# Dependent Indicators for Environmental Evaluation of Desalination Plants

Ghanima Al-Sharrah and Haitham M.S. Lababidi

Chemical Engineering Department
College of Engineering & Petroleum
Kuwait University

Next Generation Brine Desalination and Management for Efficiency, Reliability, and Sustainability

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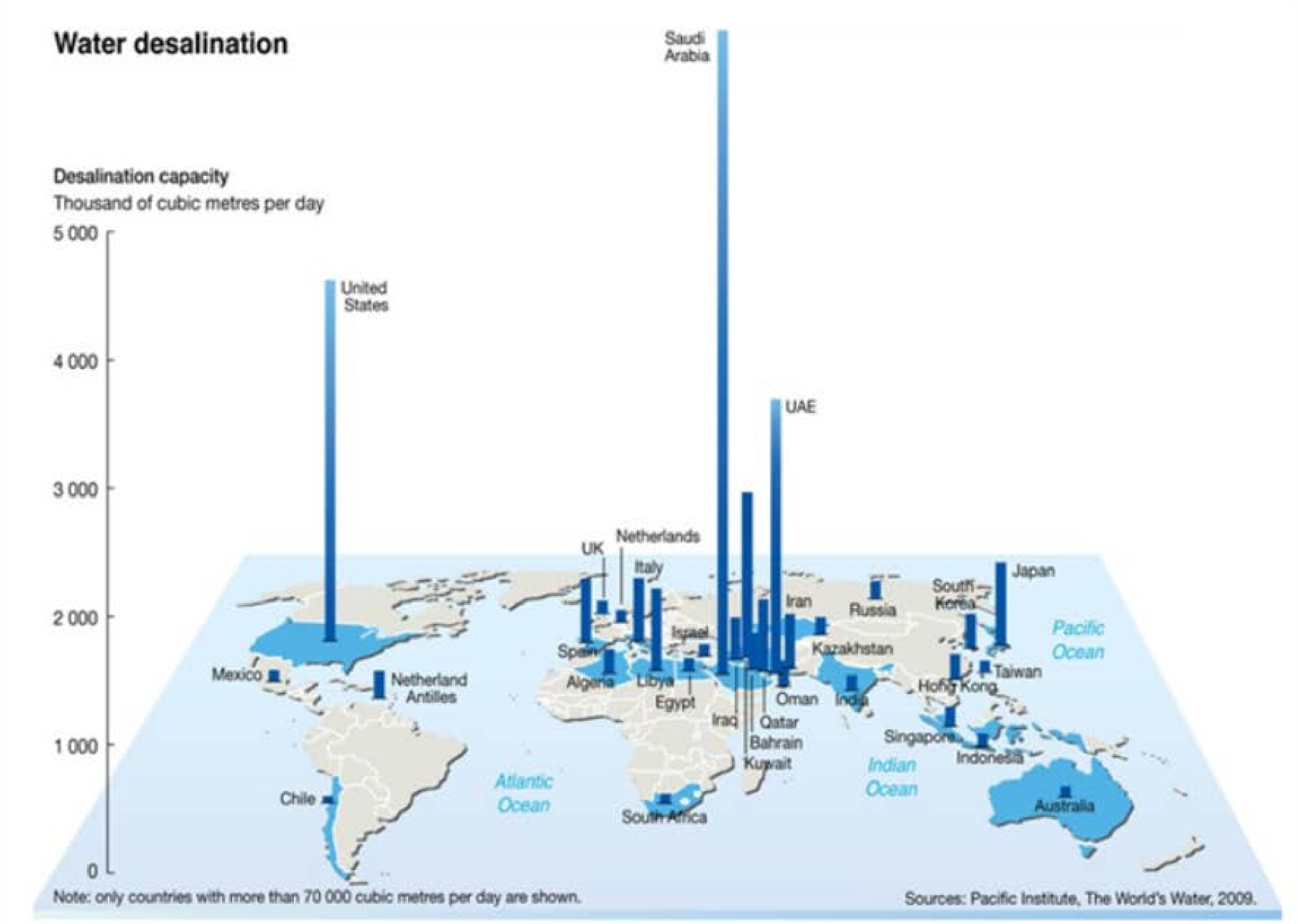
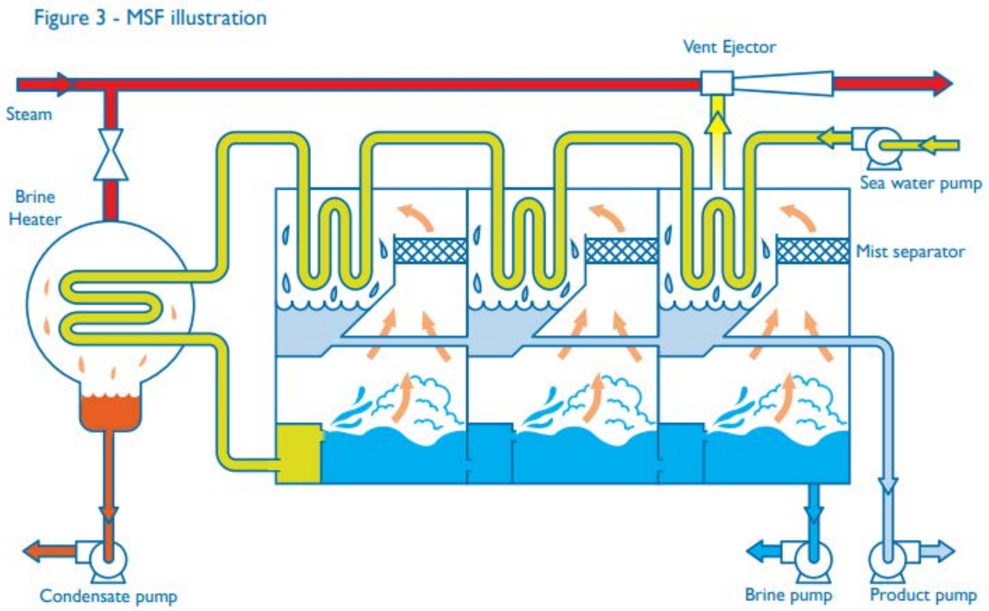
# Outline

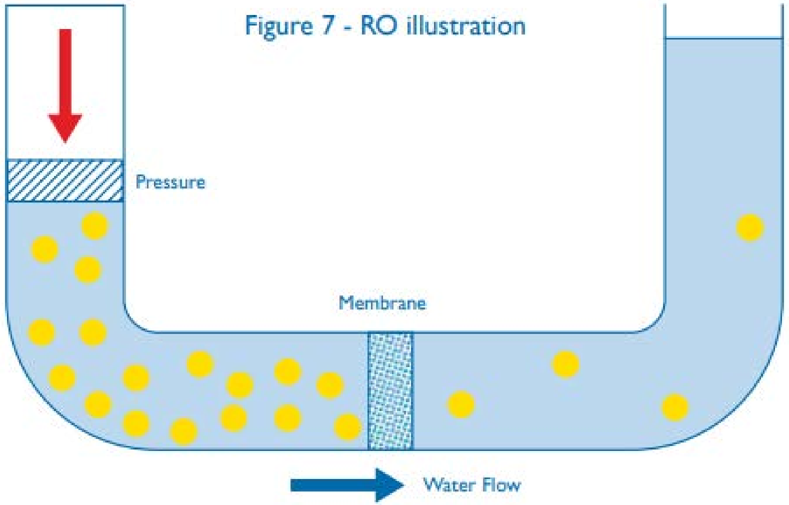
- Background
- Dependent data for brine and sea water
- Ranking with correlated data
- Case study
- Conclusions

# Background: Desalination




(Advision, 2018)



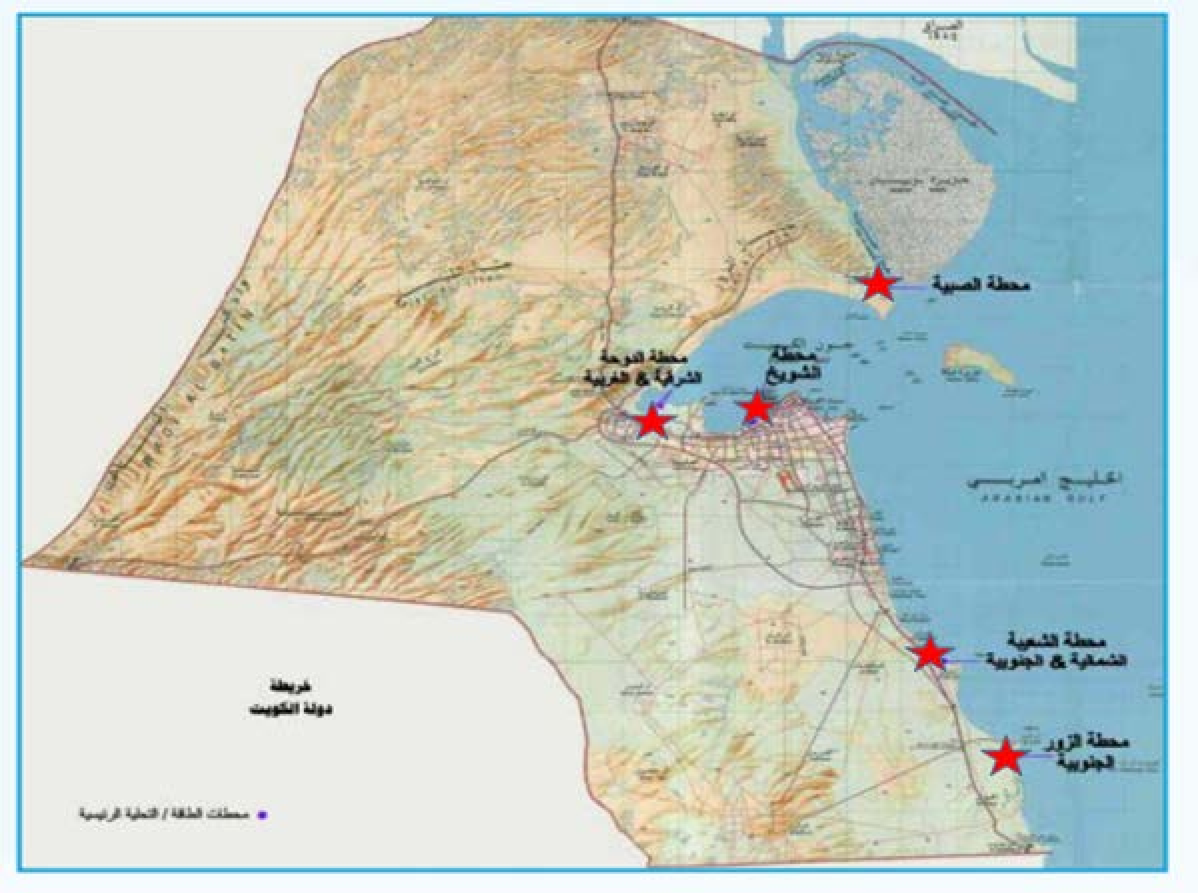

# Desalination

- MSF and RO are the main seawater desalination technologies in the GCC countries

(Desalination in the GCC, 2014)

# Desalination Plants in Kuwait

| Station | Technology | Capacity (MIG/d) |
|---|---|---|
| Shuwaikh | MSF | 19.5 |
| | RO | 30 |
| Shuaiba South | MSF | 36 |
| North | MSF | 45 |
| Doha East | MSF | 42 |
| West | MSF | 110 |
| Azzour | RO | 30 |
| | MSF | 115 |
| Sabiya | MSF | 100 |



# Dependent indicators

- We need indicators to study desalination activities.
- Limited data available.
- Some of the indicators are dependent on each other.
  - Example: energy consumption and $CO_2$ emission.
- They are usually correlated using mathematical models.
- Dependencies between indicators can be identified through:
  - Expert knowledge, or
  - Mathematically by using statistical analysis of collected data.

# Dependent Indicators for Seawater and Brine

| No | Dependent Indicators | | Note | Reference |
|---|---|---|---|---|
| 1 | Electric conductivity | chlorine ($Cl^-$) and sodium ($Na^+$) ions | linearly dependent | Fondriest (2015)<br>Sharp and Culberson (1982) |
| 2 | Total hardness , expressed as equivalent $CaCO_3$ | $Ca^{2+}$ and $Mg^{2+}$ ions | $[CaCO_3]=2.5[Ca^{2+}]+4.1[Mg^{2+}]$ | Venkateswarlu (1996)<br>LENNTECH 2016 |
| 3 | Langelier Saturation Index | total dissolved solids (TDS), concentrations of calcium ($Ca^{2+}$) and bicarbonates ($HCO_3$), and water temperature | The LSI is expressed as the difference between the actual system pH and the saturation $pH_s$ (LSI = pH – $pH_s$). The saturation $pH_s$ a log function | Alvarez-Bastida et al. (2013) |
| 4 | Density , viscosity | Temperature Salinity | Empirical correlation valid for salinities between 0 to 160 ppt and temperature between 10 to 180ºC at pressure of 1 atm | El-Dessouky and Ettouny (2002) |
| 5 | Dissolved oxygen | pH | Nonlinear | Makkaveev 2009 |
| 6 | Dissolved oxygen | Temperature Salinity | Nonlinear | Lewis (2005) |
| 7 | Total alkalinity (At) | total amount of calcium carbonate | $A_T=[HCO_3^-]+2[CO_3^{-2}]$ (mmol/l)<br>$CO_3^{-2}$ (mg/l)=0.6 At (mg/l)<br>$HCO_3^-$ (mg/l)=1.22 At(mg/l) | Danoun (2007)<br><br>California environmental protection agency (2016) |
| 8 | Carbonate ($CO_3^{-2}$ and $HCO_3^-$ ) | pH | Non-linear | Holmes-Farley (2002) |
| | | | | |

# Dependencies

- Can dependencies in indicators help?
  - How? And to what extent?
- Can correlation help reduce the number of indicators and complete/check collected data?
- Is the exclusion of indicators possible?
- What is the effect on decision making using ‘’Ranking Methods’’?
- We need to pereared before we receive data.

# Dependencies : Approach

- Original Data:
  - Sequences of uncorrelated normal distributed random indicators $X_1, X_2, \ldots, X_n$ for hypothetical objects $Obj_1, Obj_2, \ldots, Obj_m$ will be generated.
- Extended Data:
  - A correlation model is selected and a dependent indicator $Y_1$ is generated for all objects.
- Decision ranking:
  - Ranking is performed using the original and the extended data.
  - Results of ranking will order objects (assigned a numerical rank) from top to bottom to represent the most and the lease important object i.e. decision-making.
- Comparison:
  - Ranks from original and extended data are compared using the Spearman's rank correlation coefficient (SRCC).

# Ranking Method

- Modified Copeland method:
  - Sum of greater than minus less than relations in a pairwise comparison between indicators

Three Indicators ⟷ Two indicators

| | | Indicator | | | (a) | | Indicator | | (b) |
|---|---|---|---|---|---|---|---|---|---|
| | | $I_1$ | $I_2$ | $I_3$ | Copeland rank | | $I_1$ | $I_2$ | Copeland rank |
| Objects | $O_1$ | 1 | 3 | 6 | 1 | | 1 | 3 | 0 |
| | $O_2$ | 0.5 | 2 | 4 | -5 | | 0.5 | 2 | -4 |
| | $O_3$ | 5 | 1 | 2 | -4 | | 5 | 1 | -1 |
| | $O_4$ | 5 | 5 | 10 | 8 | | 5 | 5 | 5 |

# Ranking with Correlation

- Random data generated to represent *n* indicators for *m* objects.
- Different correlation models were used to represent dependencies.
- Original data extended using the correlation model (data extended to *n*+1 indicators for *m* objects).
- Ranks were evaluated for both data sets
- Ranks were compared.
- The methodology was implemented using MATLAB.

| Model for correlation | example |
|---|---|
| Linear | $Y_1 = a_0 + a_1 X_1 + \varepsilon_1$ |
| Multiple linear | $Y_1 = \rho X_1 + \sqrt{(1-\rho^2)} X_2$ |
| Non linear | $Y_1 = a_2 X_1^2 + \varepsilon_1$ |
| Complex | $Y_1 = \log(Y_2 \times Y_3) + Y_4$ |

# Ranking with Correlation : Results

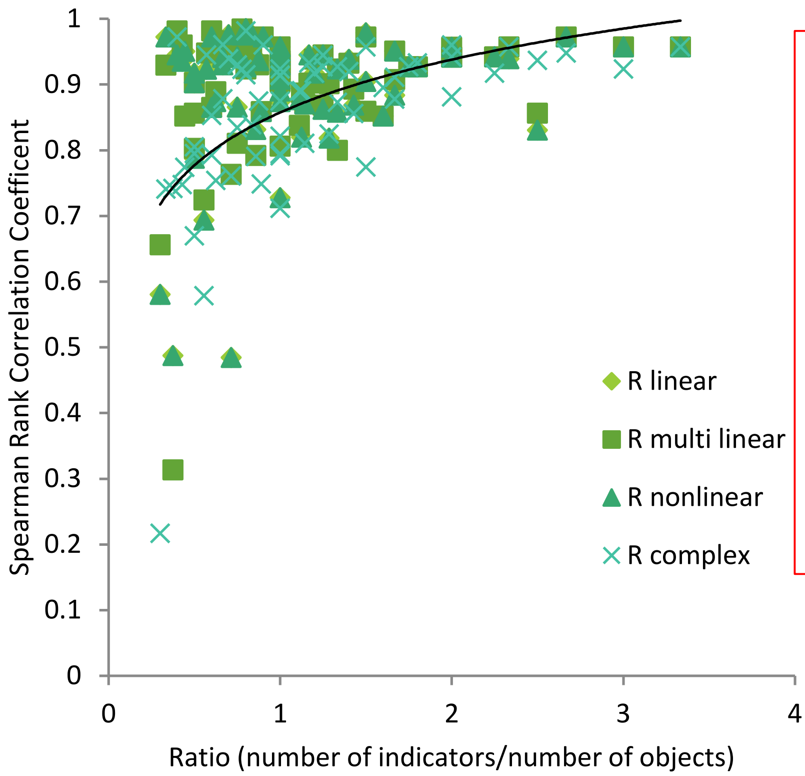
- 64 data sets
- Sizes up to 10 objects with up to 10 indicators
- Each data is ranked and then re-ranked after extension using 4 models.
- SRCC was relatively high. But is it guaranteed for all data sets?

| Model for correlation | example | SRCC |
|---|---|---|
| Linear | $Y_1 = a_0 + a_1 X_1 + \varepsilon_1$ | 0.892 |
| Multiple linear | $Y_1 = \rho X_1 + \sqrt{(1-\rho^2)} X_2$ | 0.894 |
| Non linear | $Y_1 = a_2 X_1^2 + \varepsilon_1$ | 0.892 |
| Complex | $Y_1 = \log(Y_2 \times Y_3) + Y_4$ | 0.857 |

Exclusion of dependent indicators will slightly affect rank of objects .

# Ranking with correlation

- What is the effect of data size?
- We need to know is the pervious result applicable for high/low number of indicator or high/low number of object?
- Use  ratio → Indicators/Objects
- Now test random data then test deal data.




if number of indicators are high relative to objects, excluding an indicators will not affect ranking result and vice versa

# Case Study: Desalination plants in GCC

| No | Parameter | Alssadanat, Oman (a) | Umm Alquain, UAE (b) | Hamriyah, Sharjah, UAE (c) | Saja'a Sharjah UAE (d) | Buwaib Saudi Arabia (e) | Salboukh Saudi Arabia (f) |
|---|---|---|---|---|---|---|---|
| 1 | $Ca^{++}$, mg/l | 923 | 202 | 173 | 188 | 573 | 404 |
| 2 | $Mg^{++}$, mg/l | 413 | 510 | 311 | 207 | 373 | 257 |
| 3 | $Na^{++}$, mg/l | 2780 | 3190 | 1930 | 4800 | 2327 | 1433 |
| 4 | $K^{++}$, mg/l | 81.5 | 84.5 | 50.7 | 60 | NA | NA |
| 5 | $Sr^{++}$, mg/l | 28.2 | 21.1 | 14.2 | 40 | NA | NA |
| 6 | Sum cation, meq/l | 203.06 | 192.98 | 119.48 | NA | NA | NA |
| 7 | pH | 7.21 | 7.54 | 7.66 | 7.95 | 4.1 | 4.5 |
| 8 | Electrical conductivity, mS/cm | 16.8 | 14.96 | 127.41 | NA | NA | NA |
| 9 | TDS, mg/l | 10553 | 10923 | 7350 | 12239 | 10800 | 6920 |
| 10 | $NO_3$, mg/l | 7.2 | 27.4 | 15.9 | NA | 143 | 142 |
| 11 | $F^-$, mg/l | 0 | 1.6 | 1.3 | 8.0 | NA | NA |
| 12 | $Cl^-$, mg/l | 4532 | 4108 | 2933 | 4860 | 2798 | 1457 |
| 13 | $SO_4$, mg/l | 1552 | 2444 | 1537 | 2400 | 4101 | 2840 |
| 14 | $SiO_2$, mg/l | NA | 164.09 | 133.71 | 120 | NA | NA |
| 15 | Carbonate ($CO_3^-$), mg/l | NA | NA | NA | NA | NA | NA |
| 16 | Bicarbonate ($HCO_3^-$), mg/l | 466 | 656 | 753 | NA | NA | NA |
| 17 | $N^-$ | 1.6 | 6.2 | 3.6 | NA | NA | NA |
| 18 | Sum anions, meq/l | 167.88 | 198.05 | 127.41 | NA | NA | NA |
| 19 | Ion balance | 9.48 | 4.02 | -3.21 | NA | NA | NA |
| 20 | SAR | 19.12 | 27.2 | 20.3 | NA | NA | NA |
| 21 | SER | 59.55 | 71.91 | 70.27 | NA | NA | NA |
| 22 | L.I | 1.24 | 1.04 | 1.26 | NA | NA | NA |
| 23 | R.I | 4.73 | 5.46 | 5.14 | NA | NA | NA |
| 24 | Total ion, mg/l | 10781 | 11245 | 7719 | NA | NA | NA |
| 25 | Total alkalinity | 380 | 538 | 617 | NA | NA | NA |
| 26 | Total hardness | 4041 | 2630 | 1730 | NA | 2968 | 2066 |
| 27 | Fe, meq/l | 0.06 | 0.08 | 0.05 | NA | 65.5 | NA |

Some data is missing

# Case study

- For dependencies, the analysis requires  deep analysis and subset data selection.
- The data can be divided into sets to test indicators dependencies with different data sizes.
- Data selected then correlated.

# Case study

| Sub set No | Objects | Original Indicators | Ratio= Indicator to objects | Extended Indicator | Type of Correlation | SRCC |
|---|---|---|---|---|---|---|
| **1** | a,b,c | All indicators (rows) except:<br>• $SiO_2$<br>• Carbonate<br>• Hardness | 24/3 = 8 | Carbonate | Linear | 1 |
| | | | | LSI | Complex | 1 |
| | | | | Hardness | Multi-linear | 1 |
| **2** | a,b,c | • $Ca^{++}$<br>• $Mg^{++}$<br>• pH<br>• Electrical Conductivity<br>• Bicarbonate<br>• Alkalinity | 6/3 = 2 | Carbonate | Linear | 1 |
| | | | | LSI | Complex | 1 |
| | | | | Hardness | Multi-linear | 1 |
| **3** | a,b,c,d,e,f | • $Ca^{++}$<br>• $Mg^{++}$<br>• pH<br>• $Na^{+}$ | 5/6 = 0.83 | Carbonate | Linear | 0.8286 |
| | | | | LSI | Complex | 0.89 |
| | | | | Hardness | Multi-linear | 0.9559 |

# Conclusions

- Exclusion of indicators is possible with the Copeland method.
- Exclusion of dependent indicators is safe if number of indicators to number of objects is relatively high.
- Exclusion of dependencies is safer for simple dependence relationship.
- Environmental indicators are highly dependent
- It is important to study dependencies for assessment or ranking.
- Identifying dependencies will provide a convenient way for completing missing data.