltration (UF) as practical unit operations in the late 1950's and early 1960's, the scope for their application has been continually expanding. Initially, reverse osmosis was applied to the desalination of seawater and brackish water. Increased demands on the industry to conserve water, reduce energy consumption, control pollution and reclaim useful materials from waste streams have made new applications economically attractive. In addition, advances in the fields of biotechnology and pharmaceuticals, coupled with advances in membrane development, are making membranes an important separation step, which, compared to distillation, offers energy savings and does not lead to thermal degradation of the products.

Hydranautics has over two decades of experience in desalination and over 1.7 million cubic meters of seawater treated by their SWC(seawater composition) membranes. Since the creation of the SWC4-MAX membrane, new products have been developed and existing products have undergone enhancements in their ability to improve permeate quality and lower the total cost of water.
In general, RO membranes now offer the possibility of higher rejection of salts at significantly reduced operating pressures, and therefore, reduced costs. Nanofiltration membrane technology provides the capability of some selectivity in the rejection of certain salts and compounds at relatively low operating pressures [2].

I.2 Reverse Osmosis

If water of high salinity is separated from water of low salinity via a semipermeable membrane, a natural process of transfer of water will occur from the low-salinity side to the high-salinity side of the membrane until the salinity on both sides reaches the same concentration. concentration. This natural process of water transfer through a membrane driven by the salinity gradient occurs in every living cell; it is known as *osmosis*.
The hydraulic pressure applied on the membrane by the water during its transfer from the low-salinity side of the membrane to the high-salinity side is termed *osmotic pressure*. Osmotic pressure is a natural force similar to gravity and is proportional to the difference in concentration of *total dissolved solids* (TDS) on both sides of the membrane, the source water temperature, and the types of ions that form the TDS content of the source water. This pressure is independent of the type of membrane itself.
In order to remove fresh (low-salinity) water from a high-salinity source water using membrane separation, the natural osmosis-driven movement of water must be reversed, i.e., the freshwater has to be transferred from the high-salinity side of the membrane to the low salinity side. For this reversal of the natural direction of freshwater flow to occur, the high salinity source water must be pressurized at

a level higher than the naturally occurring osmotic pressure (Fig. 1.3). If the high-salinity source water is continuously pressurized at a level higher than the osmotic pressure and the pressure losses for water transfer through the membrane, a steady-state flow of freshwater from the high-salinity side of the membrane to the low-salinity side will occur, resulting in a process of salt rejection and accumulation on one side of the membrane and freshwater production on the other. This process of forced movement of water through a membrane in the opposite direction to the osmotic force driven by the salinity gradient is known as *reverse osmosis* (RO) [1].

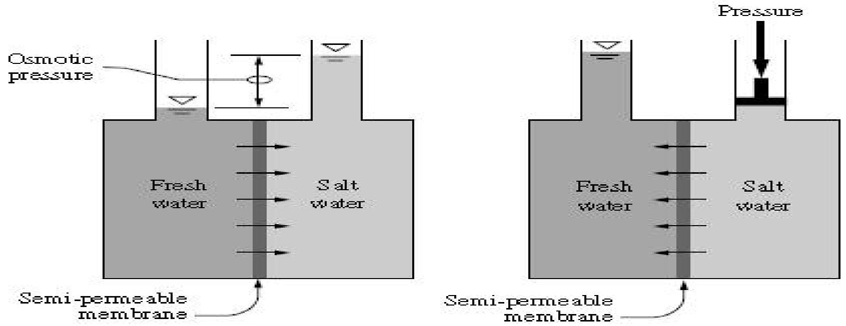


Figure 1.3 Osmosis and reverse osmosis [1].

The rate of water transport through the membrane is several orders of magnitude higher than the rate of passage of salts. This significant difference between water and salt passage rates allows membrane systems to produce freshwater of very low mineral content.

The applied feed water pressure counters the osmotic pressure and overcomes the pressure losses that occur when the water travels through the membrane, thereby keeping the freshwater on the low-salinity (permeate) side of the membrane until this water exits the membrane vessel. The salts contained on the source water (influent) side of the membrane are retained and concentrated; they are ultimately evacuated from the membrane vessel for disposal. As a result, the RO process results in two streams one of freshwater of low salinity (permeate) and one of feed source water of elevated salinity (concentrate, brine or retentate), as shown in Fig(1.4). While semipermeable RO membranes reject all suspended solids, they are not an absolute barrier to dissolved solids (minerals and organics alike). Some passage of dissolved solids will accompany the passage of freshwater through the membrane. The rates of water and salt passage are the two key performance characteristics of RO membranes [1].

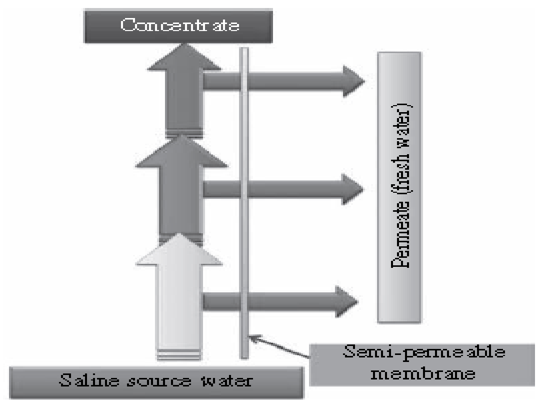


Figure 1.4 Reverse osmosis process [1].

A)Reverse Osmosis Membrane Structures, and Materials

Reverse osmosis membranes differ by the material of the membrane polymer and by structure and configuration. Based on their structure, membranes can be divided into two groups: conventional thin-film composite and thin-film nanocomposite. Based on the thin-film material, conventional membranes at present are classified into two main groups: polyamide and cellulose acetate. Depending on the configuration of the membranes within the actual membrane elements (modules), RO membranes are divided into three main groups: spiral-wound, hollow-fiber, and flat-sheet (plate-and-frame). For our project we are using the conventional thin-film composite polyamide spiral-wound membrane [1].

A.1) Conventional Thin-Film Composite Membrane Structure

The reverse osmosis membranes most widely used for desalination at present are composed of a semipermeable thin film (0.2 μm), made of either *aromatic polyamide* (PA) or *cellulose acetate* (CA), which is supported by a 0.025- to 0.050-mm microporous layer that in turn is cast on a layer of reinforcing fabric (Fig. 1.5 for a membrane with an ultrathin PA film).The 0.2-μm ultrathin polymeric film is the feature that gives the RO membrane its salt rejection abilities and characteristics.
The main functions of the two support layers underneath the thin film are to reinforce the membrane structure and to maintain membrane integrity and durability. The dense semipermeable polymer film is of a random molecular structure (matrix) that does not have pores. Water molecules are transported through the membrane film by diffusion and travel on a multidimensional curvilinear path within the randomly structured molecular polymer film matrix. While the thin-film RO membrane with conventional random matrix-based structure shown in Fig. 1.5 is the type of membrane that dominates the desalination industry, new thin-film membranes of more permeable structure are currently under development in research centers worldwide [1].

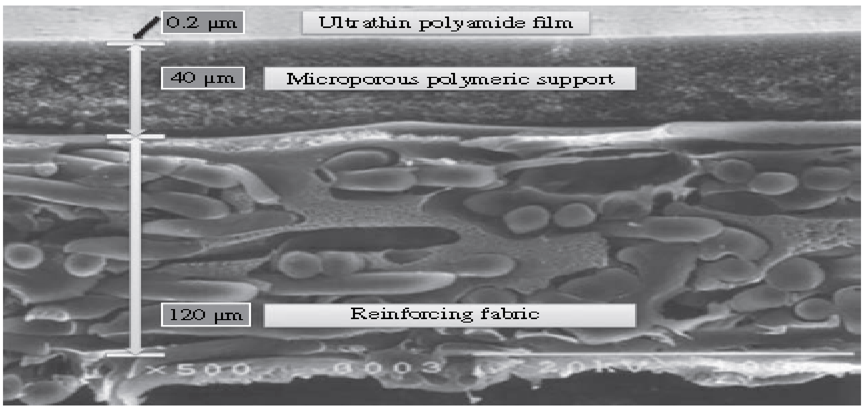


Figure 1.5 Structure of a typical RO membrane [1].

A.1.2) Aromatic Polyamide Membranes

Aromatic polyamide (PA) membranes are the most widely used type of RO membranes at present. They have found numerous applications in both potable and industrial water production. The thin polyamide film of this type of semipermeable membrane is formed on the surface of the microporous polysulfone support layer (Fig. 1.5) by interfacial polymerization of monomers containing polyamine and immersed in solvent containing a reactant to form a highly cross-linked thin film.

PA membranes operate at lower pressures and have higher productivity (specific flux) and lower salt passage than CA membranes, which are the main reasons they have found a wider application at present. While CA membranes have a neutral charge, PA membranes have a negative charge when the pH is greater than 5, which amplifies co-ion repulsion and results in higher overall salt rejection. However, it should be noted that when the pH is lower than 4, the charge of a PA membrane changes to positive and rejection is reduced significantly, to lower than that of a CA membrane.

Another key advantage of PA membranes is that they can operate effectively in a much wider pH range (2 to 12), which allows easier maintenance and cleaning. In addition, PA membranes are not biodegradable and usually have a longer useful life 5 to 7 years versus 3 to 5 years. Aromatic polyamide membranes are used to produce membrane elements for brackish water and seawater desalination, and nanofiltration.

It should be noted that PA membranes are highly susceptible to degradation by oxidation of chlorine and other strong oxidants. For example, exposure to chlorine longer than 1000 mg/L-hour can cause permanent damage of the thin-film structure and can significantly and irreversibly reduce membrane performance in terms of salt rejection. Oxidants are widely used for biofouling control with RO and nanofiltration membranes; therefore, the feed water to PA membranes has to be dechlorinated prior to separation [1].

A.3) Spiral-Wound RO Membrane Elements

Spiral-wound membrane elements (modules) are made of individual flat membrane sheets that have the three-layer structure described in the previous section (i.e., ultrathin CA or PA film; microporous polymeric support; and reinforcing fabric (Fig. 1.5). A typical 8-in.-diameter spiral-wound RO membrane element has 40 to 42 flat membrane sheets. The flat sheets are assembled into 20 to 21 membrane envelopes (leafs), each of which consists of two sheets separated by a thin plastic net (referred to as a *permeate spacer*) to form a channel that allows evacuation of the permeate separated from the saline source water by the flat sheets (permeate carrier). Three of the four sides of the two-membrane flat-sheet envelope are sealed with glue and the fourth side is left open (Fig. 1.6). The membrane leafs are separated by a feed spacer approximately 0.7 or 0.9 mm (28 or 34 mils) thick, which forms feed channels and facilitates the mixing and conveyance of the feed-concentrate stream along the length of the membrane element (Fig. 1.7). Membranes with the wider 34-mil spacers have been introduced relatively recently and are more suitable for highly fouling waters. In order to accommodate the wider spacers, fewer membrane leafs are installed within the same RO membrane module, which results in a tradeoff between reduced membrane fouling and lower membrane element productivity.

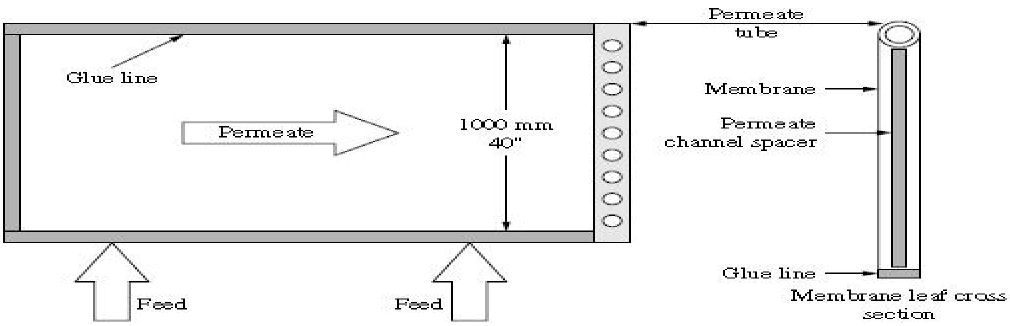


Figure 1.6 Flat-sheet membrane envelope. (*Source: Hydranautics.*)

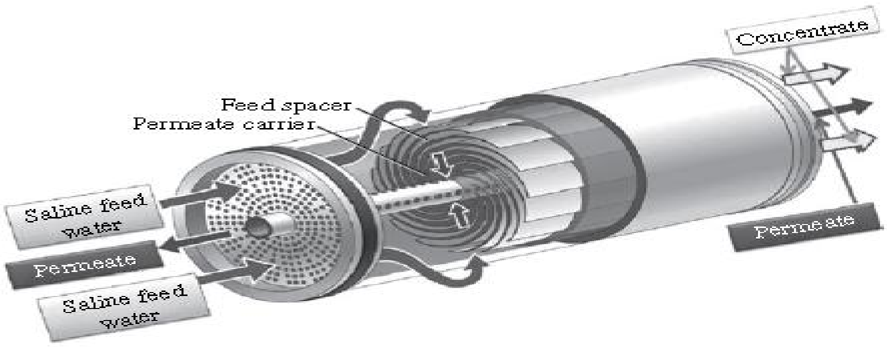


Figure 1.7 Spiral-wound membrane element [1].

Pressurized saline feed water is applied on the outside surface of the envelope; permeate is collected in the space inside the envelope between the two sheets and directed toward the fourth, open edge of the envelope, which is connected to a central permeate collector tube. This collector tube receives desalinated water (permeate) from all flat-sheet leaves (envelopes) contained in the membrane element and evacuates it out of the element.

The assembly of flat-sheet membrane leafs and separating spacers is wrapped (rolled) around the perforated permeate collector tube. The membrane leafs are kept in the spiral-wound assembly with a tape wrapped around them and contained by an outer fiberglass shell. The two ends of each RO element are finished with plastic caps referred to as *end caps*, *antitelescoping devices*, or *seal carriers*. The plastic caps are perforated in a pattern that allows even distribution of the saline feed flow among all membrane leafs in the element (Fig. 1.8). The plastic caps’ flow distribution pattern varies between membrane manufacturers.

The reason the plastic caps are often also referred to as *seal carriers* is that one of their functions is to carry a chevron-type U-cup-style rubber brine seal that closes the space between the membrane and the pressure vessel in which the membrane is installed. This seal prevents the feed water from bypassing the RO element (Fig. 1.9).

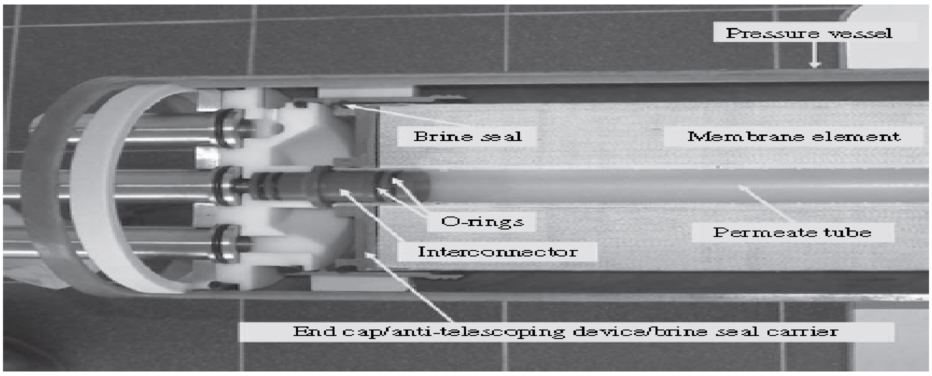


Figure 1.8 Cross-section of an RO membrane element installed in a pressure vessel [1].

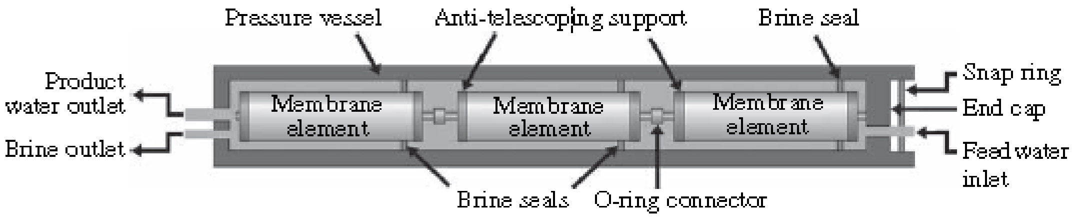


Figure 1.9 Membrane elements installed in a pressure vessel [1].

The source water flow is introduced from one end of the element and travels in a straight tangential path on the surface of the membrane envelopes and along the length of the membrane element (Figs.1.6 and 1.7). A portion of the feed flow permeates through the membrane and is collected on the other side of the membrane as freshwater. The separated salts remain on the feed side of the membrane and are mixed with the remaining feed water. As a result, the salinity of the feed water increases as this water travels from one end of the membrane element to the other. The rejected mix of feed water and salts exits at the back end of the membrane element as concentrate (brine).

As shown in Figs. 1.8 and 1.9, the permeate collector tubes of the individual RO membrane elements installed in the pressure vessel are connected to each other and to the permeate line evacuating the fresh water from the pressure vessel via interconnectors (adaptors) with integral O-rings that seal the connection points and prevent concentrate from entering the permeate collector tubes.

The interconnectors with O-rings provide flexible connections between the elements, which allow for their limited movement within the vessel, for some level of flexibility in loading membranes and also facilitate handling transient pressure surges created in the vessels as a result of abrupt shutdown and start-up of the RO system. While Fig. 1.8 shows an interconnector to the permeate line, Fig. 1.10 depicts an interconnector between two RO elements. Since broken O-rings and interconnectors are one of the most common operations challenges in RO systems, the Dow Chemical Company has introduced a different interconnection configuration (iLEC) between RO elements that requires the elements to have special interlocking end caps and allows them to be connected directly to each other rather than through conventional interconnectors (Fig. 1.11). The end caps of the iLEC RO membrane elements are configured so that they can be interlocked by twisting the installed RO element until its end cap locks with the end cap of a previously installed element. The end caps of the two elements are connected by one O-ring only, which is integrated into the end cap and cannot be rolled or pinched during installation. This minimizes the wear and tear on the O-rings from hydraulic surges and reduces the pressure drop caused by conventional interconnectors.

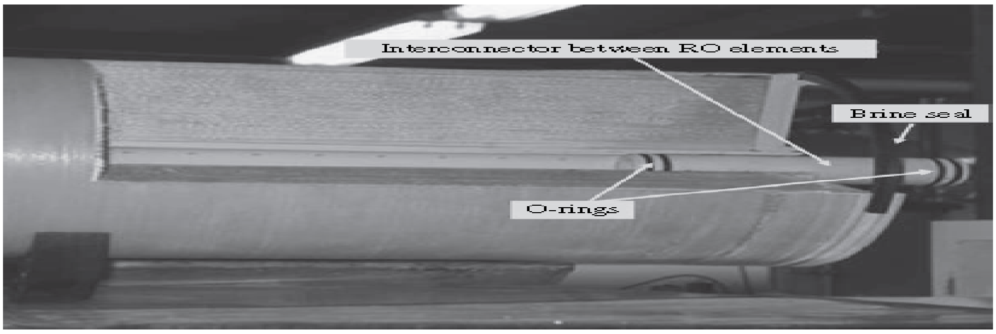


Figure 1.10 Interconnector between RO elements [1].

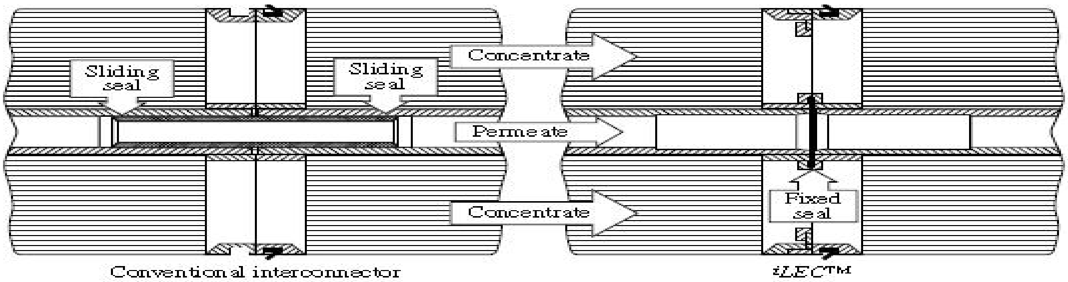


Figure 1.11 Comparison of conventional and iLEC membrane interconnectors. (*Source: DOW FilmTec.*)

Commercially available RO membrane elements are standardized in terms of diameter and length and usually are classified by diameter. Spiral-wound RO membranes are available in 2.5-in., 4-in., 6-in., 8-in., 16-in., 18-in., and 19-in. sizes. A typical 8-in. RO membrane element is shown in Fig. 1.11. At present, the most widely used and commercially available RO elements have a diameter of 20 cm (8 in.), length of 100 cm (40 in.) and brine spacer thickness of 28 mils (0.7 mm). Standard 8-in. seawater and brackish water elements in a typical configuration of seven elements per vessel can produce between 13 and 25 m3/day (3500 and 6500 gal/day) and 26 and 38 m3/day (7000 and 10,000 gal/day) of freshwater (permeate), respectively. Larger 16-in., 18-in., and 19-in. RO brackish and seawater membrane elements are also commercially available. However, to date these large elements have received limited full-scale application. While 8-in. elements and smaller can be handled manually by a single person (Fig. 1.12), larger RO elements can only be loaded and unloaded by special equipment because of their significant weight.

Standard and large-size spiral-wound thin-film composite PA membrane elements have limitations with respect to a number of performance parameters: feed water temperature (45°C), pH (2 to 10), silt density index (less than 4), chlorine content (no measurable amounts), and feed water operating pressure (maximum of 41 or 83 bar/600 to 1,200 lb/in2 for brackish and seawater RO membranes, respectively) [1].

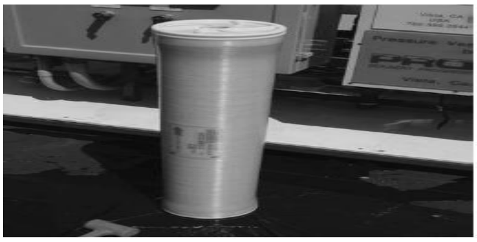


Figure 1.12 Typical 8-in. membrane element [1].

Figure 1.13 Unloading an RO membrane element from a pressure vessel [1].

B)Reverse Osmosis Process Parameters

As indicated in the previous sections, RO membranes in full-scale installations are assembled in membrane elements (modules) installed in vessels in series of six to eight elements per vessel, and the feed water is introduced to the front membrane elements and applied tangentially on the surface of the membranes in a cross-flow direction (Fig 1.14)at pressure adequate to overcome the osmotic pressure of the saline water and the energy losses associated with the separation process. A general schematic of an RO system is shown in Fig. 1.15.

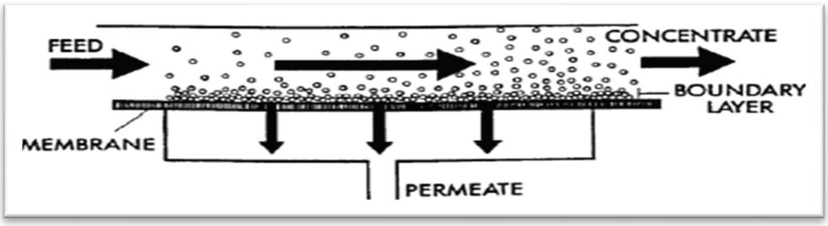


Figure 1.14 Crossflow membrane filtration [1].

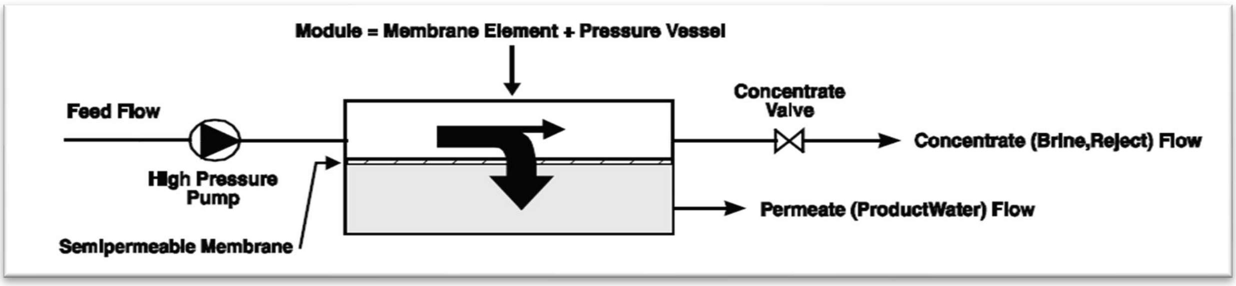


Figure 1.15 General schematic of an RO system [1].

With a high pressure pump, feed water is continuously pumped at elevated pressure to the membrane system. Within the membrane system, the feed water will be split into a low-saline and/or purified product, called permeate, and a high saline or concentrated brine, called concentrate or reject. A flow regulating valve, called a concentrate valve, controls the percentage of feed water that is going to the concentrate stream and the permeate which will be obtained from the feed [1].

The key terms used in the reverse osmosis process are defined as follows :

***Recovery* -** the percentage of membrane system feed water that emerges from the system as product water or "permeate". Membrane system design is based on expected feed water quality and recovery is defined through initial adjustment of valves on the concentrate stream. Recovery is often fixed at the highest level that maximizes permeate flow while preventing precipitation of super-saturated salts within the membrane system [2].

$$R = (Qp/Qf) \times 100\% \qquad (1.1)$$

***Passage* -** the opposite of "rejection", passage is the percentage of dissolved constituents (contaminants) in the feed water allowed to pass through the membrane [2].

$$Sp = (\mathrm{TDSp}/\mathrm{TDSf}) \times 100\% \qquad (1.2)$$

***Rejection* -** the percentage of solute concentration removed from system feed water by the membrane. In reverse osmosis, a high rejection of total dissolved solids (TDS) is important, while in nanofiltration the solutes of interest are specific, e.g., low rejection for hardness and high rejection for organic matter [2].

$$Sr = 100\% - \mathrm{Sp} = [1 - (\mathrm{TDSp}/\mathrm{TDSf})] \times 100\% \qquad (1.3)$$

***Flux J* -** the rate of permeate transported *Qp* per unit of membrane area *S*, usually measured in gallons per square foot per day (gfd) or liters per square meter and hour (L/m2h) [2].

$$J = Qp/S \qquad (1.4)$$

***Permeate* Qp –**the purified product water produced by a membrane system [2].

Or **Water Transport Rate** The water (permeate) transport rate Q*p* of an RO membrane is proportional to its water transport (water permeability) coefficient *A*, which is a unique constant for each membrane material—as well as the total membrane area *S*, and the net driving pressure (NDP):

$$Qp = A \times S \times \mathrm{NDP} \qquad (1.5)$$

As indicated in Eq. 1.4, the ratio between the water transport rate and the surface area through which water is conveyed is referred to as the membrane permeate flux *J*. Therefore, membrane permeate flux (also often referred to as the membrane flux) can be represented as follows:

$$J = A \times \mathrm{NDP} \qquad (1.6)$$

This formula indicates that membrane flux is controlled by two parameters :water permeability coefficient *A*, which is unique for each type of commercial membrane, and net driving pressure (NDP), which can be controlled by adjusting feed and permeate pressures [1].

Salt Transport Rate Qs The salt transport rate *Q*s is proportional to the salt transfer coefficient B which, as the water transfer coefficient, is unique for each membrane type , the surface area *S* of the membrane, and the salt concentration gradient ΔC, which collectively for all salts is measured as the difference between the TDS levels of the concentrate and the permeate:

$$Qs = B \times S \times \Delta\mathrm{C} \qquad (1.7)$$

Where : $\Delta C = Cb - Cp$ (1.8)

Here, *Cb* is the concentration of the solute (salt) at the boundary layer/bulk feed flow and *Cp* is the concentration of solute (salt) in the permeate. The boundary layer is a layer of laminar feed water flow and elevated salinity that forms near the surface of the membranes as a result of the tangential source water feed flow in the spacers and of permeate flow in a perpendicular direction through the membranes on the two sides of the spacer (Fig. 1.15). In Fig. 1.15, *Cb* is the concentration of the solute (i.e., salt) in the feed water, *Cs* is the concentration at the inner membrane surface (which typically is higher than that in the feed flow), and *Cp* is the concentration of the solvent (i.e., freshwater salinity) on the low-salinity (permeate) side of the membrane [1].

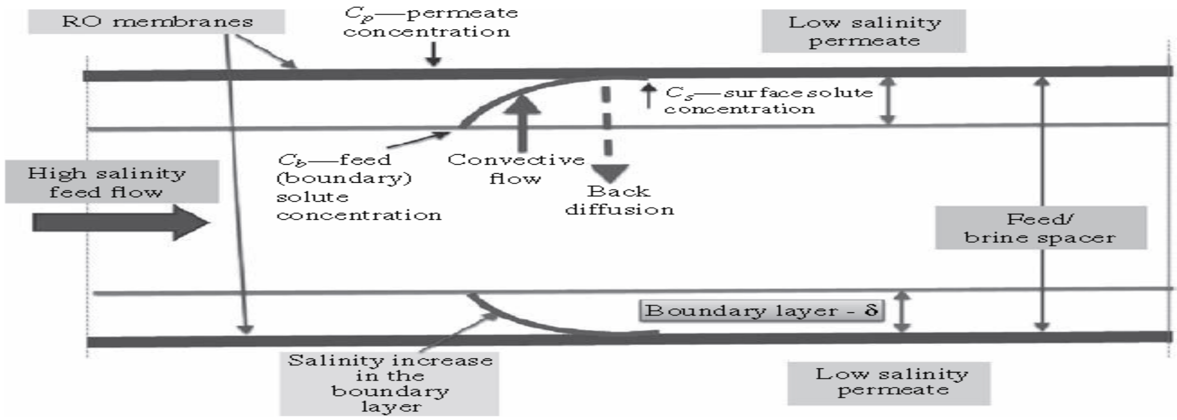


Figure 1.16 Boundary layers in a membrane feed spacer [1].

Feed flow *Qf* - is the rate of feed water introduced to the membrane element or membrane system, usually measured in gallons per minute (gpm) or cubic meters per hour (m3/h) [2].

$$Qf = Qp + Qc \qquad (1.9)$$

Concentrate flow *Qc* - is the rate of flow of non-permeated feed water that exits the membrane element or membrane system. This concentrate contains most of the dissolved constituents originally carried into the element or into the system from the feed source. It is usually measured in gallons per minute (gpm) or cubic meters per hour (m3/h) [2].

***Osmotic Pressure Op*-** for a given saline water is calculated by measuring the molar concentrations of the individual dissolved salts in the solution and applying the following equation:

$$Op = R \times (T + 273) \times\_mi \qquad (1.10)$$

where : *Op* = the osmotic pressure of the saline water (in bars—1 bar = 14.5 lb/in2)

R = the universal gas constant [0.082 (L·atm)/(mol·K) = 0.0809 (L·bar)/(mol·K)]

T = the water temperature in degrees Celsius, and Σ*mi* is the sum of the molar concentrations of all constituents in the saline water. This formula is derived from Van't Hoff's thermodynamic law, which is applied to pressure caused by dissociation of ions in solution (Fritzmann et al., 2007) [1].

***Net driving pressure* NDP-** also known as *transmembrane pressure*, is the actual pressure that drives the transport of freshwater from the feed side to the freshwater side of the membrane. The average NDP of a membrane system is defined as the difference between the applied feed pressure *Fp* of the saline water to the membrane and all other forces that counter the movement of permeate through the membrane, including the average osmotic pressure *Op* which occurs on the permeate side of the RO membrane, the permeate pressure *Pp* existing the RO pressure vessel, and the pressure drop *Pd* across the feed/concentrate side of the RO membrane. The NDP can be calculated as follows:

$$NDP = Fp - (Op + Pp + 0.5Pd) \tag{1.11}$$

The applied feed pressure *Fp* is controlled by the RO system operator and delivered through high-pressure feed pumps. The average osmotic pressure *Op* of the membrane is determined by the salinity and the temperature of the source water and the concentrate. The permeate pressure *Pp* (also known as *product water back pressure*) is a variable that is controlled by the RO plant operator and is mainly dependent on the energy needed to convey permeate to the downstream treatment and/or delivery facilities [1].

C) Factors Affecting Reverse Osmosis

Permeate flux and salt rejection are the key performance parameters of a reverse osmosis or a nanofiltration process. Under specific reference conditions, flux and rejection are intrinsic properties of membrane performance. The flux and rejection of a membrane system are mainly influenced by variable parameters including:

- pressure
- temperature
- recovery
- feed water salt concentration

C.1) Effect of Feed Pressure on Membrane Performance

membrane flux (productivity) increases along with operating feed pressure at the same source water salinity and temperature. This occurs because the increase of feed pressure results in a proportional increase of the net driving pressure through the membrane (Fig1.17) [1].

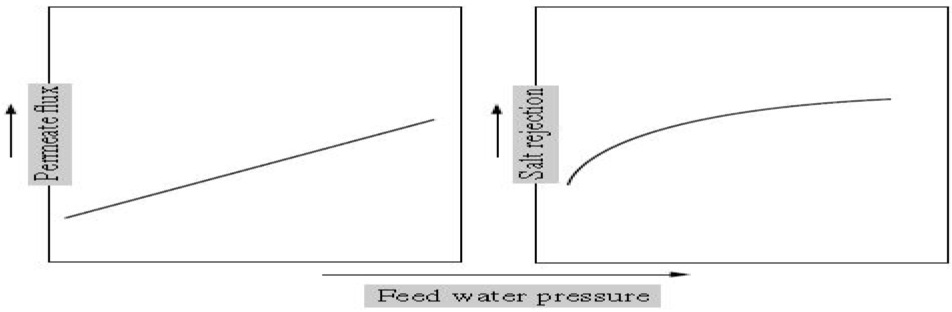


Figure 1.17 Effect of feed pressure on RO system performance [1].

C.2) Effect of Temperature on Membrane Performance

The use of warmer water reduces saline water viscosity, which in turn increases membrane permeability. Some of this beneficial impact is reduced by the increase of osmotic pressure with temperature (Eq. 1.10). However, the overall impact of temperature for most membranes is typically beneficial (Fig. 1.18). As a rule of thumb, the permeate flux increases by 3% for every 1°C of temperature increase. Because most RO membranes are made of plastic materials (polymers), warmer temperatures result in a loosening up of the membrane structure, which in turn increases salt passage (i.e., deteriorates permeate water quality). It should be pointed out that, as seen in Fig. 1.18, the rate of permeate flux gain is typically much higher than the rate of deterioration of product water quality. For source water temperatures up to 30°C (86°F), using warmer water allows reduction of the feed pressure and energy used for desalination (Greenlee et al., 2009). Because of the negative impact of temperature on osmotic pressure, operation at higher temperatures may or may not be beneficial. In addition, the use of warmer water accelerates biological fouling, which in turn also reduces membrane permeability. Operating conventional spiral-wound RO membranes at temperatures above 40°C (104°F) accelerates the compaction of the membrane support layer and is undesirable because it results in a premature and irreversible loss of membrane permeability. Most membrane suppliers recommend that the temperature of the source water processed by RO membranes should be maintained below 45°C(113°F)at all times to avoid permanent membrane damage. [1].

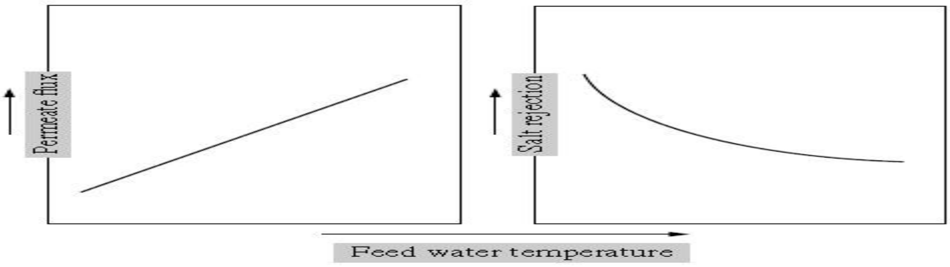


Figure 1.18 Effect of temperature on RO system performance [1].

C.3) Effect of Recovery on Membrane Performance

As indicated in Fig. 1.19, an increase in recovery results in a slow decrease in permeate flux until it reaches the point at which osmotic pressure exceeds the applied pressure and NDP is inadequate to drive flow through the membrane; at that point, freshwater flow production is discontinued [1].

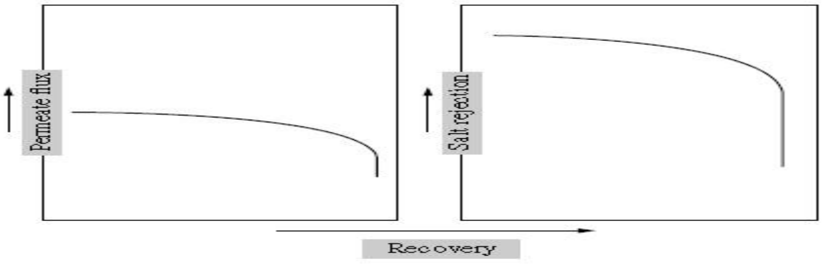


Figure 1.19 Effect of recovery on RO system performance [1].

C.4) Effect of Salinity on Membrane Performance

Figure 1.20 illustrates the effect of source water salinity (TDS concentration) fed to an RO system on the system's productivity of freshwater (permeate flux) and product water quality (salt rejection). Higher feed water salinity reduces the net driving pressure (assuming that the system is operating at the same feed pressure and recovery) because of the increased osmotic pressure of the feed water, which in turn decreases permeate flux (freshwater production). In terms of salt transport, an increase in feed water salinity increases the salt concentration gradient (ΔC in Eq. 1.8), which results in accelerated salt transport through the membranes and therefore, in lower salt rejection (deteriorating product water quality) [1].

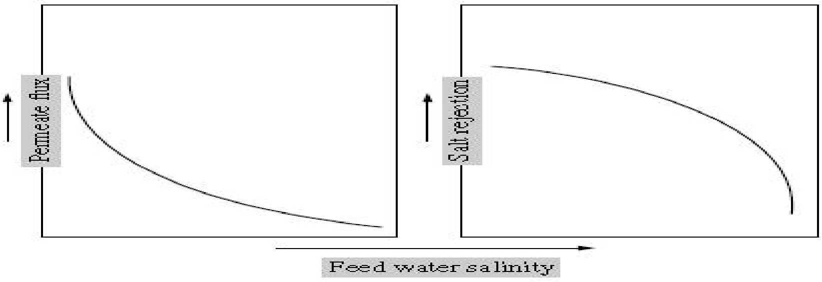


Figure 1.20 Effect of salinity on RO system performance [1].

D) Membrane Desalination Plants

As with any other natural water source, seawater contains solids in two forms: suspended and dissolved. Suspended solids occur in the form of insoluble particles (particulates, debris, marine organisms, silt, colloids, etc.). Dissolved solids are present in soluble form (ions of minerals such as chloride, sodium, calcium, magnesium, etc.).

At present, practically all RO desalination plants incorporate two key treatment steps designed to sequentially remove suspended and dissolved solids from the source water. The purpose of The first step source water pretreatment is to remove the suspended solids and prevent some of the naturally occurring soluble solids from turning into solid form and precipitating on the RO membranes during the salt separation process. The second step the RO system separates the dissolved solids from the pretreated source water, thereby producing fresh low-salinity water suitable for human consumption, agricultural uses, and for industrial and other applications.

Once the desalination process is complete, the freshwater produced by the RO system is further treated for corrosion and health protection and disinfected prior to distribution for final use. This third step of the desalination plant treatment process is referred to as post-treatment. Figure 1.21 presents a general schematic of a seawater desalination plant. The plant shown in Fig. 1.21 collects water using open ocean intake, which is conditioned by coagulation and flocculation and filtered by granular media pretreatment filters to remove most particulate and colloidal solids, and some organic and microbiological foulants. The filtered water is conveyed via transfer pumps through micronsize filters (cartridge filters) into the suction headers of high-pressure pumps. These pumps deliver the filtered water into the RO membrane vessels at a net driving pressure adequate to produce the target desalinated water flow and quality.

The reverse osmosis vessels are assembled in individual sets of independently operating units referred to as *RO trains* or *racks*. All RO trains collectively are termed the *reverse osmosis system*. The RO system usually has energy recovery equipment that allows it to reuse the energy contained in the concentrate for pumping of new source water into the membrane system. The permeate generated by the RO trains is stabilized by addition of lime or contact with calcite and by the addition of carbon dioxide to provide an adequate level of alkalinity and hardness for protection of the product water distribution system against corrosion. The conditioned water is stored and disinfected prior to delivery to the final users. The particulate solids removed from the source water by the pretreatment filters are collected in the filter backwash and further concentrated by thickening and dewatering for ultimate off-site disposal to a sanitary landfill. While this solids handling approach is adopted by many of the most recently built desalination plants, in some older facilities the concentrate and backwash water are mixed and disposed to the water body used for source water collection [1].

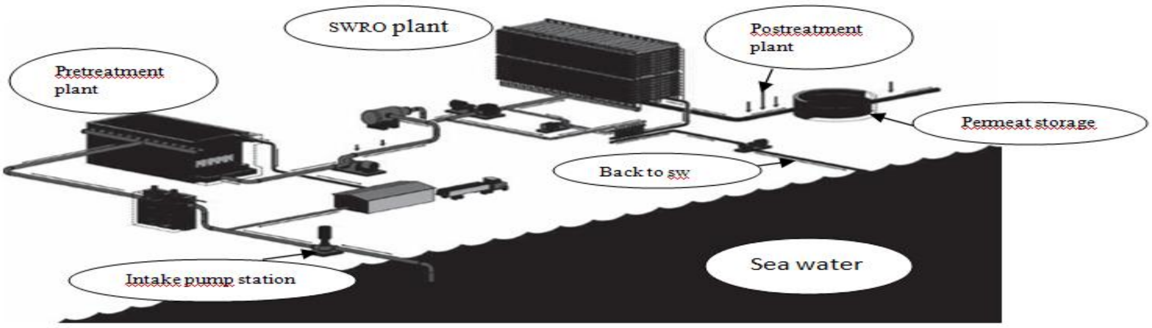


Figure 1.21 Schematic of a typical seawater desalination plant [1].

E) SWRO train components

As indicated in the previous section, RO membrane elements are installed in pressure vessels that are eight elements per vessel. Multiple pressure vessels are arranged on support structures (referred to as skids or racks). The skids are typically made of powder-coated structural steel, plastic-coated steel, or plastic. The combination of RO feed pump, pressure vessels, feed, concentrate and permeate piping, valves, couplings, and other fittings (energy-recovery system and instrumentation and controls) installed on a separate support structure (skid/rack), which can function independently, is referred to as RO train. Each RO train is typically designed to produce between 10 and 20 % of the total amount of the membrane desalination product water flow. Figure 1.22 depicts one SWRO train equipped with a pressure exchanger- type energy-recovery system. The RO trains are configured and designed such that each individual train is capable of independently controlling total permeate and concentrate flows [1].

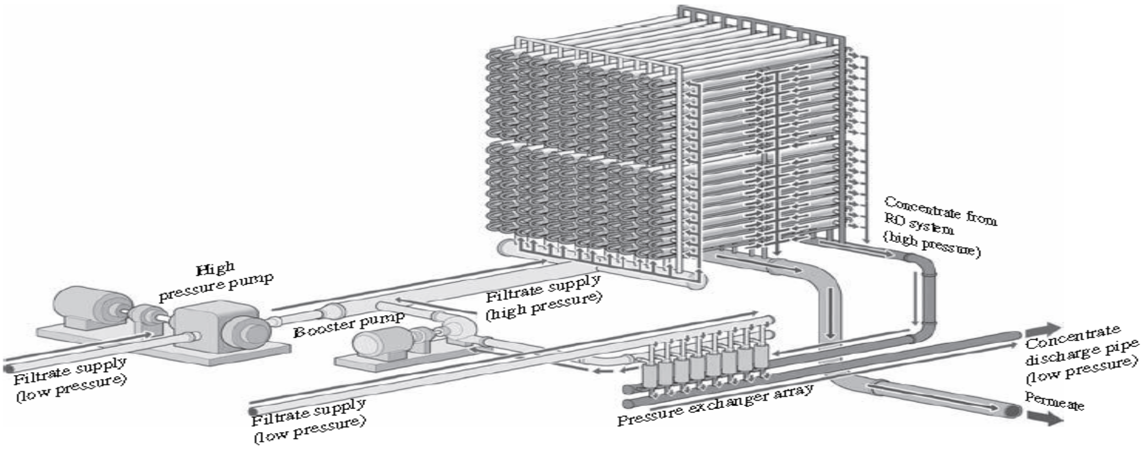


Figure 1.22 SWRO train with an isobaric energy-recovery system [1].

E.1) Filtered Supply Pump

Filtered water transfer pumps are typically vertical turbine or horizontal centrifugal pumps designed to convey filtered water to the RO system. As indicated previously, filtered water from the plant pretreatment system or plant intake (if it is of adequate quality) for desalination plant with an interim filtered water transfer , a separate pump station is installed to boost the filtered source water to the suction pressure needed for the efficient operation of the high-pressure RO pumps. In state-of-the-art designs of SWRO systems, the filtered water transfer pumps are often equipped with variable frequency drives (VFDs) to allow for the feed pressure of the RO system to be cost-effectively controlled by the feed pressure of the filtered water transfer pumps. Such control is often needed because seasonal (and sometimes diurnal) changes in source water temperature and salinity have an impact on the osmotic pressure and net driving pressure (NDP) needed for desalination which in turn require the adjustment of the RO membrane feed pressure. As source water temperature decreases and/or salinity increases, the NDP and feed pressure needed to produce the same volume of permeate increase and vice versa. In order to maintain the high-pressure RO feed pumps at their maximum performance efficiency and constant feed flow at all times, the pressure they deliver has to be adjusted to match the changes in osmotic pressure (and related NDP) triggered by source water-quality fluctuations. Installation of VFDs results in overall reduction of plant energy use. While pressure delivered to the RO vessels could alternatively be controlled by installing VFDs on the high-pressure RO pumps, because the cost of the VDFs is proportional to the size of the pump motor and usually the size of the motor of the transfer pumps is an order of magnitude smaller than the size of the motor of the high-pressure pumps significant equipment cost savings can be obtained by installing the VFDs on the filter effluent transfer pump motors instead of on the RO feed high-pressure pump motors and this holds especially true for SWRO desalination systems [1].

E.2) High-Pressure Feed Pumps

High-pressure feed pumps are designed to deliver source water to the RO membranes at pressure required for membrane separation of the fresh water from the salts, which typically is 55 to 70 bars (798 to 1015 lb/in2) for seawater desalination. The actual required feed pressure is project and water-quality specific and is mainly determined by the source water salinity, temperature, target product water quality, and the configuration of the RO system.

The pumps are sized based on required flow and operating pressures using standard performance curves supplied by pump manufacturers. All wetted pump materials should be of adequate-quality stainless steel, which is a function of the salinity of the water they process. Duplex and super-duplex stainless steel is recommended for high-salinity BWRO and SWRO applications, respectively [1].

High-Pressure Pump :

It has no VFD installed on its motors, then its feed flow and pressure is adjusted via a pressure control valve (Fig. 1.23). This valve is throttled along with the flow control valve installed on the concentrate pipe to set RO system operations at target recovery, feed flow, and pressure. As RO membranes age over time, their permeability, and therefore their productivity decreases irreversibly. Typically, an RO system loses 8 to 15 % of its initial productivity over a period of three to five years. In order to compensate for this loss of productivity, usually the RO high-pressure pumps are oversized to deliver 10 to 15 % higher pressure and flow than their initial design levels for new RO membranes.

Permeate backpressure valve (Fig. 1.23) is installed to control, within certain limits, the Beta factor (i.e., reduce concentrate polarization) in order to improve product water quality and reduce membrane fouling rate. The ability to control flux and fouling by back pressure is limited due to potential for thin-film delamination if permeate backpressure exceeds 0.3 bar (4.3 psi) above the concentrate pressure. Because of the high pressures at which RO feed pumps operate, when this pump are started their feed pressure has to be increased gradually [not more than 0.7 bars (10 lb/in2) per second] until it reaches its design level in order to avoid hydraulic surge in the feed line. Depending on their severity, hydraulic surges could dislodge the membranes within the vessels, cause O-ring breaks and membrane compaction, and result in membrane leaf telescoping and cracking of the outer shell of the membrane elements. For larger desalination plants, the RO pump motors usually are designed with "soft start" provisions, which control the motor speed at start-up in order to avoid hydraulic surges. In addition, motorized valves on the RO system feed and concentrate are typically designed to have adequately long actuation time for pressure surge prevention.

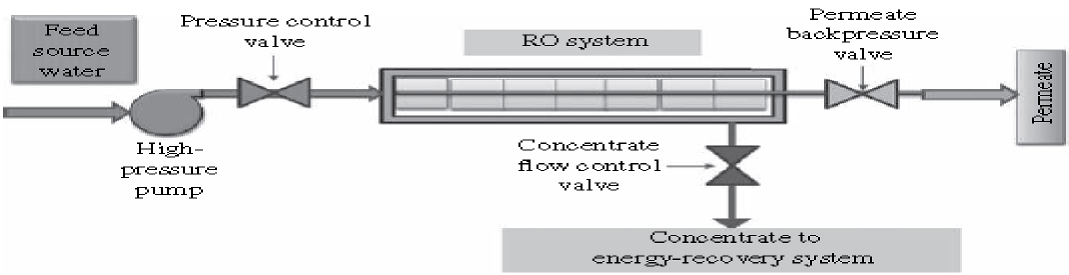


Figure 1.23 Main RO system control valves [1].

Horizontal spit-case multistage centrifugal pumps are most commonly used as high-pressure feed pumps for medium- and large-size SWRO desalination plants (Fig. 1.24). These pumps usually yield high efficiency (80 to 88 percent). The feed water inside the pumps is guided from stage to stage by a set of volute passageways and the pump impeller has an opposing surface direction design, which allows reducing a pump's net axial trust [1].

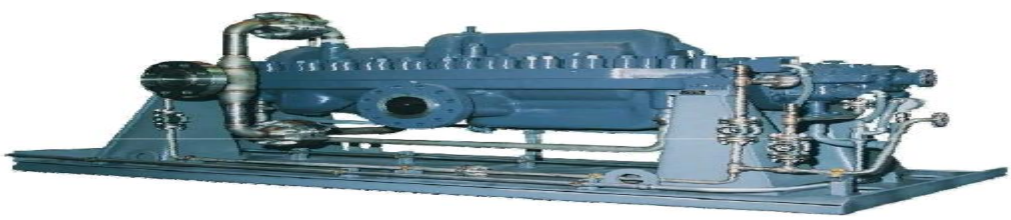


Figure 1.24 Horizontal spit-case multistage centrifugal pumps [1].

Booster Pump :

It is of end-suction single stage radially split pump type ,Such pumps are typically used for small- and medium-size desalination plants and are combined with a specific type of energy-reco very device (PX), which operate on a common shaft with the RO feed pumps and boost their pressure by applying energy recovered from the RO system concentrate. Its variable frequency drive is installed on its motors to adjust motor speed in order to maintain optimum pressure lost across the membrane and ERI, with changing feed pressure requirements driven by natural fluctuations in source water salinity and temperature. In addition, VFD allow for the pumps to maintain optimum performance when membranes foul or scale and loose permeability over time [1].

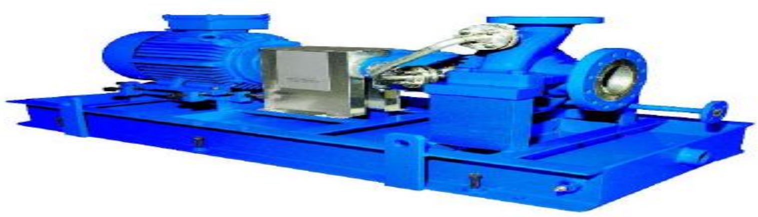


Figure 1.25 Horizontal spit-case multistage centrifugal pumps [1].

E.3) Instrumentation and Control

Instrumentation and control systems can be as basic as a manual control with automatic shutdown features for pump and membrane protection or as complicated as a supervisory control and data acquisition (SCADA) system. SCADA systems are often based on programmable logic controllers and remote telemetry units that are supervised by a host computer located in a control room near the membrane skids and high-pressure pumps. Systems designed for automatic control can monitor chemical feed systems, and they have alarm and report-generation capabilities. In many facilities, a personal computer is also used for membrane train performance normalization calculations and graph preparation, which facilitates plant performance monitoring and making of decisions on when to clean the membranes. The basic instrumentation required to monitor and control any RO system consists of control valves and devices for measuring flow, pressure, conductivity, pH, temperature, and liquid levels. Instrument location is selected such that the instruments are subjected to significant vibrations and undue turbulence. Instruments should be easily accessible because they require frequent calibration and repairs.

Magnetic Flow Meters

Magnetic flow meters are popular flow-measurement devices in large-capacity membrane plants. This equipment can be used on most water streams encountered in RO plants with the possible exception of some permeate streams. Low conductivity (i.e., 20 mS/cm or lower) water will not give an accurate flow reading, so these meters need to be carefully selected. Vortex shedding meters can be used for low conductivity applications. Typically, flow meters used at membrane plants are pulsed DC electromagnetic induction-type, which provide a signal proportional to the liquid flow rate. The recommended meter accuracy is plus or minus 0.1 percent of reading. All flow meters that are used at the desalination plant have to be factory calibrated. Magnetic meters have to be grounded per manufacturer’s recommendations. A NFMA 4X flow converter/ transmitter matched to the flow meter is typically provided for meters generating remote data signals. The output should be 4-20 mA into 0-1000 ohms. A local indication of actual flow rate and totalization display should be provided. The key advantages of magnetic flow meters, as compared with other alternative types of meters, are that the flow stream is completely free from obstacles, and, as a result, the headlosses through the meter are minimal. In addition, magnetic flow meters usually have a wider measuring range than most other types of flow meters. However, sometimes, when pipeline headloss is not a limiting factor, Venturi meters are used for measuring large plant intake flows. Venturi meters are lower-cost/lower-accuracy flow meters, which also could be equipped with remote data transfer.

Rotameters

These flow measurement devices are suitable only for small package plants and are acceptable low-cost equipment for local indication of small-volume chemical feed flows. Although rotameters can be supplied with a flow signal transmitter, this configuration is uncommon. Rotameter accuracy is sensitive to the viscosity and density of the measured liquid and to the concentration of particulates in the measured stream.

Electronic Pressure Transmitters

Electronic pressure transmitters can provide reading accuracy of 0.1 percent of their span, which is important when measuring differential pressures in critical locations at the desalination plant. These pressure transmitters can be electronically zeroed. The differential pressure transmitters are usually diaphragm actuated, microprocessor based type. They are equipped with loop-powered units with a 4-20 mA output. Each transmitter is typically provided with stainless-steel mounting hardware and a fiveway manifold. Differential pressure transmitters are used to measure the pressure drop across the following key treatment plant facilities:

• Pretreatment filters (if pressure type pretreatment filters are used)

• Cartridge filters

• Membrane train stage feed, inter-stage, concentrate, and/or stage and overall train differential pressure (feed to concentrate)

Conductivity Analyzers

The quality of the source and product water is typically monitored by conductivity analyzers.

The conductivity sensor is an in-line-type sensor unit with a local indication and a transmitter for remote accurate continuous monitoring, indicating, and recording. Although conductivity meters are usually installed on-line, valved sample points for measuring conductivity/salinity using portable apparatus should also be provided at key locations, such as the source water intake pump station, feed to the RO membrane system, concentrate discharge, and the product water lines from the individual RO trains. Conductivity is measured in μS/cm (micro-Siemens per centimeter). Typically, high conductivity readings from the analyzer located on the permeate lines from the individual RO membrane trains trigger alarm locally and remotely at the central control room.

Temperature and pH Analyzers

Online electronic pH and temperature analyzers and transmitters are widely used in RO desalination plants. Online temperature analyzers are recommended to be installed on the feed line to the RO system, if the water temperature is expected to vary significantly (more than 50°C/10°F from the annual average temperature). A pH analyzer is typically installed as a min on the product water line.

Liquid-Level Sensors

The type and operational parameters of the liquid level sensors are the same as those used in conventional water treatment plants. Ultrasonic-type level sensors/transmitters are commonly used for water tanks/wells with a relatively quiescent surface, such as product water storage and chemical feed tanks. Usually, the liquid level sensors are potted/encapsulated in corrosion-resistance housing. These sensors are provided with automatic air temperature and density compensation. A microprocessor-based transmitter/converter converts the sensor output signal to level. Level measurement accuracy of most sensors is plus or minus 1.0 percent. The output is an isolated 4-20 mA signal. For outdoor mounted units NEMA 4X enclosures with sun-shields are provided. Liquid level signals for all key tanks and pump wet wells are transmitted to the PLC and the desalination plant control room workstations for continuous monitoring and alarm generation .[1].

E.4) Pressure Exchanger

The pressure-exchanger (PX) technology developed by Energy Recovery International (ERI) consist of individual fiberglass vessels connected to common feed and concentrate manifolds, each of which contains a ceramic rotor with a number of cylinders (rotor chambers). In sequential process, the rotor chambers are filled up with low pressure pretreated seawater, rotated by the flow of water itself and then exposed to high-pressure concentrate, which pressurizes this water out of the rotor chamber and delivers it into the RO feed line. As the concentrate pushes out the fresh water from the cylinder, it transfers its energy to it, and, at the end the cycle, the same cylinder contains only low-pressure concentrate. This cylinder is then rotated and exposed to filtered water with pressure higher than that of the low-pressure concentrate, which pushes it out of the cylinder and restarts the cyclic process (Fig. 1.26). Since there are no physical pistons to separate the concentrate from the feed water, some mixing of the two occurs in the contact zone. At present, ERI pressure exchangers are the most widely used ERDs in medium and large SWRO plants worldwide. Figure 1.26 shows an example of the flow distribution of the ERI system for the Jeddah SWRO desalination plant in Saudi Arabia. It is advisable to contact the ERD supplier for assistance with the design and configuration of the ERD system for the site-specific conditions of a given project [1].

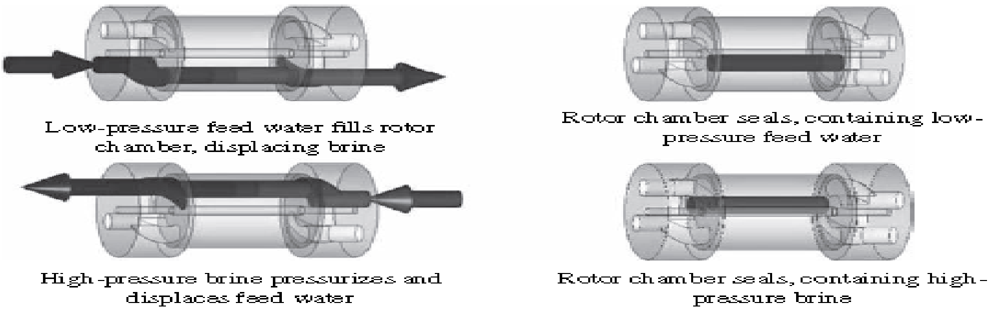


Figure 1.26 Working sequence of ERI pressure exchanger (*Source: ERI*).

I.3 Fouka station presentation

Fouka desalination station is a desalination plant, located approximately 35 km west of Algiers, its exploitation is done by the reverse osmosis process. Commissioned in early August 2011 and was built with a total capital expenditure of 180.5 million dollars. The Fouka desalination plant was built as part of a program colossal program launched by the Algerian government in 2000. With this program, the government intends to build 12 desalination plants that can produce a total of 2.26 million cubic meters of water per day. The Fouka desalination plant is designed to cover drinking water needs of the region of Zéralda and the western part of Algiers, which is the capital of the country and its largest city. The daily water treatment capacity of the plant is 120,000 cubic meters and it will cover the needs of 17 municipalities. The daily capacity of 120,000 m3 is subdivided into 60,000 m3 intended for Algiers and 60,000 m3 will be reserved for the wilaya of Tipasa for the communes of Douaouda, Fouka, BouIsmail, Chaiba, Birar, Bouharoune. The part reserved for Algiers will affect the municipalities bordering the wilaya of Tipaza, namely: Zéralda, Maelma, Staoueli and Aïn Benian. The share capital of Myah Tipaza Spa is distributed as follows: - Algerian Water Investment, S.L. (50% SNC Lavalin International Inc. / 50% Acciona Agua S.A.U.): with 51%. - Algerian Energy Company Spa: 49%. The investment amount is 180,514,000 USD with a capital of 20% and the remainder of the amount, i.e. 80%, was borrowed by the banks (CPA, BNA, BDL, BEA). The price of m3 of treated water: 0.7505 USD/m3 (52.73 DA/m3) and water buyers are: SONATRACH and ADE. The station is designed to serve a population of more than half a million people.

Figure 1.27 Explanatory diagram of the Capital of the company Myah Tipaza

The site of the Fouka seawater desalination plant is located in the wilaya from Tipaza, 20 km from the capital of the wilaya and about 35 km west of Algiers, it is criss-crossed by national road No. 11 coming from Algiers and heading towards Chlef and connected to Koléa by wilaya road N°110 and to Bousmail by wilaya road N°126. The commune of Fouka covers an area of 1,273 ha and is located in the North-East of the town of Tipaza. It is limited: - In the North: by the Mediterranean Sea. - In the South: through the commune of Koléa. - To the East: through the commune of Douaouda. To the West: through the commune of Bousmail. The site considered for the desalination plant covers an area of 4 hectares, and has a length of 300 m and a width of up to 150 m. Its tation plan includes a water production plant potable:

1- Sea water intake. 2- Sea water pumping station. 3- Pretreatment facility. 4- Reverse osmosis system. 5- Remineralization and Post-treatment System. (Lime & CO2). 6- Treated water pumping station. 7- Effluent treatment. 8- CO2 production system. 9- Deposit of chemicals. 10- 60 KV electrical substation. These constituents of the station are arranged according to the diagram given in the figure next :

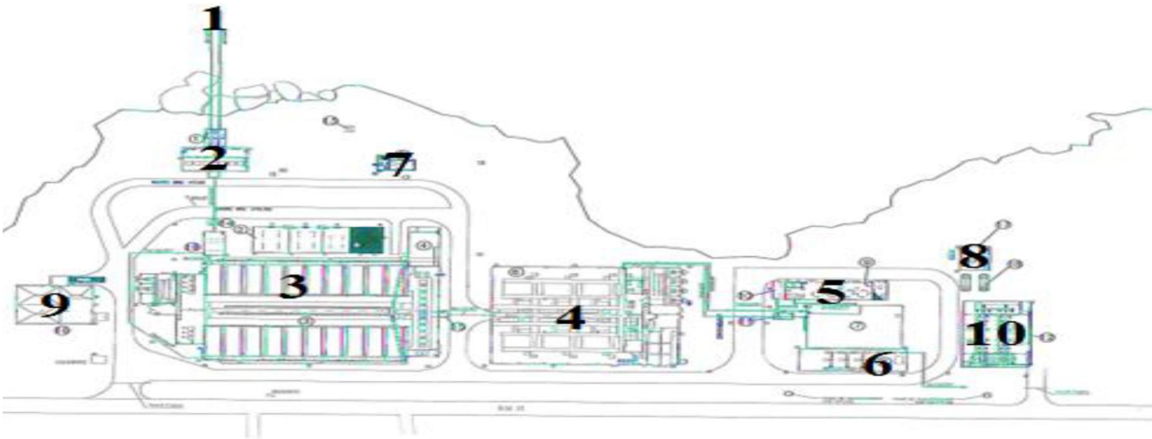


Figure 1.28 Fouka Desalination Station Plan

1. Sea water intake : Catchment Tower Made up of two steel towers and resting on a stable seabed, the openings water inlet are at a height of 6 m. To avoid the aspiration of solids into suspension and debris, bars 20 mm thick, spaced 100 mm apart are installed at the entrance to the tower. Feed pipe :Two pipes designed in High Density Polyethylene (HDPE) with a diameter of 1,600 mm convey the water to the catchment building passing through a filtration grid over a length of 845 m.

Fig 1.29 supply pump

2. The seawater pumping station pumps the water up to the filtration system. Its is made up of seven pumps (six of which are in operation and one as backup) for a capacity of 230 KW delivering 1,900 m3/h. A pump model is represented by the following figure:

Figure 1.30 Seawater pumping station

3. Pretreatment and filtration system consist of : Sand filters in order to bring the water to the necessary quality before passing over the membranes In reverse osmosis the water undergoes pretreatment or firstly the water passes through filters open, the number of which is twenty (Figure 1.30), made up of a layer of fine sand which prevents any particle larger than 20 μm from passing through, and a layer of anthracite, too known as activated carbon. Cartridge filters In order to filter small particles that may escape from sand filters and protect thus the membranes against clogging, cartridge filters (Figure 1.31) capable to filter particles down to 1 μm are installed upstream of the osmosis units. When the pressure drop across the cartridge filters exceeds a preset value (approximately 1.5 bar), the filter cartridge must be replaced. Replacement frequency is estimated at around 4 times per year. The third one is seawater treatment which consists of two steps: Pre-chrolination which is intended for raw water (i.e. chlorine gas; where calcium hypochlorite; where sodium hypochlorite) (970 l/h), The latter is used as a shock treatment for water the entrance to the station to limit the formation of biofilm in the water intake pipes and filters. Sulfuric acid It is injected at (350 l/h) to reduce the PH of seawater to value 7 before its input to the filters. The objective of this reduction is to: - Guarantee the bactericidal effect of chlorine; - Help the performance of the coagulant; - Avoid precipitation of $CaCo_3$ inside the membranes.

Figure 1.31 Sand filters

Figure 1.32 Cartrige filters

4. Reverse osmosis system : The reverse osmosis system is made up of 9,072 identical membrane elements (Figure 1.32), arranged in parallel in six racks with a unit capacity of 20,000 m3/day for total net production 120,000 m3/day based on raw water supply approximately 273,697 m3/day. Production is spread over a period of 24 hours/day, i.e. 5,000 m3/hour. The reverse osmosis system is composed of: - A high pressure pump; - A booster pump; - An energy recovery device; - Six racks of 216 pressure tubes each, where there are seven membranes in each tube vessel. The reverse osmosis system is designed in a modular way. It is composed of six (6) reverse osmosis units with a unit capacity of 20,000 m3/day each. In addition, the plant will be able to operate with one (1) of the two (2) water intake pipes off. It will then be possible to pass 100% of the flow in a single pipe for a production of 120,000 m3/day.

Figure 1.33 RO Rack

5. Effluent treatment Process discharges include concentrate (brine), discharge water lime saturators, filter washing water, membrane washing water. This water is routed to the effluent treatment tank (neutralizer) (Figure 1.33) and from there, towards the outfall made up of a polyethylene pipe with a diameter of 1400mm. The discharge point, 450 m from the coast, and equipped with a diffuser which allows almost immediate dilution of the discharge water into sea water, so as not to disturb the ecosystems.

Figure 1.34 Effluent treatment tank

6. Remineralization and CO_2 production system Demineralized water (permeate) is aggressive water that must be remineralized to meet the potability criteria. To this end, the factory is equipped with a system of remineralization which includes a CO_2 production unit from natural gas, and also a milk of lime dosage unit, these products are added to the water in order to remineralize it.
7. Treated water pumping station After remineralization the water is stored in a 3,600 m3 treated water tank, where it undergoes a final disinfection with calcium hypochlorite. The water is then

pumped back towards the external network by seven pumps (including six in operation and one in emergency), (Figure 1.34), 800 KW delivering 833 m3/h at 240 m total head.

Figure 1.35 Treated water pumping station.

8. 60 KV electrical substation The continuous supply of electricity to the factory is essential. It is ensured by two dedicated 60 KV SONELGAZ lines, supplying a transformation station made up of two 30 MVA transformers with an output voltage of 6,000 V (Figure 1.35).

Figure 1.36 30 MVA transformer.

9. External distribution network The water produced is conveyed by: - A 900 mm diameter ductile iron pipe with a length of 5 km to the reservoir Hai Mouaz of 30,000 m3 to supply localities in the east of the wilaya of Tipaza. - A 900 mm diameter ductile iron pipe with a length of 10 km towards the Sahel reservoir of 30,000 m3 to supply localities in the west of the wilaya of Algiers.

I.4 PX devices in SWRO Systems

The PX energy recovery device fundamentally changes the way a SWRO system operates. The issues presented in this and the following sections should be taken into consideration when designing a SWRO system. In addition, engineers at Energy Recovery, Inc. are available for design consultation and review of process and instrumentation diagrams.

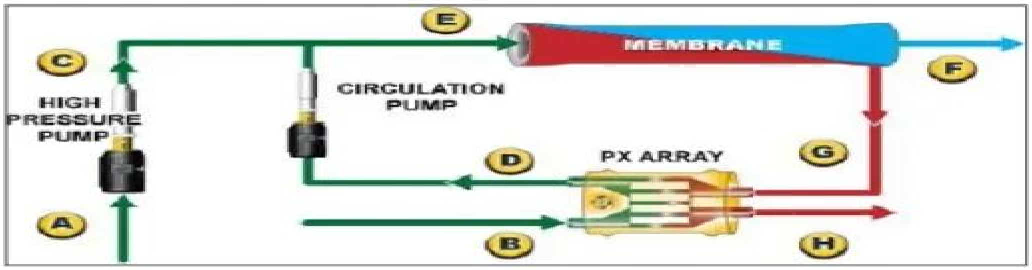


Figure 1.37 the typical flow path of SWRO system with a PX unit [3].

Figure 1.37 illustrates the typical flow path of a PX energy recovery device in a SWRO system. The reject brine from the SWRO membranes [G] passes through the PX unit, where its pressure is transferred directly to a portion of the incoming raw seawater at up to 98% efficiency. This pressurized seawater stream [D], which is nearly equal in volume and pressure to the brine reject stream, passes through a circulation pump. The circulation pump propels flow in the high- pressure loop [E-G-D] at a rate controlled by a variable frequency driver on the motor. Fully pressurized seawater from the circulation pump merges with the high-pressure pump discharge to feed the membranes.In a reverse osmosis system equipped with PX Pressure Exchanger energy recovery devices, the membrane brine reject is directed to the membrane feed as illustrated in Figure1.37. The rotor, moving between the high-pressure and low low-pressure streams, removes the reject concentrate and replaces it with feed water. The rotor spins freely, driven by the flow at a rotation rate proportional to the flow rate and lubricated by high-pressure process water. Unlimited capacity is achieved by arraying multiple PX devices in parallel. The PX devices and the check valve at the discharge of the high-pressure pump seal the high- pressure portion of the RO process. During RO-process operation, water is introduced to the high-pressure loop [D-E-G] by the high-pressure pump as stream C. Almost all of this water exits as permeate and the rest flows through narrow gaps that surround the PX device rotor, lubricating the rotor. Lubrication flow is typically about 0.5% of the total flow from the high- pressure pump and is measurable as the difference between the high-pressure pump flow rate [C] and the permeate flow rate [F]. The flow delivered by the high-pressure pump and the resistance to permeate and lubrication flows provided by the membrane elements and the PX devices, respectively, pressurize the high-pressure loop.

In a SWRO system with an ERI energy recovery device installed, the high-pressure (HP) pump is sized to equal the SWRO permeate flow plus a small amount of bearing lubrication flow, not the full SWRO feed flow. Therefore, PX energy recovery technology significantly reduces flow through the main HP pump. This point is significant because a reduction in the size of the main HP pump results in lower capital and operating costs. In a typical SWRO system with a PX unit operating at 45% recovery, the main HP pump will provide 46% of the energy, the booster will provide 2% and the PX

unit will provide the remaining 52%. Since the PX unit uses no external power, a total energy savings of 52% is possible compared to a system with no energy recovery.
An SWRO system with ERI energy recovery device(s) can operate efficiently at low recovery rates because the PX units supply the majority of the membrane feed with just the energy required to drive the circulation pump. One advantage of operating at lower recoveries with PX energy recovery devices is that a lower operating pressure is required to produce a given amount of permeate. The overall energy consumption of a SWRO plant using the PX energy recovery device typically reaches its minimum point at recovery rates of between 35-45%. Outside this recovery range, the SWRO process consumes more power to make the same amount of permeate. At lower recovery rates, the supply and pretreatment system consume excess energy. At higher recovery rates, the high-pressure pump consumes excess energy because of the higher membrane pressure. Figure 1.38 illustrates the relationship between SWRO recovery rate and overall SWRO power consumption.

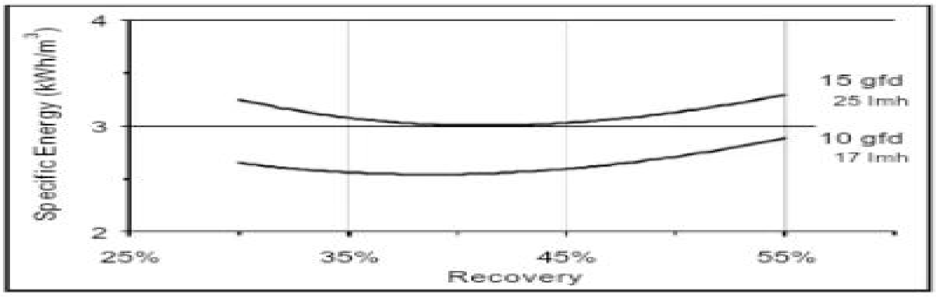


Figure 1.38 SWRO Energy Consumption versus Recovery Rate [3].

The operator can manipulate recovery to optimize RO system performance and/or compensate for feed water changes. Changing recovery in an SWRO system equipped with PX technology is easy. The variable frequency drive on the circulation pump motor is adjusted to change high- pressure flow rate through the PX device, the circulation pump and the membrane array. Then the flow rate of supply water to the PX device is adjusted to assure equal flow rates of seawater to and from the PX device. As long as the flow rates and pressures to the PX device are within the rated capacity, pressure transfer efficiency and mixing will change very little [3].

A) PX Energy Recovery Device Performance and its Rotor Lubrication

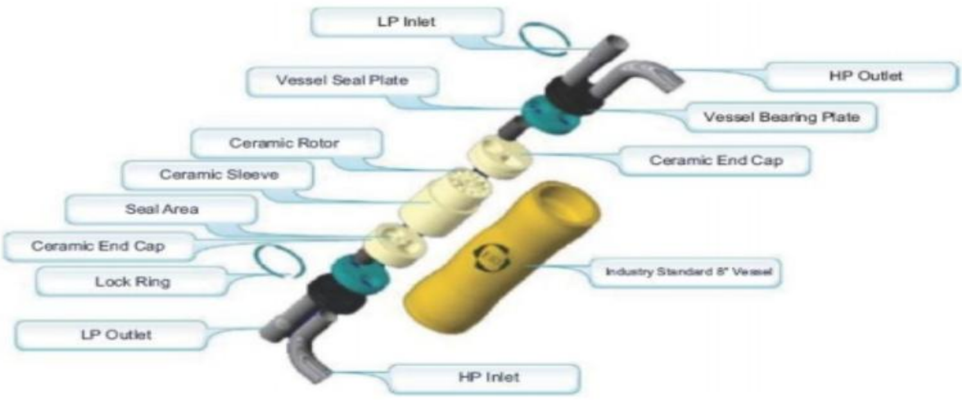


Figure 1.39 Pressure Exchanger Unit Components [3].

There are no direct controls on a PX device. The rotor is turned by the flow at a rotation rate that is proportional to the flow rate. Therefore, the flow rate, pressure, and quality of the feed streams to the PX unit must be monitored and controlled. Operation and control of a PX unit in a SWRO system can be understood by visualizing two parallel pipes, one with high-pressure water and one with low-pressure water flowing through the PX unit. With reference to Figure 1.36, the high-pressure water flows in a circuit through the membranes, the PX unit or PX unit array, the circulation pump, and back to the membranes [E-G-DE] at a rate controlled by the circulation pump equipped with a variable frequency drive. The low-pressure water flows from the seawater supply pump through the PX unit or PX unit array to the system discharge [B-H] at a rate controlled by the supply pump and a flow control valve in the brine discharge from the PX unit or PX unit array [H]. Since the high- and low-pressure flows are independent, the SWRO plant must be designed for monitoring and control of the flow rates of both streams.

Both process flow and lubrication flow are required for the PX rotor to spin. The process flows include the feed flow from the supply system introduced to the PX devices and the concentrate flow driven by the circulation pump. Lubrication flow is normally provided by the high-pressure pump. The lubrication flow rate is typically less than 1% of the high-pressure pump flow rate or less than 0.5 m^3/hr (2.2 gpm) per PX device. Without lubrication flow, the PX device rotors may stop rotating. If this occurs, the concentrate- feed water exchange will cease. With reference to Figure 1.36, flush water introduced at process location B will exit at process location H without flowing through the membrane array. With insufficient lubrication flow, rotor rotation can result in damage to the PX device's ceramic components. A grinding sound may be heard as the ceramic components rub together without lubrication. If the high-pressure pump is not on, such as during flushing, the lubrication flow necessary to keep the PX rotors spinning can be provided by osmotic (suck-back) flow through the membranes. However, if the RO process is fully depressurized, the lubrication flow necessary to keep the rotors spinning must be either pushed through the high-pressure pump by the supply pump or injected through some other point in the high-pressure loop such as a clean-in-place (CIP) inlet. If the flush water has very low salinity, the lubrication flow may exit the process through the membranes under low trans-membrane pressure. It may be necessary to block permeate flow to divert lubrication flow through the PX devices. To measure the PX Device Lubrication Flow Rate which is some of the high-pressure water flows through the hydrodynamic bearing to low-pressure regions in the assembly. If the PX device is damaged by debris, overflow or insufficient discharge pressure, excess lubrication flow may occur. Inversely, monitoring lubrication flow is a good way to check the integrity of an operating PX unit. Lubrication flow can be determined using any of the following three methods:

1. Measure the flow rate of the low-pressure seawater to the high-pressure pump and the flow rate of the permeate. The difference is the lubrication flow rate.

2. Measure the flow rate of the high-pressure brine to the PX unit and the high-pressure seawater from the PX unit. The difference is the lubrication flow rate.

3. Measure the flow rate of the low-pressure brine from the PX unit and the low-pressure seawater to the PX unit. The difference is the lubrication flow rate [3].

B) PX System Performance Specifications, Precautions, and Conditions

Successful operation of the PX Pressure Exchanger energy recovery device requires observation of some basic operating conditions and precautions. The PX unit must be installed, operated, and maintained in accordance with this manual and good industrial practice to ensure safe operation and a long service life. Failure to observe these conditions and precautions can result in damage to the equipment and/or harm to personnel .The following table provides a summary of system performance limits.

Table 1.1:Pressure Exchanger Unit Process Operation Parameters Limitaions

Parameter	Specification	
	English Units	SI Units
Maximum high pressure (HP IN or HP OUT)	1,200 psig	82.7 bar
Maximum seawater inlet pressure (LP IN)	300 psig	20.7 bar
Minimum seawater inlet pressure (LP IN)	24 psig	1.7 bar
Minimum brine discharge pressure (LP OUT)[(1)]	9 psig	0.6 bar
Minimum filtration requirement (nominal)	10 micron	
Seawater temperature range	33-120 °F	1-49 °C
pH range	1-12 (short term at limits)	
Allowable flow rates [(2)]		
PX-260	180-260 gpm	41-59 m^3/hr
PX-220	140-220 gpm	32-50 m^3/hr
PX-180	100-180 gpm	23-41 m^3/hr

The high-pressure flow and low-pressure flow through the PX unit must never exceed the maximum rated flow rate. The only reliable way to determine this flow rate is to use a high-pressure flow meter

[3].

C) Flow Control and System Balancing

Flow rates and pressures in a typical SWRO plant will vary slightly over the life of a plant due to temperature variations, membrane fouling, and feed salinity variations. The PX unit's rotor is powered by the flow of fluid through the device. The speed of the rotor is self-adjusting over the PX unit's operating range. The high-pressure flow through the PX unit is set by adjusting the circulation pump with a variable frequency drive or with a flow control valve and verified with a high-pressure flow meter. The flow rate of the high-pressure seawater out of the PX unit equals the flow rate of the high-pressure brine to the PX unit minus the bearing lubrication flow. The high-pressure flow rate must be verified with a high-pressure flow meter. The low-pressure flow through the PX unit is controlled by the seawater supply pump and a control valve in the brine discharge from the PX unit(s). This valve also adds back-pressure on the PX device required to prevent destructive cavitation. The low-pressure flow rate must be verified with a flow meter. The flow rate of the low-pressure brine from the PX unit equals the flow rate of the low-pressure seawater to the PX unit plus the bearing lubrication flow rate.

To achieve balanced flow through the PX energy recovery device, use flow meters installed in the low- and high-pressure lines. The high-and low-pressure brine should be set to equal flow rates to within 2.5% for optimum SWRO operation. Similarly, the high and low-pressure seawater flows should be set to equal flow rates to within 2.5%. Operating the PX unit with unbalanced flows can result in contamination of the seawater feed by the brine reject. The PX device is designed to minimize mixing levels such that the salinity of the membrane feed stream is within 3% of the salinity of the raw feed water. Balanced flows help limit the mixing of concentrate with the feed. A seawater inlet flow that is much less than the seawater outlet will result in lower quality permeate, increased feed pressure, and higher energy consumption.

Verification of PX Energy Recovery Device Flow Balance once the flow rates to the PX energy recovery device have been set, flow balance can be verified by checking the salinity of the high-pressure seawater from the PX unit. If the high and low- pressure flows through PX unit are balanced, the conductivity at the PX unit high-pressure outlet should be 5 to 6% higher than the conductivity of the low-pressure seawater supply. Concurrently, using sample profile the conductivity of the PX unit low-pressure outlet should be 5 to 6% lower than the conductivity of the high-pressure brine. If the conductivity of the PX unit high-pressure outlet is too high, the high-pressure flow rate is probably higher than the low-pressure flow rate causing "blow through" of brine inside the PX unit. High salinity from the PX unit increases osmotic pressure in the membranes which may reduce membrane productivity. Low conductivity in the PX unit low-pressure outlet is an indication of low-pressure overflow. Although membrane productivity is not typically compromised by excess low-pressure flow, the excess flow goes to the brine discharge and represents losses in terms of plant pretreatment costs and capacity. Care should be taken to prevent overflow of the PX unit by high low-pressure flow [3].

D) Troubleshooting

For thoroughly flush associated piping with water filtered to 10 microns before installing the PX unit such that foreign material may cause damage, the identification and correction of most problems that could occur in PX devices as listed in the following table:

Table 1.2 : PX Troubleshooting

SYMPTOM	PROBLEM CAUSE	CORRECTIVE ACTION
A. Excessive sound level	Operating PX unit(s) above rated flow rates on low-pressure & or high-pressure side or both of them . Or damaged ceramic	Immediately reduce flow rate by adjustment of booster pump and LP control valve. Balance the system. Case D
B. Excessive high pressure in SWRO system	High-pressure pump is operating at too high flow rate Or Stuck rotor	Verify that main HP pump flow rate does not exceed the membrane production capacity for a given temperature, salinity and fouling factor. Case D
C. High salinity in high-pressure seawater feed stream	Unbalanced system :low-pressure flow rate too low or high-pressure flow rate too high Or Stuck rotor	Need re-balancing Case D
D. Damaged or stuck rotor	Operating system above rated pressure or below rated permeate flow capacity Or foreign debris or particles lodged in device	Check limit pressures and flows Shutdown and replace if needed

E. Low permeate flow	Malfunctioning high-pressure pump Or high lubrication/leakage flow through PX unit(s)	Verify hp pump flow rates and pressure ; confirm all rotors are rotating (px-lp-out sampling profile)if not shutdown
F. Low brine reject flow	Excessive pressure losses through SWRO system Or malfunctioning booster pump	Contact SWRO suppliers Check booster flows& pressures

I.5 Major membrane problems

The surface of a reverse osmosis (RO) membrane is subject to fouling by foreign materials that may be present in the feed water, such as hydrates of metal oxides, calcium precipitates, organics and biological matter. The term “fouling” includes the build-up of all kinds of layers on the membrane surface, including scaling. Pretreatment of the feed water prior to the RO process is basically designed to reduce contamination of the membrane surfaces as much as possible. This is accomplished by installing an adequate pretreatment system and selecting optimum operating conditions, such as permeate flow-rate, pressure and permeate water recovery ratio. Cleaning can be accomplished very effectively because of the combination of pH stability and temperature resistance of the membrane and the element components. However, if cleaning is delayed too long, it could be difficult remove the foulants completely from the membrane surface. The most common type of fouling is :

Membrane Oxidation :A high salt passage in combination with a higher than normal permeate flow is mostly due to oxidation damage. When free chlorine, bromine, ozone or other oxidizing chemicals are present in the incoming water, the front end elements are typically more affected than the others. A neutral to alkaline pH favors the attack to the membrane. Oxidation damage may also occur by disinfecting with oxidizing agents, when pH and temperature limits are not observed, or when the oxidation is catalyzed by the presence of iron or other metals [2].

Leaking O-Ring :O-rings may leak after exposure to certain chemicals, or to mechanical stress, e.g., element movement caused by water hammer. Proper shimming of the elements in a pressure vessel is essential to minimize the wear to the seals. Sometimes, O-rings have simply not been installed, or they have been improperly installed or moved out of their proper location during element loading [2].

Organic Fouling : The adsorption of organic matter present in the feed water on the membrane surface causes flux loss, especially in the first stage. In many cases, the adsorption layer acts as an additional barrier for dissolved salts, or plugs pinholes of the membrane, resulting in a lower salt passage. Organics with a high molecular mass and with hydrophobic or cationic groups can produce such an effect. Examples are oil traces or cationic poly-electrolytes, which are sometimes used in the pretreatment. Organics are very difficult to remove from the membrane surface [2].

Compaction and Intrusion : Membrane compaction and intrusion is typically associated with low permeate flow and improved salt rejection. Compaction is the result of applied pressure and temperature compressing the membrane which may result in a decline in flux and salt passage. Intrusion is the plastic deformation of the membrane when pressed against the permeate channel spacer under excessive forces and/or temperatures. The pattern of the permeate spacer is visibly imprinted on the membrane. Intrusion is typically associated with low flow. In practice, compaction and intrusion may occur simultaneously and are difficult to distinguish from each other. Although the SW40-MAX membrane shows little compaction and intrusion when operated properly, significant compaction and intrusion might occur under the following conditions:

• high feed pressure

• high temperature

• water hammer

Water hammer occur when the high pressure pump is started with air in the system [2].

Scaling: Scaling is a water chemistry problem originating from the precipitation and deposition of sparingly soluble salts. The typical scenario is a sea water system operated at high recovery without proper pretreatment. Scaling usually starts in the last stage and then moves gradually to the upstream stages. Waters containing high concentrations of calcium, bicarbonate and/or sulfate can scale a membrane system within hours. Scaling with barium or with fluoride is typically very slow because of the low concentrations involved [2].

Biofouling : Microbial foulants are aquatic microorganisms and organic compounds excreted by them (i.e., extracellular polymeric substances, proteins, and lipids) which are deposited on the surface of RO membranes. The biofilm formed on the membrane surface contributes additional resistance (pressure head losses) to the osmotic pressure that must be overcome in order to maintain steady production of freshwater by the membrane elements [1].

Colloidal fouling : Colloidal foulants are inorganic and organic compounds that naturally exist in suspension and may be concentrated by the RO separation process and precipitate on the membrane surface, thereby causing membrane flux to decline over time [1].

The following table shows Symptoms ,causes and corrective measures:

Table 1.3: Membrane Troubleshooting

Permeate flow	Salt passage	Differential pressure	Direct cause	Indirect cause	Corrective measure
↑	⇑	→	Oxidation damage	Free chlorine, ozone, $KMnO_4$	Replace element
↑	⇑	→	Membrane leak	Permeate backpressure; abrasion	Replace element, improve cartridge filtration
↑	⇑	→	O-ring leak	Improper installation	Replace O-ring
↑	⇑	→	Leaking product tube	Damaged during element loading	Replace element
⇓	↑	↑	Scaling	Insufficient scale control	Cleaning, scale control
⇓	↑	↑	Colloidal fouling	Insufficient pretreatment	Cleaning, improve pretreatment
↓	→	⇑	Biofouling	Contaminated raw water, insufficient pretreatment	Cleaning, disinfection, improve pretreatment
⇓	→	→	Organic fouling	Oil; cationic polyelectrolytes water hammer	Cleaning, improve pretreatment
⇓	↓	→	Compaction	Water hammer	Replace element or add elements

↑ Increasing ↓ Decreasing → Not changing ⇑ Main symptom

I.6 Summary:

With 71% ocean areas desalination became the best solution for lack of potable water problem .The best type of the later is membrane desalination with SWRO membranes has high rejection rate that handles the high salinity of sea water producing drinkable water , and with help of ERI devices now the RO process could provide higher amounts of the final product with less energy consumption .

II.1 Introduction

The main objective of this project is to study the PX alarm prediction (including unbalanced, out of range flows, equipment damage) problem in SWRO systems and make the alarm easily to predict understand its different sources. Based on numerical type of sample source, this project aims to develop a supervised machine learning modelfor prediction then studying thePX alarm cases. Such that the designed system involves preprocessing like Normalization, to avoid bias and contribute equally the variables to the model fitting. This features scaling technique is used with the top winner competitive models which are NaïveBayes classifier, KNN and Logistic Regression algorithm.

II.2 Building the model‘s steps

II.2.1Data Pre-processing

The data mining technology in computer science is for discovering meaningful patterns and knowledge from large amounts of data. However, before a data mining model can be applied, the raw data must be preprocessed to ensure that it is in a suitable format for analysis. Data preprocessing is an essential step in the data mining process and can greatly impact the accuracy and efficiency of the final results. The four major tasks in data preprocessing are : Data cleaning where we make sure to remove the incorrect ,incomplete,inaccurate data from the database manually; Data integration where we detect and resolve data value concepts as the data were taken from different sources so when merging it the attribute values of two classes data where different so we make sure to be the same ; Data transformation where we need to change the structure of our data by adding the labels to the samples and gathering them into one database then shuffling them . The fourth one is Feature scaling that is described in the following section [4].

II.2.2Features Scaling

Feature scaling is the final step of data pre-processing which is a technique to standardize the independent variables of the dataset in a specific range. One of the challenges of numerical categorization is learning from large different scalehigh dimensional data that can hurt the accuracy and performance of the classifiers, thus making the variables in the same range and in the same scale so that no any variable dominate the other variable, The method we used is:

MinMaxScaler:

Normalization, a vital aspect of Feature Scaling, is a data preprocessing technique employed to standardize the values of features in a dataset, bringing them to a common scale. This process enhances data analysis and modeling accuracy by mitigating the influence of varying scales on machine learning models.Normalization is a scaling technique in which values are shifted and rescaled so that they end up ranging between 0 and 1. It is also known as Min-Max scaling. the following equation is the normalized variable in "i"dimension :

$$x_{norm}^{(i)} = \frac{x^{(i)} - x_{min}}{x_{max} - x_{min}} \quad (2.1)$$

The Scikit-learn provide the implementation of sklearn.preprocessing.MinMaxScaler [5].

II.2.3 Algorithms used for Classification

This section deals with training the classifier. Different classifiers were investigated to predict the class of the text. We explored specifically the three top winner machinelearning algorithms – Multinomial Naïve Bayes, Knn, and Logistic regression. The implementations of these classifiers were done using Python library Sci-Kit Learn.

A) Naïve Bayes Classifier

This classification technique is based on Bayes theorem, which assumes that the presence of a particular feature in a class is independent of the presence of any other feature [7]. It provides way for calculating the posterior probability **P(C / X)** as the following:

$$\mathbf{P(C/X)} = \frac{\mathbf{P(X/C) * P(C)}}{\mathbf{P(X)}} \quad (2.2)$$

P(c|x)= posterior probability of class given predictor P(c)= prior probability of class

P(x|c)= likelihood (probability of predictor given class) P(x) = prior probability of predictor

B) Logistic Regression:

It is a classification not a regression algorithm. It is used to estimate discrete values (Binary values like 0/1, yes/no, true/false) based on given set of independent variable(s). In simple words, it predicts the probability of occurrence of an event by fitting data to a logit function.

Hence, it is also known as logit regression. Since, it predicts the probability, its output values lies between 0 and 1 (as expected) as the following:

$$\boldsymbol{\phi(z)} = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e^{-z}}} \qquad (2.3)$$

The output of this sigmoid function is the probability of a certain sample to belong to class 1 given its features X parametrized by the weights W as: $\boldsymbol{\phi}(\mathbf{z}) = \mathbf{P}(\mathrm{y} = 1/\ x; w)$such that z is the net input which is a linear combination of weights , and sample features [7] as:

Z = logit(p(y=1 / x)) = W0X0 + ……….+WnXn = Sum(WiXi) (2.4)

C) KNN:

KNN is a***Supervised learning algorithm*** distance-based classifier, meaning that it implicitly assumes that the smaller the distance between two points, the more similar they are. In KNN, each column acts as a dimension. It is quite particular compared to the other classifiers because during the “fit” step, KNN just stores all the training data and corresponding labels and no distances are calculated at this point.All the work it is done during the “predict” phase. During this step, KNN takes a point that we want a class prediction for, and calculates the distances between that point and every single point in the training set. It then finds the K closest points or ***Neighbors*** with help of an appropriate distance metric(Manhattan, Euclidean, Minkowski distance), and examines the labels of each to vote for the class that has the highest count among all of the k-nearest neighbors .

Euclidean distance:

For each dimension, we subtract one point’s value from the other’s to get the length of that “side” of the triangle in that dimension, square it, and add it to our running total. The square root of that running total is our Euclidean distance[6].The formula to calculate Euclidean distance is:

$$\boldsymbol{d}(\mathbf{Xtest, Xtrain}) = \sum_{i=1}^{n}(\boldsymbol{Xtest(i) - Xtrain(i)}) \qquad (2.5)$$

II.3summary

As a conclusion to all what we have seen in this chapter that to build a prediction model for (non-alarm / alarm) samples we need a binary classifier that learn from a massive amount of numerical RO process equipment values samples after normalizing the features from our dataset using the MIN-MAX technique .

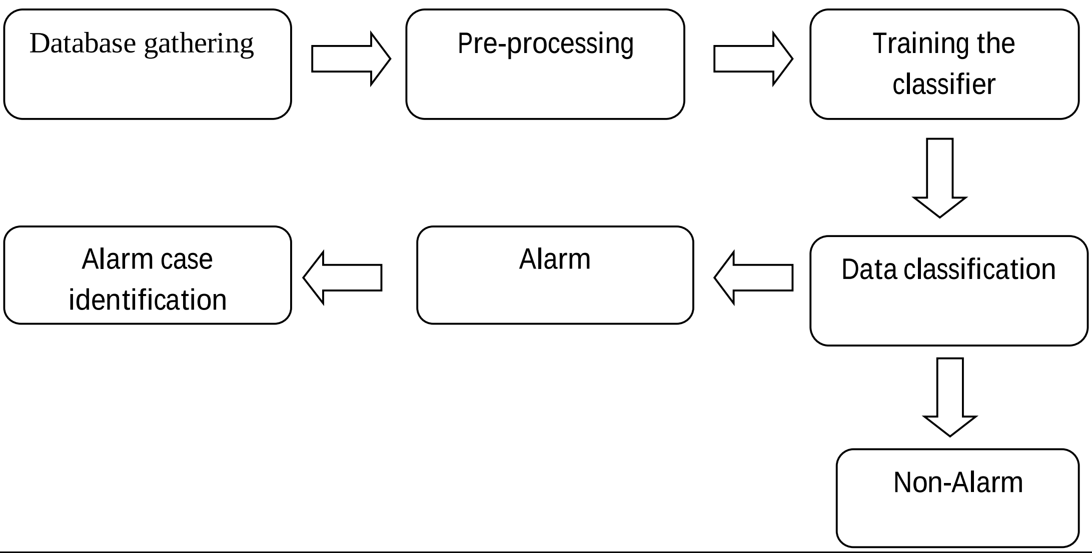
III .1 Introduction

We have seen in chapter two, the different machine learning classification algorithms that we are going to use to create the top three winners learning models, we fit each using the different reverse osmosis instruments values (flows, feed pressure, differential pressure of membrane rack ; booster pump and PX array, feed sea water temperature ,conductivity of both permeate and feed water) giving total of 17 feature in each input sample then, the learned models used to predict the labels assigned to the testing data as positive class for alarm cases and negative class for the non-alarm. The best model should have good performance measurements specially for positive class thus to get it we are going to investigate and compare three different machine classification techniques and Improve for the winner model its positive class predictions.

III.2 Experiment steps

Primarily, we take input in the form of a dataset then split the features from label columns , then the feature columns are normalized using the technique build based on a Min-Max scaler, after that we use the normalized data to train and compare the different classifiers to get the best model of the highest performance metrics values ,then for further optimization we shouldn’t get FN predicted samples since we don’t want alarm cases to be predicted as non-alarm cases , then to remove them we’ve to get TPR=1 (FN=0) using ROC curve and confusion matrix in determining the ideal threshold . The final product is tested for source of alarm identification by taking the test sample input features and checking its shutdown cases first then it will be passed in the section that identify the problem source.

Figure 3.1 PX Alarm Prediction Model Creating Steps



III.3 Tools

The used algorithms were written in python, and the frameworks that we used are: pandas, numpy, matplotlib, and sklearn. Our chosen algorithm was trained using jupyter notebook that uses our computer CPU and memory, the final code section was created to identify the cases of the tested sample .

A) Pandas

It is a software library written for the Python programming language for data manipulation and analysis. In particular, it offers data structures and operations for manipulating numerical tables and time series. It is free software released under the three-clause BSD license. The name is derived from the term "panel data", an econometrics term for data sets that include observations over multiple time periods for the same individuals. Its name is a play on the phrase "Python data analysis" itself. Wes McKinney started building what would become pandas at AQR Capital while he was a researcher there from 2007 to 2010.

B) NumPy

It is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays. The ancestor of NumPy, Numeric, was originally created by Jim Hugunin with contributions from several other developers. In 2005, Travis Oliphant created NumPy by incorporating features of the competing Numarray into Numeric, with extensive modifications. NumPy is open-source software and has many contributors.

C) Matplotlib

It is a plotting library for the Python programming language and its numerical mathematics extension NumPy. It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits like Tkinter, wxPython, Qt, or GTK. There is also a procedural "pylab" interface based on a state machine (like OpenGL), designed to closely resemble that of MATLAB, though its use is discouraged.SciPy makes use of Matplotlib

D) Python

Python is an interpreted high-level general-purpose programming language. Python's design philosophy emphasizes code readability with its notable use of significant indentation. Its language constructs as well as its object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects.

E) Scikit-learn

(Formerly scikits.learn and also known as sklearn) is a free software machine learning library for the Python programming language. It features various classification, regression and clustering algorithms including support vector machines, random forests, gradient boosting, k-means and DBSCAN, and is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy.

F) Jupyter notebook

The Jupyter Notebook is an open source web application that you can use to create and share documents that contain live code, equations, visualizations, and text. Jupyter Notebook is maintained by the people at Project Jupyter. Jupyter Notebooks are a spin-off project from the IPython project, which used to have an IPython Notebook project itself. The name, Jupyter, comes from the core supported programming languages that it supports: Julia, Python, and R. Jupyter ships with the IPython kernel, which allows you to write your programs in Python, but there are currently over 100 other kernels that you can also use.

III.4 Evaluation metrics:

A) Confusion Matrix:

It is nothing but a table used to describe the performance of classification model or classifier on set of data set. The macro average of any metric is calculated as the mean of respective values of all classes by giving equal weightage to all classes. On the other hand, the weighted average of any metric is calculated by giving weightage based on the number of data points in respective classes. In our output, numbers 0 and 1 denote negative and positive classes respectively and column support refers to the number of data points in those classes.

B) Accuracy:

It can be defined as the ratio of the number of correctly classified cases to the total of cases under evaluation. The best value of accuracy is 1 and the worst value is 0. We obtain the accuracy based on how well our classifiers are working and the data set is bet fit in it. Accuracy is calculated based on true and false positives and negatives:

$$\textbf{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \qquad (3.1)$$

1. TN / True Negative: the case was negative and predicted negative
2. TP / True Positive: the case was positive and predicted positive
3. FN / False Negative: the case was positive but predicted negative
4. FP / False Positive: the case was negative but predicted positive

C) Precision: *What percent of your predictions were correct?*

Precision can be defined with respect to either of the classes. The precision of negative class is intuitively the ability of the classifier not to label as positive a sample that is negative. The precision of positive class is intuitively the ability of the classifier not to label as negative a sample that is positive. The best value of precision is 1 and the worst value is 0.

$$\textbf{Precision} = \frac{TP}{(TP+FP)} \qquad (3.2)$$

D) Recall: *What percent of the positive cases did you catch?*

Recall can also be defined with respect to either of the classes. Recall of positive class is also termed sensitivity and is defined as the ratio of the True Positive to the number of actual positive cases. It can intuitively be expressed as the ability of the classifier to capture all the positive cases. It is also called the True Positive Rate (TPR). Recall of negative class is also termed specificity and is defined as the ratio of the True Negative to the number of actual negative cases. It can intuitively be expressed as the ability of the classifier to capture all the negative cases. It is also called True Negative Rate (TNR). We are going to use Recall of positive class Fraction of positives that were correctly identified.

$$\textbf{Recall} = \frac{TP}{(TP+FN)} \qquad (3.3)$$

F) F1-score: What percent of positive predictions were correct?

F1-score is considered one of the best metrics for classification models regardless of class imbalance. F1-score is the weighted average of recall and precision of the respective class. Its best value is 1 and the worst value is 0. F1 scores are lower than accuracy measures as they embed precision and recall into their computation. As a rule of thumb, the weighted average of F1 should be used to compare classifier models, not global accuracy.

$$\textbf{F1 Score} = \frac{\mathbf{2*(Recall * Precision)}}{\mathbf{(Recall + Precision)}} \qquad (3.4)$$

Accuracy, Precision, Recall, and F1-score can altogether be calculated using the method classification_report in python print (metrics.classification_report(y_test, preds)).

G) ROC and AUC score:

ROC is the short form of Receiver Operating Curve, which helps determine the optimum threshold value for classification. The threshold value is the floating-point value between two classes forming a boundary between those two classes. Here in our model, any predicted output above the threshold is classified as class 1 and below it is classified as class 0. ROC is realized by visualizing it in a plot. The area under ROC, famously known as AUC is used as a metric to evaluate the classification model. ROC is drawn by taking false positive rate in the x-axis and true positive rate in the y-axis. The best value of AUC is 1 and the worst value is 0. However, AUC of 0.5 is generally considered the bottom reference of a classification model.

J) Sensitivity:

Sensitivity / True Positive Rate / Recall Sensitivity, tells us what proportion of the positive class got correctly classified. A simple example would be to determine what proportion of the actual real news were correctly detected by the model.

$$\textbf{TPR} = \frac{\mathbf{TP}}{\mathbf{(\ TP + FN\ )}} \qquad (3.5)$$

H) Specificity:

It tells us what proportion of the negative class got correctly classified. Specificity would mean determining the proportion of fake news which is correctly identified by the model.

$$\textbf{Specificity} = \frac{\mathbf{TN}}{\mathbf{(TN + FP)}} \qquad (3.6)$$

I) False Positive Rate FPR (1- Specificity) :

Tells us what proportion of the negative class got incorrectly classified by the classifier. A higher TPR and a lower FPR is desirable since we want to correctly classify the negative class.

$$\textbf{false\_positive\_rate} = \frac{\mathbf{FP}}{(\mathbf{TN + FP})} \qquad (3.7)$$

III.5Data manipulation on jupyter notebook*:*

A) Data collection:

The input of our model are numerical Data-set gathered along the total year 2023 with its salinity and temperature variation , we take only ERI shutdown cases and set it as class 1 and other good online RO operation samples are labeled as class 0, then we shuffled our samples then download the file and convert it into csv file in order to create the pandas data frame and loading it using the method " read_csv" for the upcoming data manipulation and analysis .Extracting the input(features) arrays as " x" and the output (labels) as "y" such that x and y are sequence of indexables with same length .

B) Data preprocessing:

We import the necessarily packages to go through our data step by step making the preprocessing techniques. We use the train_test_split validation function to split the dataset (x,y) to 80% training data inputs and outputs (x_train, y_train)using the argument test_size =0.2 that makes by default the train size the complement of the other , and the rest samples for having an unbiased model prediction evaluation using them as a test data .

random_state=0 , this integer (random seed of the random number generator) is a parameter that may be provided whenever randomization is part of sklearn algorithm, such that it used in controlling the random number generator by initializing its random seed , which means passing that value will have an effect on the reproducibility of the result returned by the function each time we run the code so that it will produce the same results across different calls then for any fixed integer we will make the tests reproducible and get random split with same output for each function call .

C) Feature scaling:

Using the imported MinMaxScaler function we normalize our data input samples to restrict them in [0-1] range as shown:

```
In [9]: Ms_x_train

Out[9]: array([[0.79487179, 0.9137931 , 0.2421875 , ..., 0.02975821, 0.85714286,
         0.97958696],
        [0.20512821, 0.95689655, 0.375     , ..., 0.03781773, 0.03174603,
         0.93756715],
        [0.87179487, 0.9137931 , 0.3515625 , ..., 0.04525728, 0.31746032,
         0.94079026],
        ...,
        [0.74358974, 0.88793103, 0.203125  , ..., 0.02913825, 0.68253968,
         0.97779635],
        [0.66666667, 0.89655172, 0.21875   , ..., 0.02851829, 0.42063492,
         0.96275516],
        [0.74358974, 0.94827586, 0.234375  , ..., 0.03285803, 0.34126984,
         0.96860451]])
```

III.6Experiments:

In the upcoming experiments we are working on getting a 100% alarm positive class prediction model going through these steps:

III.6.1 *Experiment 1*

We train and compare different supervised machine learning binary classifiers applying the normalized data and evaluate each of them to get the best performance metrics model. The top three models are listed in the following table with their positive class precision, recall and F1-score:

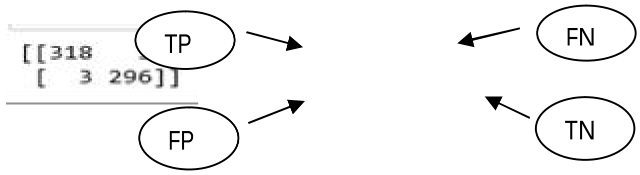
Table 3.1: **Classification Performance metrics for our experience**

Classifier	Accuracy score	Precision	recall	F1-score
KNN	99.03%	0.99	0.99	0.99
MultinomialNB	86.29%	0.85	0.86	0.86
LogisticRegression	81.45%	0.87	72	79

A) Results

Since Classification accuracy alone is not enough to determine the effectiveness of the model; we compare the performance of the winner algorithms using precision and recall for both classes. As we can see from the previous table: the comparison of the previous classifiers using a 20% samples of test set ,the best accuracy score of 99.03% was obtained using KNN model with 0.99 positive class precision and recall and f1-score. The accuracy for LogisticRegression was the lowest at 81.45% and lowest recall and f1-score. Making our decision based on those four evaluation metrics to check if the predictions are right or wrong: Since Precision is the ability of a classifier not to label an instance negative that is actually positive and that what we need since what matters is to not classify alarm case as non-alarm not necessarily the opposite, the confusion matrix of winner model with highest precision is:

Figure 3.2 Confusion Matrix Output



B) Discussion :

This section discusses the results of various experiments. The type of data used for training and the range of features that affect the classifier performance. As observed from the result normalizing the data increase the performance of the system so that KNN classifier gives the lowest false positive FP and false negative FN values. Experiment evaluation yields the best performance using MinMax scaler with KNN classifier was performed better than all other classifiers.

III.6.2Experiment 2

Since our dataset was slightly not balanced and our aim is to reduce the false negative predictions from the last matrix as much as we can without reducing the total performance then the best ways to do so with minimal effort is to adjust the threshold that decide the class based on the probabilities predictions made for each tested sample.

A machine learning classification model can be used to predict the actual class of the data point directly or predict its probability of belonging to different classes. The latter gives more control over the result. We can determine our own threshold to interpret the result of the classifier. This is sometimes more prudent than just building a completely new model. Setting different thresholds for classifying positive class for data points will inadvertently change the Sensitivity and Specificity of the model. And one of these thresholds will probably give a better result than the others, depending on whether we are aiming to lower the number of False Negatives or False Positives.

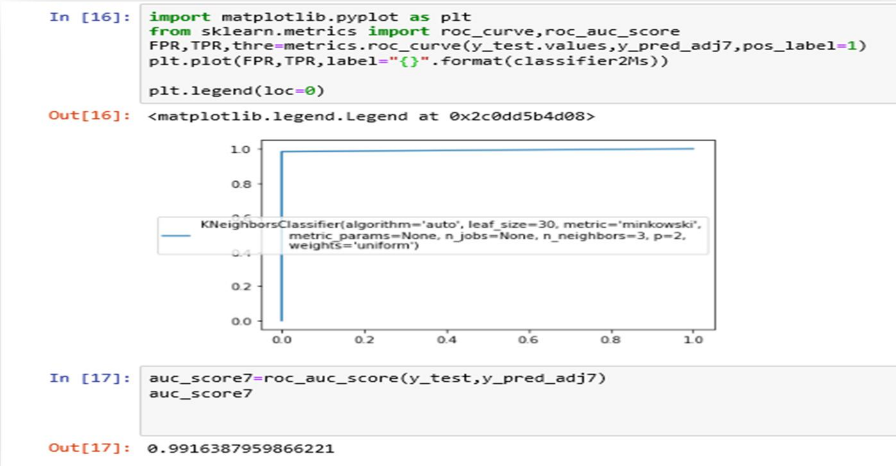
A) Step 1 : getting the predicted probabilities output values :

Getting our probabilities predicted values for positive class using “predict_proba()” function and store it in the predicted labels (y_pred) object that will be passed in the “threshold-Adjusting” function that classifies as a positive class the values that are above threshold (t) , and stored it in the adjusted prediction values” y_pred_adj ” to use it later in observing for which threshold we get false negative cases FN=0 using confusion matrix.

```
[[312    9]
 [   1  298]]
[[312    9]
 [   1  298]]
[[312    9]
 [   1  298]]
[[318    3]
 [   3  296]]
[[318    3]
 [   3  296]]
[[318    3]
 [   3  296]]
[[321    0]
 [   5  294]]
[[321    0]
 [   5  294]]
[[321    0]
 [   5  294]]
```

B) Step 2 : Roc curve best threshold values sensitivity verification

Visualizing the effect of changing threshold values on the sensitivity (true positive rate TPR) and 1-specificity(false positive rate FPR) using the roc curve which is a probability curve that plots the TPR against FPR at various threshold values and essentially separates the ‘signal’ from the ‘noise’. The Area Under the Curve (AUC) is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve .The higher the AUC, the better the performance of the model at distinguishing between the positive and negative classes . Sklearn has a very potent method roc_curve() which computes the ROC for the classifier and returns the FPR, TPR, for the best threshold value we get the following roc_curve and its auc_score:



For varying threshold values we have varying TPR and FPR values so we aim to have a one TPR result and getting FPR as low as possible closer to zero, since decreasing the FN values would increase the FP ones that would decrease the selectivity .The point corresponding to a perfect classifier would lie on the graph, It is on the top-left corner of the ROC graph corresponding to the coordinate (0, 1) in the Cartesian plane. It is here that both, the Sensitivity and Specificity, would be the highest and the classifier would correctly classify all the positive and negative class points.

C) Results

As we can see from the previous picture that as we increase the threshold values the False-positive-rate decrease hence the specificity increases by the same amount and the decreased false negative predictions will increase the Precision value to a one, we can say that the optimal case was 0.7 that gives TPR=1 while increasing the specificity value, also increased the accuracy to 99.19%. Since we know that the best model will make FPR= 0 & TPR = 1 that gives FP=FN =0 or in other words classifies all the positive classes as positive and the negative ones as negative, but from the roc curve we can’t obtain that value obviously but we notice that the optimal point was closer to an almost zero FPR and 1TPR value which is the most close one to the perfect case.

accuracy classifier: 99.19%

	precision	recall	f1-score	support
0	0.98	1.00	0.99	321
1	1.00	0.98	0.99	299
accuracy			0.99	620
macro avg	0.99	0.99	0.99	620
weighted avg	0.99	0.99	0.99	620

D) Discussion

A confusion matrix shows the proper labels on the main diagonal (top left to bottom right). The other cells show the incorrect labels, often referred to as false positives and false negatives. Depending on the problem, one of these might be more significant. For our example, the ERI Alarm problem, it is more important to not label alarm cases as non-alarm if so, the researcher might want to eventually weight the accuracy score to better reflect this concern. This was done across random test of twenty percent test set of the whole process dataset. Sensitivity is how sensitive the classifier is to predict alarm, while Specificity is how selective or specific the model is in predicting non-alarm. Choosing the metric depends on what kind of application is going to be developed. The negative class in this binary classification is class “non-alarm”. Therefore, Sensitivity should be higher, because false positive are more acceptable than false negative in this classification problem. Optimizing more for Sensitivity, we get better results such that the Sensitivity is increased to1 by increasing the threshold to 0.7 for predicting alarm cases. This would increase the number of false positives but it won’t hurt as the high predictive false negative ones. As a result to that modification the false negative predicted values were reduced from 3 to 0 in tested sample, also our chosen model gives a good AUC value of 0.991 which means it is able to make the right prediction most of time .

III.7 summary

This chapter studied the followed steps to create a 100% precise model for predicting the alarm positive classes, going by preprocessing the collected data then fit it to the different supervised machine learning classifiers to choose the best model then modify its output probability threshold, where this last model output prediction is used in next section testing to identify the problem source.

III.8general discussion

From the above experiments the concluded results was that KNN algorithm, using MinMax scaler with a 0.7 threshold value gave the yes rformance .Finally, it was chosen as the best model to determine the ERI alarm case. So based on this conclusion the testing cases to where the alarm belong was developed in the next part .The goal of this project is to comprehensively review, summarize, compare and evaluate the current research on ERI alarms and their problem source .

Since KNN performs 99.13% ,the classification error is 0.87% which was better than ensemble algorithms like LogisticRegression and linear classifier like multinomial NaïveBayes , then the prediction values will be used in determining the case it belongs .

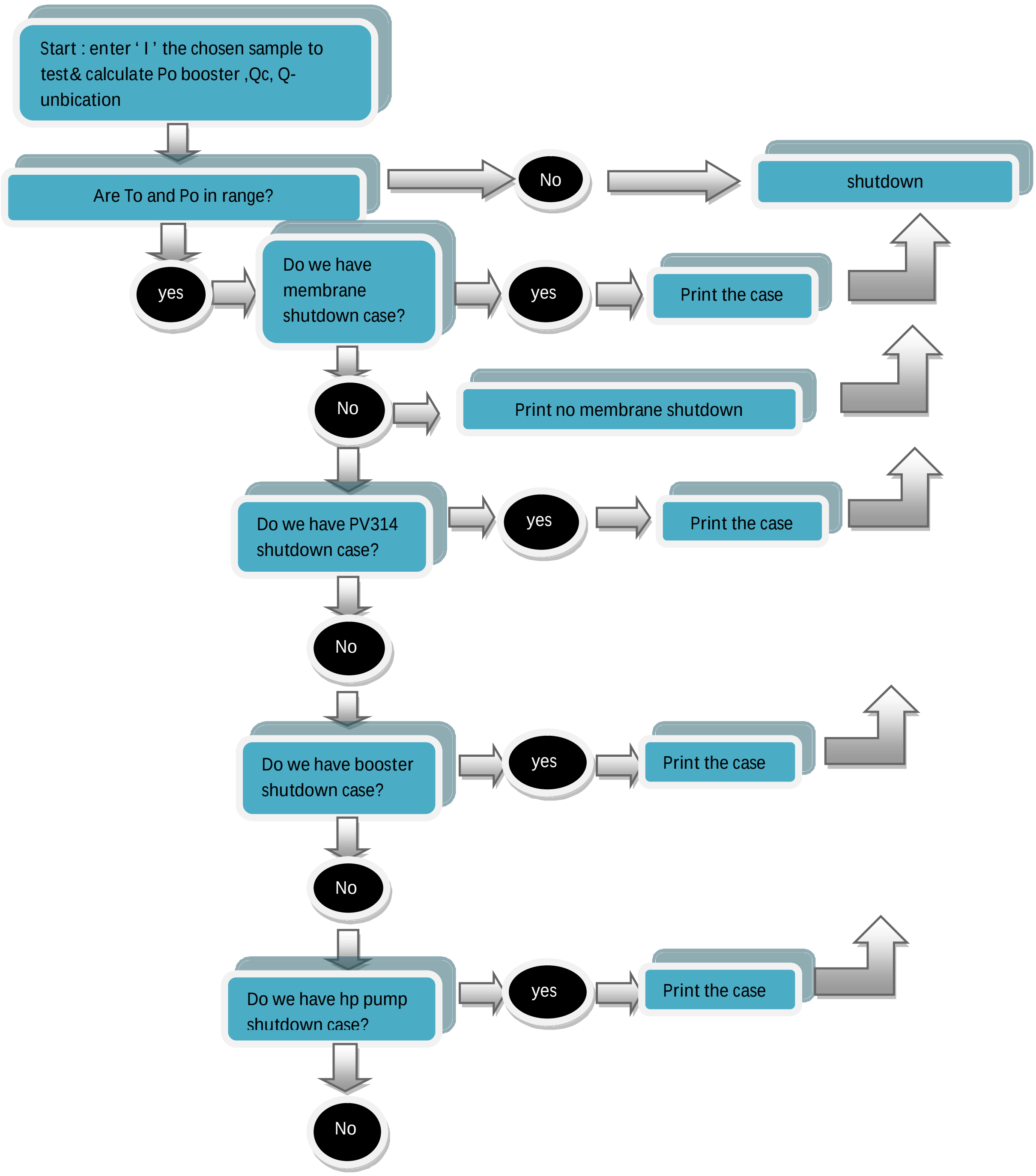
III.9Testing source of alarm cases

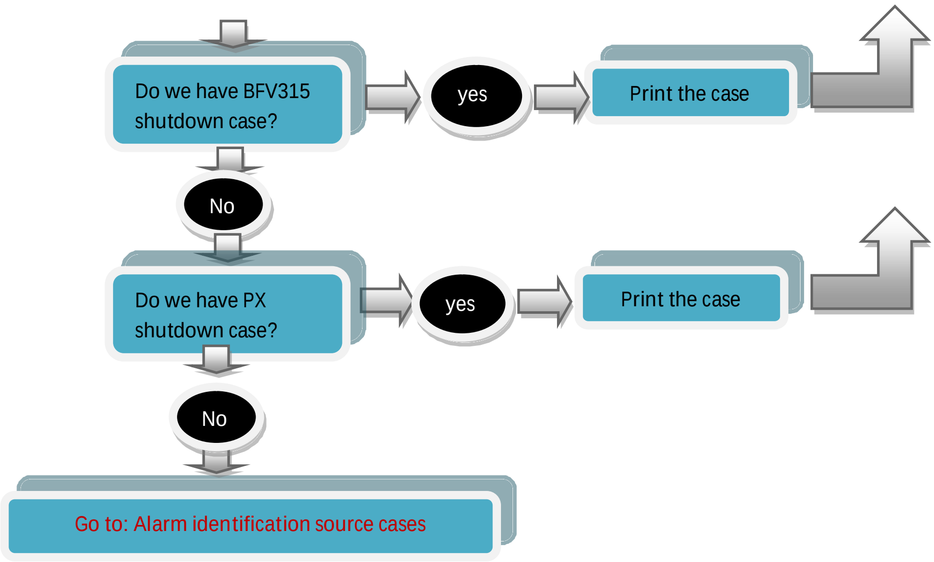
Since PX is a flow controlled equipment meaning that its lubrication flow amount decide its performance efficiency; Then the stuck or damaged states when being under or over the limits. Its balanced flows are in range of 2.5% for each others , and the mixing case is when the high pressure outlet flow is greater than low pressure inlet flow meaning that a portion of concentrate high pressure inlet flow enters in the high pressure outlet with its high salinity leading to an increase in the total feed salinity of feed seawater when joined with the rest 45% coming from HP pump causing a sudden increase in feed pressure to membrane Po thus may damage the membrane or resulting in high brine flow that comes back to PX as severe unbalanced input flow case causing over-lubrication and a much severe mixing.

The abbreviation used in this section: (lp=low pressure, hp=high pressure, in=input, ot=output)

From fig1.36the flows are as the following: A=Qhp pump input , B= Qpx-lp-in , C=Qhp pump output ,D=Qpx-hp-output , E=Qfeed(or Qo) , F=Qp(permeat) ,G=Qc(concentrate) ,H=Qpx-lp-output .Plus we have BFV315 a controlling valve at the low pressure outlet of the PX for preventing it from cavitation by keeping it above the minimum limit and with help of booster it rebalances the PX output flows, PV314 is also a percentage controlling valve of feed pressure to the membrane Po since HP-pump is of fixed pressure .

For this section we are using chapter one Membrane and PX troubleshooting tables we resume the alarm cases as: The case D is a shutdown ERI case when its lubrication flow is below the minimum limit making no flow for ceramic rotor to rotate with and for exceeding its maximum limits makes the ceramic rotor get damaged .The cases A,B and C are the major cases where E&F are sub-cases of them . Since the samples were taken from the desalination station of Fouka where the SCADA stuff are good labors we did not get any sample for case A and B ending up with the mixing and wasted water through the LP-output channel for the unbalanced and balanced cases. For this section purpose we write the following code with the shutdown verification part then alarm source identification part as described in the following schema:





The calculated cases are:

Booster output Pressure = output pressure of pv314 – membrane differential pressure – PX array differential pressure.

Brine flow = input hp pump flow + PX hp output flow – permeate flow.

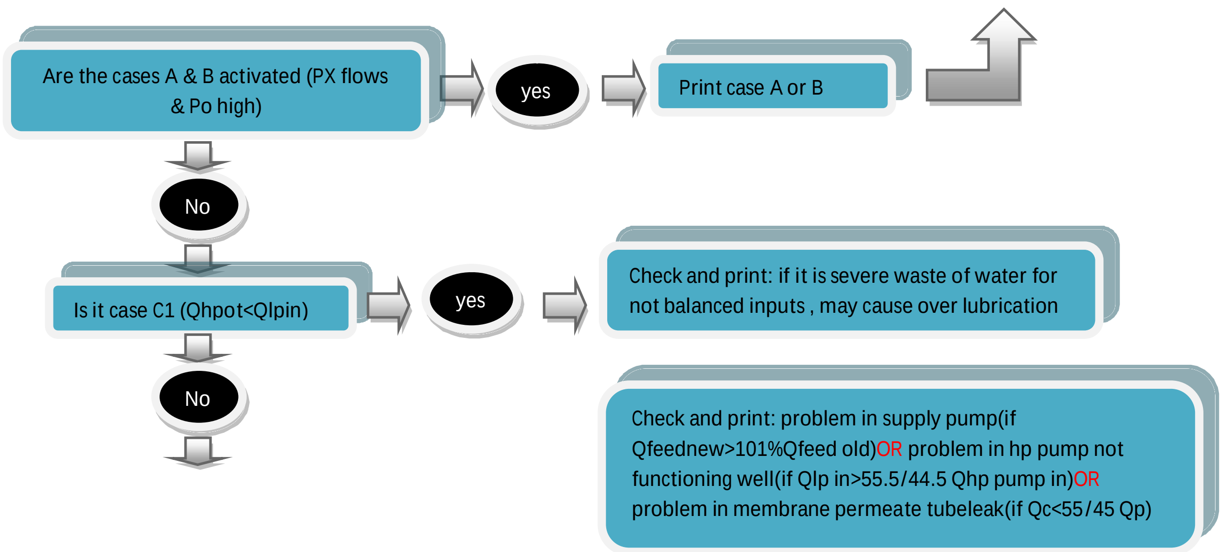
Lubrication flow = PX inlet hp flow - PX outlet hp flow.

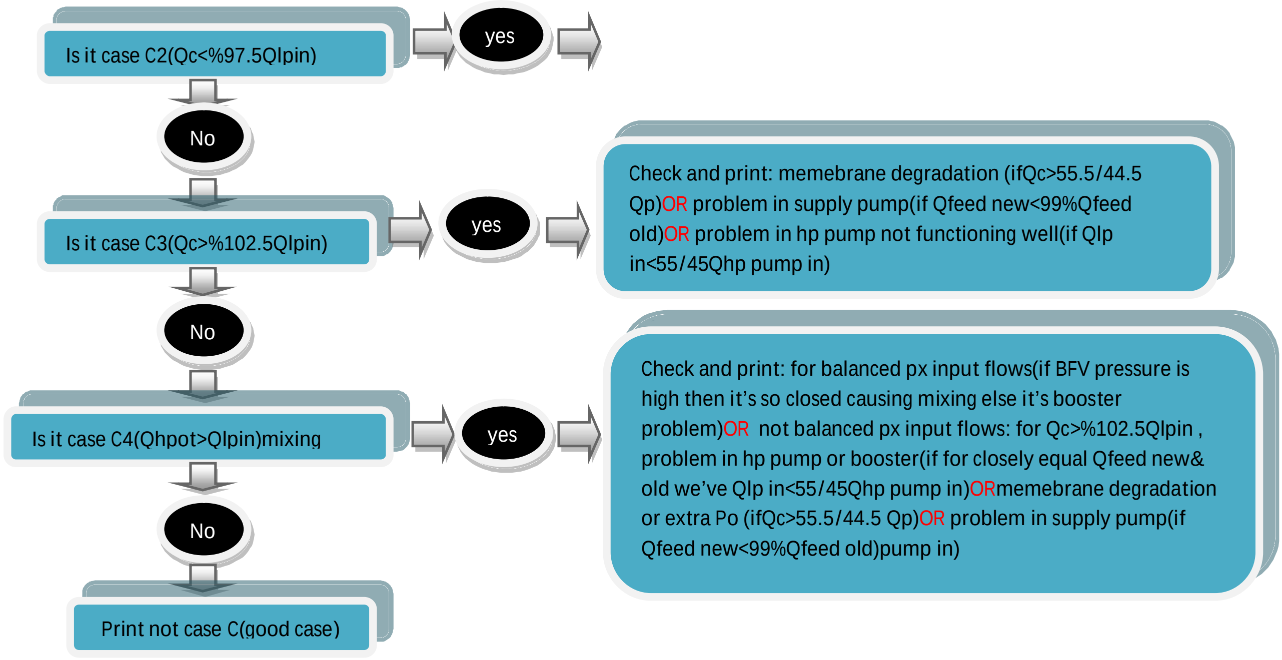
For case c we have four main sub-cases that are:

Case1: of unbalanced output flows with no mixing but wasted water at the px low pressure outlet that may or not lead to over lubrication.

Case2&3: unbalanced input flows two cases where in each of them one is greater than the other (out of the balanced limits) that may or not lead to mixing according to the booster and LP outlet valve (BFV315) state.

The last case: is the mixing case. As shown in the following schema:





Since we choose the ERI only alarm cases for more precise model for this shutdown case, non of testing results (alarm or non-alarm) gives other shutdown cases, and since we train our model for 24/7 online process with the same day and day before the alarm for the alarm cases and the rest good state days for non-alarm, the tested samples gives the following results:

1. Alarm case gives:
   A. day before alarm where the shutdown case is not activated but give a hint for one or more cases of case c that could give shutdown :

```
y_test.iloc[0]
1
```

```
enter the sample you want to check0



no shutdown case membrane

 no shutdown case pv314
no booster shutdown case

no shutdown case hp pump
no shutdown case BFV315

no ERI shutdown case
```

```
unbalanced inputflows Qc greater than Qlpi rebalance your system


low Qlpi :problem in hp pump
mixing Qhpo greater than Qlpi

Qc greater than Qlpi
low Qlpi problem in hp pump or booster


caseC checked ypred number:

0
```

B. same day alarm(just before the alarm) so the shutdown case is detected and one or more cases of case c:

```
y_test.iloc[12]
1
```

```
enter the sample you want to check12



no shutdown case membrane

 no shutdown case pv314
no booster shutdown case

no shutdown case hp pump
no shutdown case BFV315
shutdown case ERI over lubricated
no ERI low lubrication flow shutdown case
```

```
unbalanced inputflows Qc greater than Qlpi rebalance your system
high Qc:membrane degradation or Po problem

low Qlpi :problem in hp pump

caseC checked ypred number:

12
```

2. Non-Alarm case gives:

A. Non of cases of case c detected (good case) :

```
y_test.iloc[3]
0
```

```
enter the sample you want to check3



no shutdown case membrane

 no shutdown case pv314
no booster shutdown case

no shutdown case hp pump
no shutdown case BFV315
no ERI high lubrication flow shutdown case
no ERI low lubrication flow shutdown case
```

```
 not case C
caseC checked ypred number:

3
```

B. One or more cases of case c detected:

```
y_test.iloc[4]
```

```
0
```

```
enter the sample you want to check4



no shutdown case membrane

 no shutdown case pv314
no booster shutdown case

no shutdown case hp pump
no shutdown case BFV315
no ERI high lubrication flow shutdown case
no ERI low lubrication flow shutdown case
```

```
unbalanced inputflows Qc greater than Qlpi rebalance your system
high Qc:membrane degradation or Po problem

low Qlpi :problem in hp pump
mixing Qhpo greater than Qlpi

Qc greater than Qlpi
low Qlpi problem in hp pump or booster
high Qc problem in membrane or extra Po

caseC checked ypred number:

4
```

III.9*Future work*

For future work we aim to apply this prediction model and identification cases to the SCADA data system to minimize the pressure exchanger alarm as possible giving hints to SCADA stuff for the upcoming alarm and from which flow source, since the percentage relation between its different flows is hard to be calculated instantaneously while keeping eyes on the process values fast changing!

Also, I aim to do the solution re-balancing following part with help of the automation engineer of the station when he makes it to Algeria, studying the control loops and the parallel ones to the new PX alarm solution to get the minimum response time thus the best prediction time to avoid the alarm case.

Conclusion

Conclusion

The purpose of this project is to develop a prediction model for pressure exchanger alarm using a machine learning approach that can serve as a basic building block for this application. To meet this purpose we collected manually and carefully the SWRO rack online process values of only the PX alarm and other good cases ending up with 17 features in 3100 samples of both classes.

The designed system for PX alarm prediction involves Normalization as pre-processing feature scaling technique to verify for no biasing of the resulting model predictions , based on this technique different classification algorithms was trained with the collected data .The performance of the models was compared on the same testing set using the most significant metrics by which a machine learning model performance is measured like : accuracy, Confusion matrix, Classification Report(Precision ,Recall) , ROC(sensitivity, 1-specificity) & AUC score.

The model K-nearest-neighbors with MinMax scaler gives the highest performance metrics of 99.13% accuracy and 100% sensitivity for positive alarm class, the rest 0.87% error is of false positive cases, which is acceptable to have non-alarms predicted as alarms.

The Output of the model is checked with a following code to identify the problem source, which are four cases that include mixing (and/or) unbalancing in PX flows, each of different equipment.

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REFERENCES:

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ABBREVIATION

ERI Energy Recovery International

SW Sea Water

RO Reverse Osmosis

SWRO Sea Water Reverse Osmosis

PX Pressure Exchanger

LP Low Pressure

HP High Pressure