A combined probabilistic framework to support investment appraisal under uncertainty in desalination projects: an application to Kuwait's water/energy nexus

M. Skourtos, D. Damigos, A. Kontogianni, C. Tourkolias, A. Marafie and M. Zainal

ABSTRACT

Quantifying uncertainty over technologies, costs, and prices that stem from site-specific conditions, technological particularities and future projections is an important element in the investment appraisal of desalination facilities. Yet, the majority of economic assessments in the field of desalination plants, so far, use deterministic estimation methods based on 'best guess' estimates and ceteris paribus sensitivity analyses. Aiming to fill this gap, this paper introduces a new approach towards comparing alternative technological options for desalination facilities under uncertainty based on the Levelized Cost of Water (LCOW). The proposed framework combines Monte Carlo simulations with scenario analysis and random-walk-based models to account for the cone of uncertainty of the LCOW. For purely illustrative purposes, five alternative combinations of desalination technologies and energy sources are examined in the State of Kuwait. The findings show that the proposed framework, although it cannot eliminate uncertainty, can assist decision-makers in managing it by framing the range of possible outcomes of the LCOW. In this way, it offers an insight into the accuracy of the estimates and allows the validation of the impact of risks and uncertainties against the acceptable tolerance level. Yet, several issues need to be addressed in future research.

Key words | desalination, investment appraisal, Monte Carlo simulation, random walk models, renewable energy

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HIGHLIGHTS

- Uncertainties loom large in desalination investments.
- Majority of assessments use deterministic estimation methods.
- New approach comparing alternative desalination projects under uncertainty.
- Monte Carlo simulations, scenario analysis and random-walk-based models are combined.
- Five combinations of desalination technologies and energy sources examined in Kuwait.

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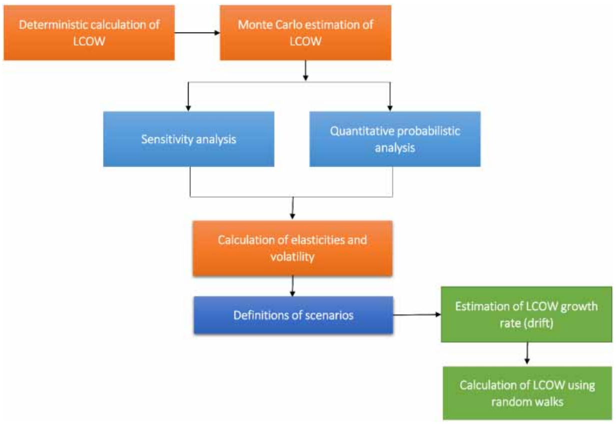
GRAPHICAL ABSTRACT



INTRODUCTION

Desalination has become one of the most sustainable alternative solutions to provide fresh water for many communities and industrial sectors over the last 30 years (Shatat *et al.* 2013). Since 2010, the number and size of desalination projects worldwide have been growing at a rate of 5% to 6% per year (Voutchkov 2018). In 2018, 18,426 desalination plants were reported to be in operation in over 150 countries, producing 87 million m^3/day of freshwater and supplying over 300 million people (World Bank 2019). In the decades to come, changing climate patterns and population growth will make already limited water resources scarcer and access to freshwater an increasingly crucial challenge. Thus, desalination, of seawater in particular, will play a greater role and investments in desalination will increase. In parallel, technological advancements are expected to significantly lower the cost of desalinated water, i.e. by 20% in the next five years and by up to 60% in the next 20 years (Voutchkov 2018). BCC Research (2016) reports that global cumulative investments in desalination plants will reach nearly $48.2 billion by 2020, with a compound annual growth rate (CAGR) of 17.6%. Further, Gao *et al.* (2017), based on socioeconomic data and modelling techniques, estimate that the total global desalination population will increase by 3.2-fold in 2050 compared with the present.

Investment in desalination is essential for meeting future water demand and sustaining economic growth. The sheer size and financial needs of desalination investments call for a thorough quantification of uncertainty in project appraisal. Nevertheless, the majority of economic assessments in the field of desalination plants use deterministic estimation methods (Moser *et al.* 2015). Against this backdrop, the present paper aims to improve investment planning by introducing a new approach for comparing alternative options under uncertainty focused on desalination projects. Knight (1921), in his seminal work, drew a sharp distinction between risk, referring to events for which outcomes are known or have knowable probability distributions, and uncertainty, referring to events where it is not possible to specify numerical probabilities (Bock & Trück 2011; Toma *et al.* 2012). Hence, in practice, the term uncertainty is used interchangeably with that of risk. Uncertainties in desalination investments are related to design, construction and operational phases of the project, e.g. licensing, construction, water quality, power supply and water demand (World Bank 2019). In our approach, we are mostly interested in uncertainties over technologies, costs and prices in the energy/water nexus context. This suggestion is supported by recent empirical evidence that energy savings potential, as shown by engineering calculations, is rarely exhausted in practice (ICF 2015).

The proposed methodology combines in sequential steps Monte Carlo simulations and random-walk-based estimates for comparing alternative technology options for desalination units based on the Levelized Cost of Water (LCOW). LCOW is a commonly used approach for comparing desalination plants (e.g., Olwig *et al.* 2012; Moser *et al.* 2013, 2015; Caldera *et al.* 2016). The term 'levelized' expresses the unit cost of desalinated water (e.g., USD/m^3) as the sum of fixed and variable annual costs of the plant (including the annualized capital costs) divided by the total annual water production. Although the methodology was originally developed for the analysis of desalination units, it may apply to other infrastructure projects after proper modifications.

For illustrating the methodology, five alternative combinations of desalination technologies and energy sources are examined using the State of Kuwait as a case study. Kuwait was selected – as further discussed in the section below on 'An illustrative application in the State of Kuwait' – for the following reasons. First, due to the significant oil price-drop since mid-2014, Kuwait's overall fiscal surplus fell from 18.5% of GDP in 2014/15 to 0.5% of GDP in 2016/17 (IMF 2018; KISR 2019, p. 37). Second, Kuwait relies practically entirely on the desalination of seawater and plans to build several new desalinating facilities as the average per capita water consumption shows an increasing trend. Third, the efficiency of Kuwait's electricity and water supply system is questioned from both an environmental and economic viewpoint. Finally, and perhaps most importantly, the opportunity cost of using oil to generate electricity and water – even at current low oil prices – is high.

The paper is structured as follows: the next section provides an overview of the water/energy project appraisal. The third section describes the proposed new framework for probabilistic assessment in the water/energy nexus, while the fourth section details the empirical application and presents the results. The final section concludes with a synopsis and a look ahead.

LITERATURE REVIEW

Efficient water/energy projects

Considering that the seawater desalination process is energy-intensive, and that energy and water production are closely associated, several research efforts seek to shed light on alternative, more energy-efficient solutions. The renewable energy desalination (RED) systems – even though at present less than 1% of installed desalination capacity – are witnessing an increasing growth worldwide as the technologies continue to improve and conventional sources of energy become scarcer and, consequently, more expensive. According to Alkaisi *et al.* (2017), more than 130 RED plants have opened within the last few years. Papapetrou *et al.* (2010), Al-Karaghouli & Kazmerski (2011), IEA-ETSAP & IRENA (2013), Goosen *et al.* (2014), Shatat & Riffat (2014), Cipollina *et al.* (2015), and Xevgenos *et al.* (2016) provide technical and economic information on the most adopted brackish and seawater RED systems. Practically, all forms of RES technologies (e.g., solar thermal, photovoltaics – PV, wind, geothermal, and wave energy) can be used as energy sources for desalination systems. However, the most promising RED systems are solar energy (both solar thermal and PV) with multistage flash distillation (MSF); multi-effects distillation (MED); reverse osmosis (RO); thermal vapor concentration (TVC); mechanical vapor concentration (MVC) and electro-dialysis (ED); wind energy with MVC, RO, and ED; medium-temperature geothermal energy with MSF and MED; high-temperature geothermal energy with MSF, MED, TVC, MVC, RO, and ED; and wave energy with MED, TVC, MVC, RO and ED (see Jalihal & Venkatesan 2019). Combined systems (e.g., wind with solar energy) can also be integrated with different desalination processes (Papapetrou *et al.* 2010; Al-Karaghouli & Kazmerski 2011; IEA-ETSAP & IRENA 2013; Xevgenos *et al.* 2016).

Most of the RED technologies have been tested extensively (although in some cases mainly on a pilot-scale), and their technical feasibility has been established. What is of main concern, though, is the cost of each option, which will finally determine the configuration of the desalination facility. Focusing on the cost of RED, which is the main aim of this study, several cost comparison methodologies have so far been implemented. These approaches are mainly based on the LCOW. Key inputs in calculating the LCOW are capital costs, operation and maintenance (O&M) costs, replacement costs, useful life, water production and discount rate.

Current methodological pitfalls

Several factors influence the LCOW: cost of fossil fuels, price of metals involved in desalination or RES units, energy mix, changes in weather conditions, salinity and temperature of seawater, environmental regulations concerning climate change and emissions of pollutants, technological improvements etc. (e.g. Moser *et al.* 2013, 2015; Fattouh & Mahadeva 2014; Wood & Alsayegh 2014). Previous research in the field shows that not all desalination plants are impacted by all these parameters, nor are they equally affected. The impact of each parameter on a specific desalination technology differs, and so does the ability to quantify its uncertainty. For instance, MED is more vulnerable than other technologies to metal price fluctuations because the cost of MED evaporators depends to a notable extent on the price of copper and nickel. Yet, the impact of fossil fuel price on the LCOW of MED plants is of considerable significance compared with copper or nickel price.

The majority of economic assessments in the field of desalination plants – as already mentioned – are based upon 'best guess' estimates of the input variables (Moser *et al.* 2015). They neglect the fact that desalination plants are sophisticated and technologically advanced projects and, consequently, most of the LCOW parameters are characterized by uncertainty and variability stemming from site-specific conditions, technological particularities, and future projections. Hence, it is not surprising that accurately estimating the costs of desalination plants is almost always a unique challenge for engineers, state agencies, and contractors. To cope with these difficulties, sensitivity analysis is usually performed invoking the ceteris paribus assumption (i.e., only one variable is changed at a time 'other things being equal') to determine how much the LCOW might vary. In some cases, sensitivity analysis uses 'what if' scenarios based on combinations of possible values around the 'single-point-base-estimates' (i.e., worst- and best-case situations).

Although this analysis is useful in determining the influence of each variable on the LCOW, the assessment of desalination projects calls for a significant number of 'what if' scenarios to be examined, given the number of the parameters involved. Further, sensitivity analysis fails to answer critical questions from the viewpoint of policy- and decision-makers, e.g., 'what will be the best outcome and the probability of that occurrence?' 'what is the probability of being above or below certain LCOW values?' etc. These questions could be answered using a probabilistic approach like the one proposed in the present paper. This type of analysis assigns probability distributions to the critical variables of the desalination project to generate several possible scenarios by accounting for every possible value that each variable can take. Then it recalculates the expected values of financial performance indicators weighing each scenario by the probability of occurrence. The probabilistic analysis provides many benefits: it offers an insight into the accuracy of the estimates of financial indicators, it allows engaging managers in a meaningful conversation about the risks of the project, it helps decision-makers to frame the range of possible outcomes more meaningfully and to validate the impact of uncertainties and risks against the organization's tolerance level, etc. (e.g., Pergler & Freeman 2008; Platon & Constantinescu 2014). To the authors' best knowledge, this is the first attempt at using a probabilistic approach that combines Monte Carlo simulation with scenario analysis and random-walk modelling in an integrated framework for assessing the performance of different desalination systems through the LCOW concept.

A NEW FRAMEWORK FOR PROBABILISTIC ASSESSMENT IN THE WATER/ENERGY NEXUS

The proposed methodological framework to address uncertainty in the LCOW parameters comprises a sequence of analytical steps as presented in Figure 1.

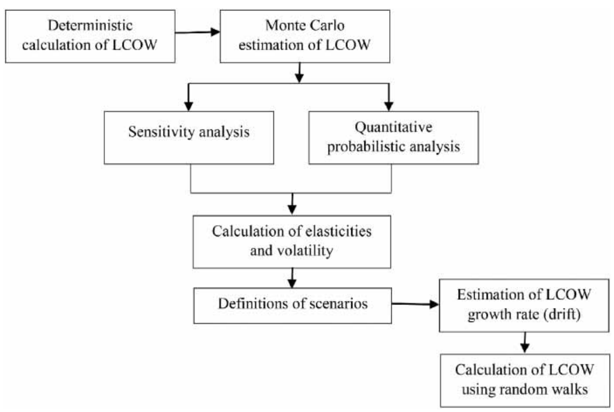


Figure 1 | The outline of the proposed methodology.

The steps are analyzed as follows:

Step 1: Deterministic estimation of LCOW

The calculation of the LCOW is similar to that of the Levelized Cost of Energy (LCOE), i.e., it is based on the estimation of investment and operating costs and the volume of production from the plant under investigation. Following Moser *et al.* (2015), the calculation of LCOW follows (Equation (1)):

$$LCOW = \frac{\sum_{t=1}^{n} \frac{C(t)_{\text{investment}} + C(t)_{\text{operation}}}{(1+r)^t}}{\sum_{t=1}^{n} \frac{W(t)}{(1+r)^t}} \quad (1)$$

where LCOW ($\$/m^3$) is the levelized cost of desalinated water; $C(t)_{\text{investment}}$ (mil \$/y) is the capital cost in year t; $C(t)_{\text{operation}}$ (mil \$/y) is the operating cost in year t; $W(t)$ (mil m^3/y) is the annual water production in year t; n (years) is the economic life of the plant; and r (%) is the annual discount rate.

Step 2: Monte Carlo estimation of LCOW

The Monte Carlo method is used to analyze the influence of uncertain parameters (e.g., future fuel prices, electricity production from RES, etc.) on the LCOW. It involves the conversion of the uncertainty into probability distributions for each parameter, simulation of thousands of possible scenarios (1,000 in this study), calculation of the LCOW for each scenario, and analysis of the probability distribution of LCOW. Even though the method cannot eliminate uncertainty, it can make it easier to understand by ascribing probabilistic characteristics to the inputs and outputs of the LCOW model. The purpose of Monte Carlo simulations in the proposed methodology is twofold. First, the analysis may be used to directly answer questions posed by policy- and decision-makers (e.g., probability of observing specific LCOW values). Second, and equally important, it is used to estimate critical parameters for implementing random-walk-based LCOW models, as will be described in detail later, using sensitivity analysis and quantitative probabilistic analysis.

Step 3: Calculation of elasticities and volatility

The sensitivity analysis which is applied in different disciplines (e.g., science, engineering, and economics) can be used for calculating the Sensitivity Ratio (SR), also known as 'elasticity'. The elasticity is equal to the percentage change in output (e.g. LCOW) divided by the percentage change in input for a specific input variable (e.g., O&M costs) according to Equation (2):

$$Elasticity = \frac{\Delta LCOW\%}{\Delta Input\%} \quad (2)$$

As discussed in Step 5, once the elasticity of input variables has been defined and different scenarios have been formed, the total growth rate of future LCOW values can be estimated.

Volatility (σ) is a measure of the variability of the LCOW over the lifetime of the desalination plant and signifies the uncertainty associated with its total cost and production volume. Volatility is an important input variable for the structure of random walk models and can have a significant impact on the stochastic estimates. Several methods are used to estimate volatility; in this paper the logarithmic present value (LPV) approach is implemented (Mun 2006). The LPV method collapses all future cash-flow estimates into two sets of present values, one to time 0 and one to time 1. The present values are then summed, and the logarithmic ratio X is calculated as follows:

$$X = \ln\left(\frac{\sum_{i=1}^{n} PVTC_i}{\sum_{i=0}^{n} PVTC_i}\right) \quad (3)$$

where $PVTC_i$ is the present value of the total cost of desalination in year i.

Monte Carlo simulation is performed to obtain the distribution of X. The standard deviation of the distribution of X is the volatility (σ) used in the random walk model. It is noted that only the numerator is simulated; the denominator remains unchanged (Mun 2006). Furthermore, a single 'aggregate' volatility factor is estimated, although uncertainties are related to several variables. If necessary, however, different volatility factors can be estimated and be incorporated in the random walk model.

Step 4: Definition of scenarios

This step involves defining the alternative scenarios that will be examined via random walks. The scenarios are formed based on future trends of input parameters (e.g., fossil fuel price). The trend is expressed as the compound average annual growth rate (CAAGR) of the input variable, i.e., the mean annual growth rate over the lifetime of the plant, which is estimated according to Equation (4):

$$CAAGR = \left(\frac{Ending\ value}{Beginning\ value}\right)^{\left(\frac{1}{\#\ of\ years}\right)} - 1 \quad (4)$$

Step 5: Estimation of LCOW growth rate (drift)

To examine the effect of an input variable on the change of LCOW, it is necessary to consider both the input variable elasticity of LCOW and the growth rate of the input variable, as follows:

$$\Delta LCOW_i = e_i * CAAGR_i = \alpha_i \quad (5)$$

where $\Delta LCOW_i$ (α_i) is the change in LCOW attributed to input variable i; e_i is the elasticity of input variable i and $CAAGR_i$ is the compound average annual growth rate of input variable i.

Given that each factor has an independent and additive effect on the evolution of future LCOW values, the total growth rate α_{tot} of LCOW is the sum of shifts over time given by:

$$\frac{\dot{LCOW}}{LCOW} = e_1 \frac{\dot{V}_1}{V_1} + e_2 \frac{\dot{V}_2}{V_2} + \cdots + e_k \frac{\dot{V}_k}{V_k} \quad (6)$$

When the right-hand expression is constant, the solution is:

$$LCOW_t = LCOW_0 * e^{d_{\text{tot}} t} \quad (7)$$

where $LCOW_t$ is the future LCOW at time t; $LCOW_0$ is the present LCOW; t is the time in years (assuming that α_{tot} and discount rates are expressed on a yearly basis), and α_{tot} is the total growth rate of LCOW with $\alpha_{\text{tot}} = \alpha_1 + \alpha_2 + \ldots + \alpha_k$.

Step 6: Calculation of LCOW using random walks

The total growth rate of LCOW is likely to change over time in an unknown way, similar to commodity spot and forward prices. Towards modelling the evolution of possible future outcomes through time, sophisticated time-series models are used. These models assume that past patterns of the parameter under investigation will tend to recur in the future and, thus, establish a clear connection between historical data and forecast values (e.g., Newell & Pizer 2003). One such model is the random walk. Random-walk-based stochastic simulations with and without drift have been used in finance and economics, e.g. in predicting the effect of technological progress on the cost of different technologies (Farmer & Lafond 2016), in understanding and predicting the behaviour of stock market prices (Smith 2002; Borges 2011), interest rates (Newell & Pizer 2003; Bacchetta & van Wincoop 2007), growth and inequality (Scalas 2006), etc. Random walks have also been used or tested in modelling energy prices (Felder 1995; Pindyck 1999; Geman 2007).

The random walk process is equivalent to Brownian motion. Formally, the random walk is a Wiener process. The random walk with drift is given by the following equation (the random walk model without drift is briefly described in Appendix A: Supplementary Material):

$$Y_t = Y_{t-1} + \delta + u_t \quad (8)$$

where δ is the drift, which can take either a positive or a negative value for an upward or downward drift respectively.

The expected value of Y_t and the variance are as follows:

$$E(Y_t) = Y_0 + t * \delta \quad (9)$$

$$\text{var}(Y_t) = t * \sigma^2 \quad (10)$$

Based on the general model with drift, the change in LCOW in a period Δt is approximated, as follows:

$$\Delta LCOW = \alpha_{\text{tot}} * LCOW * \Delta t + \sigma * LCOW * u * \sqrt{\Delta t} \quad (11)$$

where $\alpha_{\text{tot}} * LCOW_t * \Delta t$ represents the drift and $\sigma * LCOW * u * \Delta t^{1/2}$ is the random noise in each step.

AN ILLUSTRATIVE APPLICATION IN THE STATE OF KUWAIT

Background information

The State of Kuwait lies at the northeast edge of the Arabian Peninsula at the head of the Arabian Gulf and occupies a total area of 17,820 km^2 of mostly desert land (FAO 2009). Kuwait's renewable groundwater sources are negligible; it is estimated that only 20 Mm^3/year flow into the groundwater systems through lateral underflow from Saudi Arabia (FAO 2009). Due to its limited freshwater resources, Kuwait relies practically entirely on the desalination of seawater to produce fresh water through multi-stage flash desalination and reverse osmosis that operate in the form of cogeneration power–desalination plants (CPDP) (Alhajeri et al. 2018).

The average per capita water consumption is high with an increasing trend. In 2014, the average water consumption per capita was 442 l/d/capita, one of the highest among industrialized and other developing countries (Mukhopadhyay & Akber 2018). In comparison with 2009, future water demand is forecast to increase by approximately 25% in 2020–30 and by approximately 60% in 2040–50 (World Bank 2012). Towards meeting its water needs, Kuwait plans to build several new desalinating seawater facilities (KDIPA 2016) and to tender a program for 30 RO mobile units each with a 100,000-gallon capacity (International Water Summit 2018).

Kuwait relies on fossil fuels (i.e., natural gas, gas oil, crude oil, and heavy fuel oil) to generate electricity and water. Yet, the efficiency of Kuwait's electricity and water supply system is questioned from an environmental and economic viewpoint. The consumption of fossil fuel causes deterioriation of the air quality and contributes to climate change due to emission of air pollutants and greenhouse gases (Mezher et al. 2011). Further, electricity generation units consume a large amount of freshwater in steam power stations and produce a large amount of waste (Alhajeri et al. 2018). As a result, the desalination plants may damage aquifers and aquatic ecosystems from the routine discharge of effluents and the disposal of concentrate of relatively high-temperature and elevated salinity (Miller et al. 2015). The concentrate contains pretreatment chemicals, corrosion materials, and even nuclear contaminants that cause acute or long-term effects on aquatic organisms (Mezher et al. 2011; Miller et al. 2015). The increased temperature of water effluents can also harm the aquatic life in the discharge area, especially the benthic marine organisms (Younos 2009). The impacts of elevated salinity, increased temperature and discharged chemicals depend on the environmental and hydro-geological factors characteristic of the site and, thus, differ geographically. So far, however, there is limited research particularly on the long-term ecological impacts of desalination (Miller et al. 2015). Finally, the operation of desalination plants may cause noise pollution and chemical spills (Mezher et al. 2011). From an economic point of view, considering the increasing consumption and the current production rate, all produced energy will probably be consumed locally by 2027 (Alotaibi 2011). Further, the opportunity cost of using oil to generate electricity, as compared with selling it in the international market, has become too high (Darwish & Darwish 2008; Breyer et al. 2010; Capital Standards 2013). Thus, the Government of Kuwait plans to invest approximately USD 25 billion to increase the electricity production capacity to 17,200 MW in 2016 and 25,000 MW in 2025 (KDIPA 2016) and contemplates generating at least 10% of its electricity needs from renewable sources.

Basic assumptions

For purely illustrative purposes, two alternative desalination technologies, namely seawater reverse osmosis (SWRO) and multi-effect distillation (MED), are considered. The desalination plants are assumed to supply 100,000 m^3/day with an availability of 92% and an economic plant life of 20 years and to be operated at base load (i.e., 8,000 hours per year) meaning constant production over the year. Moreover, three alternative energy sources, namely photovoltaics (PV), concentrating solar power (CSP) and natural gas, are coupled with each plant forming the following combinations:

- SWRO plant powered by PV and a natural gas combined cycle plant;
- SWRO plant powered by CSP and a natural gas combined cycle plant;
- SWRO plant powered solely by a natural gas combined cycle plant;

- MED plant powered by CSP and a natural gas combined cycle plant;
- MED plant powered solely by a natural gas combined cycle plant.

Given the low-quality feed water (i.e., Arabic Gulf), the SWRO plant operates with open intake and a DAF pretreatment (dissolved air flotation) followed by gravity filters and pressure filters. An indicative cost of such a plant is approximately 2,100 US\$/m^3/day (e.g., Moser *et al.* 2013). The total operation and maintenance costs, excluding energy, are estimated at 0.35 US\$/m^3 and the specific electricity consumption amounts to 4.2 kWh/m^3 (Fichtner 2011). Based on the total supply and the specific electricity consumption, the total energy requirements amount to 141,036 MWh per year.

The MED plant has a dual-purpose configuration: it is designed to work at a seawater temperature of 35 °C and to be fed with a 0.30–0.35 bar steam and it is based on 14 subsequent effects operating at a gain output ratio (GOR) of 12 (Fichtner 2011). An indicative cost of such a plant is approximately 3,100 US\$/m^3/day. The total operation and maintenance costs – excluding energy – are estimated at 0.32 US\$/m^3 (Fichtner 2011). The energy demand in terms of electricity is 1.6 kWh/m^3 and the required thermal energy is 53 kWh_{th}/m^3. The required thermal energy corresponds to 3.6 kWh_e/m^3 based on the equivalent electrical energy approach since the extracted heat from the turbine is considered as electricity loss for the power plant (Fichtner 2011). The total energy requirements expressed as equivalent electrical energy are estimated at 174,616 MWh annually.

For the analysis, some simplified yet reasonable assumptions have been adopted. First, desalination plants are simply seen as power consumers. Second, it is assumed that the RE cogenerated power plants (i.e. PV and CSP) generate on an annual basis 40% of the electrical energy required by each desalination plant (i.e., 56,414 MWh per year for the SWRO plant and 69,846 MWh per year for the MED plant); the rest of the power is provided by a natural gas combined cycle plant. Hence, the annual energy cost is calculated by multiplying the LCOE of the energy source with the corresponding amount of electricity used from that energy source. In the same direction, issues related to the capacity and stability of the grid are not taken into consideration. As a consequence, we presume an ideal, infinite storage capacity available at no additional cost and free of energy losses to buffer renewable energy fluctuations (Moser *et al.* 2013). Finally, as regards the alternative energy sources, the basic economic and technical assumptions are based on Lazard's Levelized Cost of Energy (LCOE) analysis (Lazard 2017) and are summarized in Table 1. It is noted that the fuel price is related to the Henry Hub contracts, which tend to become an international price setter. The annual discount rate is set equal to 6%.

Results

Following the methodology described above in the section on 'A New Framework for Probabilistic Assessment in the Water/Energy Nexus', we calculate first the deterministic LCOW for the five alternative configurations. The results are provided in Table 2.

To conduct the probabilistic analysis, some assumptions were made related to the uncertainty and variability of critical variables (e.g., fuel price, capacity factor, investment and

Table 1 | Basic assumptions for the alternative energy sources

	PV-crystalline	Solar thermal power with storage	Natural gas combined cycle
Total capital cost (\$/kW)	1,200	7,500	1,000
Fixed O&M (\$/kW-year)	10	75	6.0
Variable O&M (\$/MWh)	–	–	3.0
Heat rate (Btu/kWh)	–	–	6,300
Capacity (MW)	26	14/18	50
Capacity factor (%)	25%	45%	65%
Efficiency of NG plant (%)	–	–	54%
Fuel price (US\$/MMBtu)	–	–	3.2
Facility life (years)	30	35	20

Table 2 | Deterministic LCOW for the alternative desalination plant configurations

Desalination plant	LCOW (US \$/m^3)	CAPEX (%)	OPEX w/o energy (%)	Energy cost (%)
SWRO-PV	1.10	49%	32%	19%
SWRO-CSP	1.28	43%	27%	30%
SWRO-NG	1.12	49%	31%	20%
MED-CSP	1.60	50%	20%	30%
MED-NG	1.40	58%	23%	20%

operating costs, etc.); these assumptions are detailed in Table S1 (Appendix A: Supplementary Material). The choice of input distribution was based on information available for each parameter. Further, to represent the broader range of uncertainty, the Maximum Entropy approach was chosen, i.e., a distribution was formulated such that it maximizes the uncertainty in the data, subject to known constraints (Meyer & Booker 2001).

The Monte Carlo simulation statistics for the LCOW are presented in Table 3 and the sensitivity-ratio-based elasticities of the input variables are presented in Table 4.

Based on Equation (3) and the results of Monte Carlo simulations, the volatility (σ) for each LCOW is calculated as follows: $\sigma_{\text{SWRO-PV}} = \sigma_{\text{SWRO-CS}} = \sigma_{\text{SWRO-NG}} = 0.11$, $\sigma_{\text{MED-CSP}} = 0.12$ and $\sigma_{\text{MED-NG}} = 0.04$.

Further, Table S2, in the Supplement, illustrates the simulated comparisons between the alternative configurations, together with the probability of observing a positive difference between the competitive technologies.

To estimate the total growth rate of future LCOW values, a scenario is formed under the following assumptions:

- CAAGR for NG price is estimated at 3.8% using Deloitte's forecasts (Deloitte 2018).
- CAAGR for PV and CSP CAPEX are taken equal to −8.0% and −4.5%, respectively using IRENA's predictions (IRENA 2016).
- CAAGR for PV and CSP OPEX are estimated to increase at approximately 0.5%.
- CAAGR for RO and MED CAPEX and OPEX are assumed to be equal to −0.5%.

Table 3 | Monte Carlo simulation statistics for the LCOW

Desalination configuration	Mean	Median	St. dev.	Minimum	Maximum
LCOW SWRO-PV (US $/m^3)	1.10	1.09	0.06	0.94	1.32
LCOW SWRO-CSP (US $/m^3)	1.28	1.27	0.07	1.07	1.54
LCOW SWRO-NG (US $/m^3)	1.11	1.10	0.06	0.92	1.32
LCOW MED-CSP (US $/m^3)	1.58	1.58	0.10	1.32	1.97
LCOW MED-NG (US $/m^3)	1.39	1.39	0.02	1.34	1.48

Table 4 | Elasticities of LCOW for alternative configurations and critical input variables

	SWRO-PV	SWRO-CSP	SWRO-NG	MED-CSP	MED-NG
Availability of DES plant	−0.450	−0.387	−0.444	−0.457	−0.577
CAPEX-RO	0.494	0.426	0.488	–	–
OPEX-RO	0.317	0.273	0.313	–	–
Specific energy-RO	0.188	0.301	0.198	–	–
Heat rate-NGCC	0.179	0.154	0.294	0.152	0.291
Fuel price	0.085	0.073	0.140	0.072	0.138
Capacity factor-PV	−0.061	–	–	–	–
CAPEX-PV	0.061	–	–	–	–
Capacity factor-NGCC	−0.032	−0.028	−0.053	−0.027	−0.052
CAPEX-NGCC	0.033	0.029	0.055	0.028	0.054
OPEX-PV	0.007	–	–	–	–
Capacity factor-CSP	–	−0.179	–	−0.177	–
OPEX-CSP	–	0.025	–	0.025	–
CAPEX-CSP	–	0.172	–	0.170	–
CAPEX-MED	–	–	–	0.502	0.574
OPEX-MED	–	–	–	0.200	0.228
Specific energy-MED	–	–	–	0.298	0.196

Given the abovementioned assumptions and the estimated elasticities, the LCOW total growth rates are: $GR_{\text{SWRO-PV}} = -0.6\%$, $GR_{\text{SWRO-CS}} = -0.8\%$, $GR_{\text{SWRO-NG}} = 0.1\%$, $GR_{\text{MED-CSP}} = -0.8\%$ and $GR_{\text{MED-NG}} = 0.5\%$. For each alternative configuration, 100 random walk simulations were conducted for the next five years using a time step $\delta T = 0.1$ years. For conciseness reasons, only the minimum and maximum values of all LCOWs in each time step are illustrated in Figure 2 (in the Supplement the results for the $LCOW_{\text{SWRO-PV}}$ are given for illustrative purposes in Fig. S1 and the minimum and maximum values of all LCOWs for a time step of six months are given in Table S3).

Discussion

Based on the results of the analysis (Table 3), the SWRO-PV and the SWRO-NG are the most preferred options in terms of LCOW, followed by the SWRO-CSP plant. The MED desalination plants produce more expensive water (ca. 0.3 US$/m^3) compared with the respective SWRO plants. The probabilistic analysis does not alter the overall

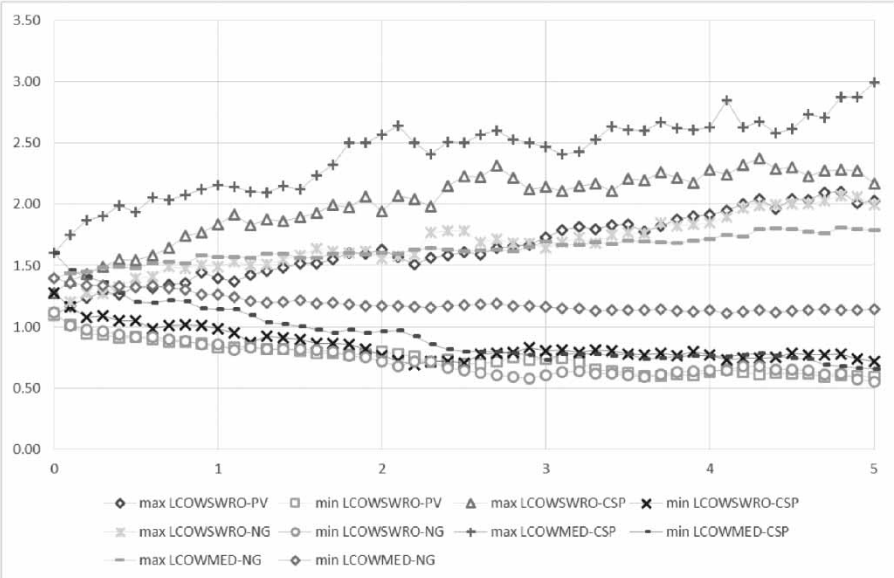


Figure 2 | Min and max values of all LCOWs in each time step based on the random walk simulations.

conclusion. In the majority of comparisons, the SWRO-PV has the lowest LCOW. These findings coincide with results of previous studies (e.g. Olwig *et al.* 2012; Shatat & Riffat 2014).

The desalination plants that are powered by CSP present the highest LCOW. This is not surprising since the LCOE for CSP equals 150 US$/MWh whereas the LCOE for the PV and NGCC plants is 44.5 US$/MWh and 52.7 US $/MWh, respectively. The role of energy cost is also depicted in Tables 2 and 3. The cost of energy comprises about 30% of the LCOW in the case of CSP-powered desalination plants, approximately 10% higher than that of PV- and NG-powered desalination plants. Similar remarks regarding the impact of energy cost are made by Olwig *et al.* 2012 and Moser *et al.* (2015). Moreover, the elasticity of specific energy required per m^3 of water is higher in the case of CSP desalinated plants (i.e., 0.3 compared with 0.2 for the other energy sources).

As shown in Table 4, the most critical factors in terms of elasticity (apart from the availability of the desalination plant) are related to the CAPEX and OPEX of the desalination technology, followed by the specific energy. To wit, in the case of SWRO-PV configuration, the CAPEX-RO elasticity is 0.494 (i.e., 10% change in the CAPEX of the RO plant increases the LCOW by approximately 5%), followed by the OPEX-RO and the specific energy elasticities. The same stands for the SWRO-NG and SWRO-CSP configurations. In the case of SWRO-CSP, however, the specific energy elasticity is more important than the OPEX-RO elasticity owing to the higher cost of CSP energy. Similar conclusions are drawn with regard to the MED desalination plants. More particularly, the CAPEX-MED is the most critical factor (elasticity higher than 0.5) followed by the OPEX-MED and the specific energy elasticities. Again, the specific energy elasticity is higher in the case of CSP-powered MED than that of OPEX-MED. The NG elasticities (e.g., CAPEX-NGCC, fuel price, etc.) affect, as expected, all the configurations examined. Nevertheless, these elasticities are almost twice as large for the NG-powered desalination units.

The random walk simulations conducted to predict the LCOW values within the next five years illustrate in a very characteristic way the uncertainty inherent in the calculation of LCOW. The range of minimum and maximum values in each time step is affected by the drift of the model (i.e., the total growth rate of the LCOW) and the volatility of the estimates (which in turn are affected by the variability and uncertainty of the parameters employed in the estimation of LCOW). As a result, the 'minimum value path' of a more 'expensive' configuration (e.g., MED-NG) may be lower than the 'maximum value path' of a less 'expensive' configuration (e.g., SWRO-PV). For instance, according to Table S2 in the Supplement, the chance of producing more expensive water from a SWRO-NG plant in comparison with a MED-NG plant is negligible today. Nevertheless, due to the different volatility in the estimates of the two technologies (the standard deviation of the LCOW produced by the SWRO-NG plant is three times higher than that of the MED-NG plant), the situation may change in the future. The predicted maximum LCOW value of the SWRO-NG plant is quite comparable to or higher than that of the MED-NG plant, as shown in Table S3 in the Supplement. These results clearly show that in real case applications practitioners and policymakers should carefully design a number of future scenarios in order to explore a broad spectrum of possible LCOW values before taking a final decision. Moreover, the presented methodology can be employed in the security management process of water supply systems. For instance, the methodology could be used for assessing alternative water supply systems to determine the most effective solutions in the sense of risk reduction while considering the economic factor, as Rak & Pietrucha-Urbanik (2019) note.

CONCLUSIONS AND FUTURE WORK

So far, the alternative options related to the selection of the desalination technology are primarily evaluated based on the LCOW. As noted in the related literature, the calculation of LCOW involves several technical and economic parameters that are characterized by both variability and uncertainty. Despite this fact, however, the majority of economic assessments in the field of desalination plants use deterministic estimation methods coupled with the interpretation of 'one-variable' sensitivity analysis, which fails to capture the synergistic effect of simultaneous changes in the input parameters.

Towards filling this methodological gap, this paper presents a proposal for a new framework to support decision-making under uncertainty. The framework combines, in sequential steps, Monte Carlo simulations, scenario analysis and random-walk-based estimates of the LCOW values produced by different desalination plant configurations. It is being developed in such a way so as to be simple enough for policymakers and practitioners but also complex enough to address the uncertainty involved in the estimates. To the authors' best knowledge, this is the first attempt at such a framework in this field. To illustrate the proposed methodological framework, five alternative combinations of desalination technologies (i.e., SWRO and MED) and energy sources (i.e., PV, CSP, and NGCC) are examined using realistic (albeit simplified) assumptions. The findings of the analysis show that RED systems are not only technically feasible but also cost-effective when considering the continuous decrease in RES cost and the projected increase in the price of fossil fuels. These remarks, even though derived from the examination of certain technologies and referring to site-specific conditions of the region under examination, are generally in accordance with the results of similar surveys (e.g. Shatat & Riffat 2014; Azinheira *et al.* 2019). To this end, it can be argued that the findings of this study can be generalized to other areas sharing similar characteristics in the Middle East and Africa, where solar energy is plentiful. Therefore, decision-makers need to be very careful and not to neglect these issues during decision-making processes.

Although the proposed framework might be helpful in this direction, several issues need to be addressed in future research. For instance, the framework incorporates a single 'aggregate' volatility factor. Provided that uncertainties are related to several variables, different volatility factors could be estimated and used in the random walk model. Furthermore, although the probabilistic nature of the model is very helpful in dealing with the uncertainty in the parameters involved, it cannot correctly value embedded risks and opportunities (e.g. increases or decreases in the cost of fossil fuels or price of metals involved in desalination or RES units, changes in environmental regulations concerning climate change and emissions of pollutants, etc.) because it operates within a 'now-or-never' decision-making framework and, thus, it falls short of answering the (in many instances critical) question 'when is the best time to invest in RED?' To this end, perhaps new management approaches, like Real Options Analysis (ROA), offering the flexibility required to minimize the different kinds of risks in irreversible investments, should be considered.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

REFERENCES

Alhajeri, N. S., Al-Fadhli, F. M., Aly, A. Z., Reimers, A. & Webber, M. E. 2018 Electric power system profile in Kuwait: electricity and water generation, fuel consumption, and cost estimation. *ACS Sustainable Chemistry and Engineering* **6** (8), 10323–10334.

Alkaisi, A., Mossad, R. & Sharifian-Barforoush, A. 2017 A review of the water desalination systems integrated with renewable energy. *Energy Procedia* **110**, 268–274.

Al-Karaghouli, A. A. & Kazmerski, L. L. 2011 Renewable energy opportunities in water desalination, desalination trends, and technologies. In: *Desalination* (M. Schorr, ed.), InTechOpen, London, UK, pp. 149–184.

Alotaibi, S. 2011 Energy consumption in Kuwait: prospects and future approaches. *Energy Policy* **39** (2), 637–643.

Azinheira, G., Segurado, R. & Costa, M. 2019 Is renewable energy-powered desalination a viable solution for water stressed regions? A case study in Algarve, Portugal. *Energies* **12** (24), 4651.

Bacchetta, P. & van Wincoop, E. 2007 Random walk expectations and the forward discount puzzle. *American Economic Review* **97** (2), 346–350.

BCC Research 2016 *Seawater and Brackish Water Desalination*. Report Highlights. Retrieved from https://www.bccresearch.com/market-research/membrane-and-separation-technology/seawater-brackish-water-desalination-report.html.

Bock, K. & Trück, S. 2011 Assessing uncertainty and risk in public sector investment projects. *Technology and Investment* **2** (2), 105–123.

Borges, M. R. 2011 Random walk tests for the Lisbon stock market. *Applied Economics* **43** (5), 631–639.

Breyer, C., Gerlach, A., Schäfer, D. & Schmid, J. 2010 Fuel-parity: new very large and sustainable market segments for PV systems. In: *2010 IEEE International Energy Conference and Exhibition, EnergyCon 2010*, IEEE, Piscataway, NJ, USA, pp. 406–411.

Caldera, U., Bogdanov, D. & Breyer, C. 2016 Local cost of seawater RO desalination based on solar PV and wind energy: a global estimate. *Desalination* **385**, 207–216.

Capital Standards 2013 *Kuwait Utilities Sector*. A research study by Capital Standards, Safat, Kuwait. Available at: https://www.prodes-project.org/fileadmin/Files/ProDes_Road_map_on_line_version.pdf.

Cipollina, A., Tzen, E., Subiela, V., Papapetrou, M., Koschikowski, J., Schwantes, R., Wieghaus, M. & Zaragoza, G. 2015 Renewable energy desalination: performance analysis and operating data of existing RES desalination plants. *Desalination and Water Treatment* **55**, 3120–3140.

Darwish, M. A. & Darwish, A. M. 2008 Energy and water in Kuwait: a sustainability viewpoint, part II. *Desalination* **230** (1–3), 140–152.

Deloitte 2018 *Deloitte's Oil and Gas Price Forecast June 30, 2018*. Deloitte, Calgary, AB, Canada. Available from: https://www2.deloitte.com/content/dam/Deloitte/ca/Documents/REA/ca-en-Oil-Gas-REA-Price-Forecast-Jun2018.pdf.

FAO 2009 Kuwait. Water Report 34, Food and Agriculture Organization of the United Nations (FAO). Available from: http://www.fao.org/nr/water/aquastat/countries_regions/KWT/KWT-CP_eng.pdf.

Farmer, J. D. & Lafond, F. 2016 How predictable is technological progress? *Research Policy* **45** (3), 647–665.

Fattouh, B. & Mahadeva, L. 2014 *Price Reform in Kuwait's Electricity and Water Sector: Assessing the Net Benefits in the Presence of Congestion*. OIES Paper MEP 9, Oxford Institute for Energy Studies, University of Oxford, Oxford, UK. Available from: https://www.oxfordenergy.org/wpcms/wp-content/uploads/2014/04/MEP-9.pdf.

Felder, F. A. 1995 Modeling natural gas prices as a random walk: the advantages for generation planning. *The Electricity Journal* **8** (9), 61–67.

Fichtner 2011 *MENA Regional Water Outlook, Phase II, Desalination Using Renewable Energy*. Study commissioned by the World Bank, Fichtner, Stuttgart, Germany.

Gao, L., Yoshikawa, S., Iseri, Y., Fujimori, S. & Kanae, S. 2017 An economic assessment of the global potential for seawater desalination to 2050. *Water* **9** (10), 763. https://doi.org/10.3390/w9100763

Geman, H. 2007 Mean reversion versus random walk in oil and natural gas prices. In: *Advances in Mathematical Finance, Applied and Numerical Harmonic Analysis* (M. C. Fu, R. A. Jarrow, J.-Y. J. Yen & R. J. Elliott, eds), Birkhäuser Boston, Cambridge, MA, USA, pp. 219–228.

Goosen, M. F. A., Mahmoudi, H. & Ghaffour, N. 2014 Today's and future challenges in applications of renewable energy technologies for desalination. *Critical Reviews in Environmental Science and Technology* **44** (9), 929–999.

ICF Consulting Limited 2015 *Study on Energy Efficiency and Energy Saving Potential in Industry and on Possible Policy Mechanisms*. ICF Consulting, London, UK.

IEA-ETSAP and IRENA 2013 *Water Desalination Using Renewable Energy*. Technology Policy Brief I12, Energy Technology System Analysis Programme and International Renewable Energy Agency. Available from: https://iea-etsap.org/E-TechDS/PDF/I12IR_Desalin_MI_Jan2013_final_GSOK.pdf.

International Monetary Fund 2018 *Kuwait: Selected Issues*. Country Report 18/22, IMF, Washington, DC, USA. Retrieved from https://www.imf.org/~/media/Files/Publications/CR/2018/cr1822.ashx.

International Water Summit 2018 Energy Efficient Desalination – meeting the GCC's water needs in an environmentally sustainable way. In: *International Water Summit*, January 15–18, Abu Dhabi, United Arab Emirates. Available from: https://www.internationalwatersummit.com/__media/Energy-Efficient-Desalination-2018.pdf.

IRENA 2016 *The Power to Change: Solar and Wind Cost Reduction Potential to 2025*, (M. Taylor, P. Ralon & A. Ilas, eds). International Renewable Energy Agency (IRENA). Available from: http://www.irena.org/documentdownloads/publications/irena_power_to_change_2016.pdf.

Jalihal, P. & Venkatesan, R. 2019 Advanced desalination technologies. In: *Sustainable Water and Wastewater Processing* (C. M. Galanakis & E. Agrafioti, eds), Elsevier Publishing, Amsterdam, The Netherlands, pp. 93–131.

KDIPA 2016 *Investing in Kuwait: A Guide for Investment Opportunities in Kuwait*. Kuwait Direct Investment Promotion Authority (KDIPA), Kuwait. Available from: https://e.kdipa.gov.kw/main/1infrastructure.pdf.

Knight, F. H. 1921 *Risk, Uncertainty and Profit*. Houghton Mifflin Company, Boston and New York, USA.

Kuwait Institute for Social Research (KISR) 2019 *Kuwait Energy Outlook*. KISR, Kuwait.

Lazard 2017 *Lazard's Levelized Cost of Energy ('LCOE') Analysis – Version 11.0*. Available from: https://www.lazard.com/media/450337/lazard-levelized-cost-of-energy-version-110.pdf.

Meyer, M. A. & Booker, J. M. 2001 *Eliciting and Analyzing Expert Judgment: A Practical Guide*. ASA-SIAM Series on Statistics and Applied Probability, SIAM, Philadelphia, PA, USA.

Mezher, T., Fath, H., Abbas, Z. & Khaled, A. 2011 Techno-economic assessment and environmental impacts of desalination technologies. *Desalination* **266** (1–3), 263–273.

Miller, S., Shemer, H. & Semiat, R. 2015 Energy and environmental issues in desalination. *Desalination* **366**, 2–8.

Moser, M., Trieb, F., Fichter, T. & Kern, J. 2013 Renewable desalination: a methodology for cost comparison. *Desalination and Water Treatment* **51** (4–6), 1171–1189.

Moser, M., Trieb, F., Fichter, T., Kern, J. & Hess, D. 2015 A flexible techno-economic model for the assessment of desalination plants driven by renewable energies. *Desalination and Water Treatment* **55** (11), 3091–3105.

Mukhopadhyay, A. & Akber, A. 2018 Sustainable water management in Kuwait: current situation and possible correctional measures. *International Journal of Sustainable Development and Planning* **13** (3), 425–435.

Mun, J. 2006 *Real Options Analysis: Tools and Techniques for Valuing Strategic Investments and Decisions*, 2nd edn. John Wiley & Sons, Inc., Hoboken, NJ, USA.

Newell, R. G. & Pizer, W. A. 2003 Discounting the distant future: how much do uncertain rates increase valuations? *Journal of Environmental Economics and Management* **46** (1), 52–71.

Olwig, R., Hirsch, T., Sattler, C., Glade, H., Schmeken, L., Will, S., Ghermandi, A. & Messalem, R. 2012 Techno-economic analysis of combined concentrating solar power and desalination plant configurations in Israel and Jordan. *Desalination and Water Treatment* **41** (1–3), 9–25.

Papapetrou, M., Wieghaus, M. & Biercamp, C. 2010 *Roadmap for the Development of Desalination Powered by Renewable Energy*. Deliverable 2.2 of the Prodes Project, Promotion of Renewable Energy for Water Desalination, Fraunhofer IRB, Stuttgart, Germany. Available from: https://www.prodes-project.org/fileadmin/Files/ProDes_Road_map_on_line_version.pdf.

Pergler, M. & Freeman, A. 2008 *Probabilistic Modeling as an Exploratory Decision-Making Tool*. McKinsey Working Papers on Risk 6, McKinsey & Company.

Pindyck, R. S. 1999 The long-run evolutions of energy prices. *Energy Journal* **20** (2), 1–28.

Platon, V. & Constantinescu, A. 2014 Monte Carlo method in risk analysis for investment projects. *Procedia Economics and Finance* **15**, 393–400.

Rak, J. R. & Pietrucha-Urbanik, K. 2019 An approach to determine risk indices for drinking water-study investigation. *Sustainability* **11** (11), 3189.

Scalas, E. 2006 The application of continuous-time random walks in finance and economics. *Physica A: Statistical Mechanics and Its Applications* **362** (2), 225–239.

Shatat, M. & Riffat, S. B. 2014 Water desalination technologies utilizing conventional and renewable energy sources. *International Journal of Low-Carbon Technologies* **9** (1), 1–19.

Shatat, M., Worall, M. & Riffat, S. 2013 Opportunities for solar water desalination worldwide: review. *Sustainable Cities and Society* **9**, 67–80.

Smith, G. 2002 Tests of the random walk hypothesis for London gold prices. *Applied Economics Letters* **9** (10), 671–674.

Toma, S.-V., Chiriţă, M. & Şarpe, D. 2012 Risk and uncertainty. *Procedia Economics and Finance* **3**, 975–980.

Voutchkov, N. 2018 Energy use for membrane seawater desalination – current status and trends. *Desalination* **431**, 2–14.

Wood, M. & Alsayegh, O. A. 2014 Impact of oil prices, economic diversification policies and energy conservation programs on the electricity and water demands in Kuwait. *Energy Policy* **66**, 144–156.

World Bank 2012 *Renewable Energy Desalination: An Emerging Solution to Close the Water Gap in the Middle East and North Africa*. MENA Development Report, World Bank, Washington, DC, USA.

World Bank 2019 *The Role of Desalination in an Increasingly Water-Scarce World*. World Bank, Washington, DC, USA.

Xevgenos, D., Moustakas, K., Malamis, D. & Loizidou, M. 2016 An overview on desalination & sustainability: renewable energy-driven desalination and brine management. *Desalination and Water Treatment* **57** (5), 2304–2314.

Younos, T. 2009 Environmental issues of desalination. *Journal of Contemporary Water Research & Education* **132** (1), 11–18.

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