

The Economic Synergies of Modelling the Renewable Energy-Water Nexus Towards Sustainability

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Abstract

This study investigates the role of the water-energy-nexus in transition plans to achieve a future system with a higher share of renewable energy and lower excess water extraction. Applying a novel nexus approach, an interactive multi-period model is proposed to study the synergies of sustainable water and energy supply planning, taking into account operational flexibility of the water sector and its compatibility with inherent intermittency of variable renewable resources.

For investigating synergies in designing both energy systems and water systems together, the path of technology cost reduction is assumed to be a function of experience and knowledge and estimated using two-factor learning curves. The learning-by-searching rate was higher than the learning-by-doing rate for utility-scale wind, photovoltaic and reverse osmosis desalination technologies, ensuring research & development investment can play a chief role in the development of these industries.

The levelized cost and capacity factor of photovoltaic and wind resources in the Middle East were calculated using data from 81 projects. The results showed that planning the water and energy sectors as endogenous parts one integrated system brings potential synergies. The levelized cost of variable renewable energy decreased by 20 percent and the levelized cost of desalinated water dropped 4 percent.

Keywords: desalination, renewable energy, nexus approach, learning curve

1 Introduction

Due to climate change, the number of countries is facing stress on renewable water resources is increasing [1]. As an alternative solution, some of these countries have plans to increase the share of desalination in their water supply, which may increase

energy consumption for water provision, as it is an energy-intensive technology. In the meantime, many countries have targets to reduce dependency on fossil fuels and move towards energy systems with higher shares of variable renewable resources (VRE), which can cause problems such as instability in electricity systems due to the inherent fluctuation of renewable energy resources. There are solutions to overcome this instability, including the installation of energy storage systems (ESS), to increase the flexibility of demand (demand response) and, exchanging renewable electricity with neighboring countries or regions [2].

There are two types of fluctuation which need to be dealt with. First, fluctuations for short periods (minutes to hours) which are studied in this research and second, fluctuations for long periods (days to weeks). The security and resilience of energy systems with a high share of variable renewable resources highly hinge on designing and planning solutions to these two types of fluctuations in order to avoid instability in energy systems. Moreover, solutions that provide long-term storage (such as hydrogen) play a chief role in mitigating risks associated with reliance on the exchange of renewable energy with neighboring countries (such as potential political conflicts and technical failures). It is considered that the integration of water systems (which have a share of desalination supplies) with the energy systems (which include a share of variable renewable resources) could offer potential to solve this instability to some extent through the provision of flexible demand [3].

On the other hand, energy is one of the most important factors affecting the extent and feasibility of desalination projects, between 30% to more than 50% of the cost of water produced by the desalination process is related to energy [4]. Energy affects not only the cost of the water produced by desalination but also the technology of the desalination process itself. For example, to use thermal processes, the largest desalination plants, which are located in the Middle East, make use of their rich fossil fuel reserve [4]. Currently, desalination facilities are mostly based on fossil fuel energy resources [5]. Powering desalination plants by renewable resources is an attractive solution to decrease their carbon footprint and eliminate the dependency of water cost on fuel costs [6].

The desalination technologies are categorized into two groups: desalination with phase-change technologies and desalination with single-phase technologies. These technologies are summarized in Table 1. Reverse Osmosis (RO), multi-stage flash distillation and multi-effect distillation, and hybrid desalination which is a combination of these technologies, are the current dominant technologies for water desalination [7]. Thermal energy is the main energy source needed for the phase change technologies while the main energy sources required for single-phase desalination technologies are electricity and hydraulic pressure. Hybrid desalination plants are a combination of RO desalination plants with a thermal desalination facility to make use of the waste heat from a co-located power plant. These combined RO and thermal plants are practical to compensate for the aforementioned long-term fluctuations with wide diurnal or seasonal variation in power or water demand. For instance, in the Middle East, peak electricity demand accrues in summer and this creates a situation in which over 50 percent of power generation capacity is not used [1]. While the demand for desalinated water is almost constant during the year. This allows the hybrid plant to correct this imbalance between demand for electricity and water, and to save considerable energy costs by diverting the excess electricity to water.

Table 1. Desalination technologies.

Phase-change processes	Membrane-based processes
Multi-stage flash (MSF)	Reverse osmosis (RO)
Multiple effect distillation (MED)	Electrodialysis (ED)
Vapor compression (VC)	Membrane Distillation (MD)
Freezing	
Humidification/dehumidification	
Solar stills	

RO units operate at low energy consumption ranging from 2 to 4 kWh/m³ which is close to the theoretical thermodynamic limit (1 kWh/m³ for seawater) [8], [9], in consequence the CO₂ emissions from reverse osmosis desalination technology are typically the lowest among the desalination technologies [10] and are therefore chosen as the desalination technology for this study.

Wind and solar energy resources are the most widely deployed renewable technologies to couple with RO units, respectively contributing 32 and 19 percent of the renewable-powered desalination systems worldwide [11]. Due to affordability, availability and zero water consumption for power production compared to other renewable resources, wind and photovoltaic (PV) resources have been recommended by several studies to operate RO plants [12]–[16]. Current large-scale reverse osmosis units coupled with renewable resources are grid-connected, such as an RO unit in Saudi Arabia with 60,000 m³/day capacity powered by PV supply and the national grid to ensure stable electricity supply to the facility and constant water production [17]. The economic feasibility of such plants depends on the availability of renewable resources and typically some form of financial support such as a feed-in tariff [17], [18]. However, large-scale RO plants are energy-intensive units, for instance, the share of desalination electricity consumption is estimated to be 4 to 12 percent of total electricity consumption in the Persian Gulf Cooperation Council countries [19], [20].

With regards to short-term fluctuations, desalination can be considered as a potential flexible load. There are several key features to determine the adequacy of desalination loads as flexible load resources to overcome short-run fluctuations (in other words, to support ancillary services in electric grids) including [21]:

- Initial-response time: the time lag to change a power set-point.
- Ramp-rate: the change rate in the amount of power consumption.
- Settling-time: the settle-time period after changing an operating power set-point.
- Duration: the period of time after settling-time at which it is possible to maintain the new power set-point.
- Power-capacity: the rated operation power.
- Minimum turn-down: the lowest operation power point for the plant, below which the plant must turn off.

According to the above factors, reverse osmosis desalination units are considered an attractive solution to operate as a flexible load to compensate for the fluctuation due to variable renewable resources. RO desalination units are able to operate with unlimited minimum turn-down. Authors [21] examined the operation capability of an RO plant to integrate with an energy system with variable renewable resources. The results of this study indicate that RO units are capable of responding quickly, settle to the desired power set point in a reasonable time, and operate continuously for long

133 enough (duration), in the meantime, maintaining the quantity and quality of required
134 water demand. This means that such RO units can be effectively powered by energy
135 systems with renewable fluctuating power production without ESS, as water is
136 desalinated based on energy availability and stored as a final product [22]. This direct
137 consumption of renewable power production improves the efficiency of the energy
138 systems, due to the avoidance of energy loss of ESSs in each charge-discharge-cycle.
139 For instance, battery systems operate with a typical charge-cycle efficiency of 75% to
140 98% [23], [24].

141 Authors [25] showed that applying large-scale energy storage systems for
142 renewable-powered desalination units is impractical, because they increase the
143 capital cost and make the system more complicated due to additional required
144 equipment, such as charge controllers. Specifically, applying battery units negatively
145 influences the economic feasibility of desalination projects powered by renewables
146 because of the high capital cost and relevantly short life-time [25], [26]. In previous
147 studies [27], [28], the cost of water desalination for renewable-powered RO units was
148 compared with and without battery storage. The obtained costs increased from 8.7 to
149 9.3 \$/m³ in one study [27] and from 10 to 13 \$/m³ in another study [28]. Moreover, high
150 ambient temperature, which is common among the regions facing water scarcity,
151 increases the self-discharge rate of battery systems and influences the performance of
152 these systems [29]. For example, a small-scaled reverse osmosis unit coupled with a
153 PV-battery system and tested for 6 months in Malaysia to study the performance and
154 operation of RO units coupled with renewables [29] showed a significant performance
155 decrease in high ambient temperature conditions. On the other hand, energy storage
156 systems are favorable for small standalone desalination units to couple with
157 renewable resources and supply water as needed without relying on external inputs
158 [30]–[32].

159 By providing flexibility of RO units and decreasing the required battery capacity,
160 a study [33] showed that the levelized cost of energy could be decreased by 3 percent
161 in a 100-percent renewable-supply scenario for Saudi Arabia. Other authors [34]
162 introduced an alternative water supply for a region in Australia. After calculating the
163 surplus electricity production from roof-top PV systems for the region, this excess
164 electricity production was considered as an energy source for RO units. This
165 alternative system could provide a reduction of 20 percent levelized cost of energy
166 (LCOE) for the PV system and 10 percent levelized cost of water (LCOW) compared
167 to a system with no control on the water system. It should be noted that the surplus
168 electricity production from the roof-top PV systems was assumed as waste energy with
169 zero cost and zero benefit in this study [34].

170 While many studies have been done to date, there is a gap in the scope of studies
171 regarding the design and planning of energy systems with a share of variable
172 renewables while having water desalination as a source of water systems. Studies
173 have typically followed a sequenced approach for planning such systems: one sector is
174 considered as an existing system with a fixed shape, based on which the other system
175 is designed, planned or optimized. Furthermore, operational flexibility of the
176 desalination units, water transfer and water storage are key factors that needs to be
177 considered in long-run planning of such systems due to its compatibility with inherent
178 intermittency of VREs. To achieve a realistic understanding in this regard,
179 considering just a few days of operation, is not adequate to study the influence of the
180 renewable power fluctuations on planning and designing such a system. This
181 operational flexibility has only been considered in studies focusing on the operational

aspect of the desalination systems powered by VREs [35]–[37]. On the other hand, the time horizon of months to years is required to study a realistic roadmap towards the transition to energy systems with a share of renewables and water systems with a share of desalination. This research aims to investigate the future shape of these sectors by applying a nexus approach and elaborating potential economic synergies in designing both energy systems and water systems together.

2 Methodology

Optimization modeling has been increasingly used for long-run planning of the water supply [34]. One study [38] reviewed the optimization methods used in water resource planning. Another study [39] presented a review on the application of hybrid evolutionary algorithms in designing optimal water reservoirs. Studies [40], [41] have also developed multi-objective optimization problems for water distribution planning. Others [41] applied a two-stage stochastic programming to capture demand uncertainties. Another study [42] addressed various aspects of long-term desalination supply planning by developing a supply chain approach. Other studies developed multi-period construction and capacity expansion planning of desalination water supplies at city scale [43] and regional scale [34], [44].

In the energy sector, four key categories of models are standard in planning transitions to expand the share of variable renewable resources. They include network analysis models, production cost models, geo-spatial planning models, and long-term energy planning models [45]. Advanced modeling tools tend to cover multiple planning features, as a result distinction among these modeling categories are not typically not stringent.

Network analysis models are dedicated to assessing the stability and reliability of power systems and operational aspects, typically spanning a period of weeks to several years. Capacity mix, network infrastructure and its topography and dispatch scenario are all inputs in order to evaluate a network at a particular given point of time. Examples of network analysis tools include DIgSILENT GmbH and Siemens PTI [46].

Production cost models simulate power system operations typically on a one-year timescale, during which the mix of VRE capacity is assumed constant. These models investigate the techno-economic impacts of alternative energy policies and market configurations such as capacity markets and ancillary markets. Generally, investment costs are out of scope of these models. Therefore, production cost models are not designed to be the sole basis for long-run investment decision-making. Examples of production cost modeling software are EnergyPlan and PLEXO [47].

Geo-spatial planning models provide network topography analysis as a starting basis for the described detailed technical network models. These models assist to achieve an economic trade-off between location-specific variable renewable power productivity and transmission investment requirements for expansion of the VREs. Examples of GIS software used in the renewable energy planning are ArcGIS, ILWIS and Global Mapper [34].

Long-term energy planning models are increasingly used to determine the optimal long-run mix of renewable technologies and investment paths to meet the national and regional targets during a time horizon typically ranging from 20 to 40 years [45], or even longer. Examples of such modeling include MARKAL and OSeMOSYS, and WASP. The proposed model in the current study, fits in this modeling category. Long-term planning models employ reduced-form dispatch and simplified approaches to avoid the model becoming computationally unwieldy [45], [48]. As explained in the

introduction, the integration of VREs into power grids is challenging due to fluctuating power production. Therefore, considering these fluctuations is essential in long-term energy supply planning. There are four method classification for solar radiation and wind speed prediction [49] including (1) artificial intelligence and statistical techniques, (2) remote-sensing techniques, (3) numerical climate forecasting approaches, and (4) the hybrid forecasting approaches. A statistical approach has been used to validate the results in this study.

The nexus concept is deemed necessary to design future inherently interconnected sectors in a holistic manner from the start of the design process [50]. This approach is different from concepts such as the integrated management approach which is suitable for existing systems. In the nexus approach, one of the targets is to identify the inherently interconnected future sectors. The outcomes of the nexus approach elaborate two focal points, first, highlighting potential synergies and second, identifying critical conflicts to be dealt with [51]. This outcome is a benchmark for trade-offs among integration which increases the complexity of processes and systems to the point that the decision-making in the integrated system is delayed or incapacitated and designing the sectors in a separated manner without this complexity.

Two system types are assumed for investigation in this study including:

1. **Separated System:** The water sector is considered as an exogenous factor for the energy system, in which there is no control over it.

2. **Integrated System:** Both energy and water systems are studied as an integrated system, which are endogenous parts of one integrated system.

There are four modules within the model developed in this study (as shown in Fig. 1): (1) developing a supply-demand module, (2) proposing an energy storage module, (3) obtaining the two-factor learning curves for the case study in Iran and, (4) conducting an economic analysis.

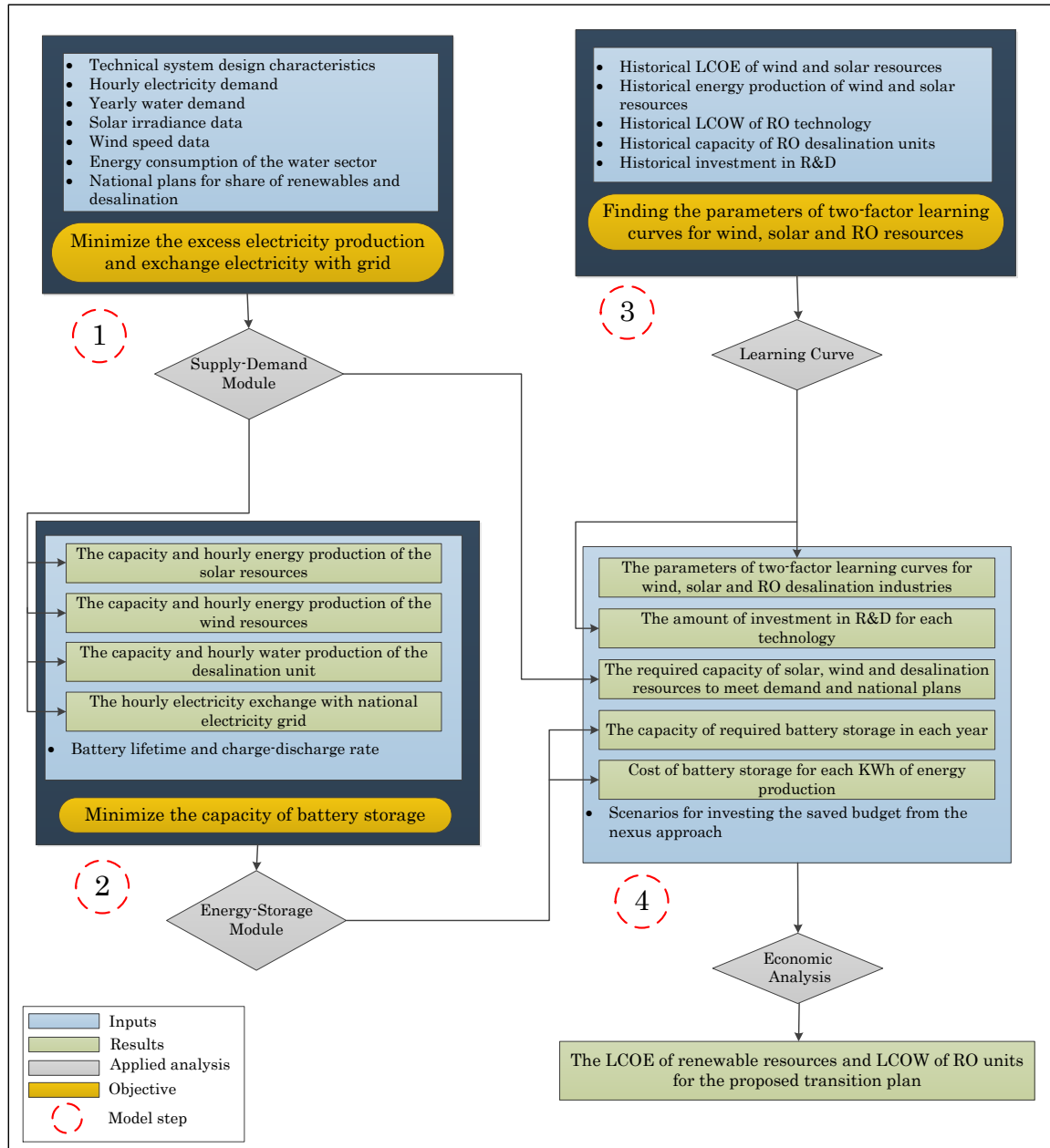


Fig. 1. The proposed model in this study for an energy system with VRE and water supply with desalination.

The following describes the details of the modules and their decision procedures in Fig. 1.

1) Supply-demand module

In the first step, a supply-demand module is developed to investigate the technical aspects of these systems. In this module, the energy demand curves are estimated based on demographic trends, historical data and resource limitations. Technology trends, system configurations, and national plans & goals are considered in these optimization models. This optimization supply-demand model is described in detail in Appendix A. The objective function of this model is to minimize the exchange of

270 electricity with the grid which is explained as:

$$\text{Min} \sum_{t,y} |p_{grid}(t, y)| \quad (1)$$

271 Where p_{grid} is the absolute value of hourly electricity exchange with the national
 272 grid including both negative (for selling electricity to the grid) and positive values (for
 273 purchasing electricity from the grid).

274 The model is applied to a sample of hourly data for 5 days in July for the integrated
 275 system. The daily water demand is 9,389 m³, 50 percent of which is planned to be
 276 provided by desalination supply. Fig. 2 shows the hourly non-water electricity
 277 demand. The share of renewable resources from the total power generation is set at
 278 20 percent.

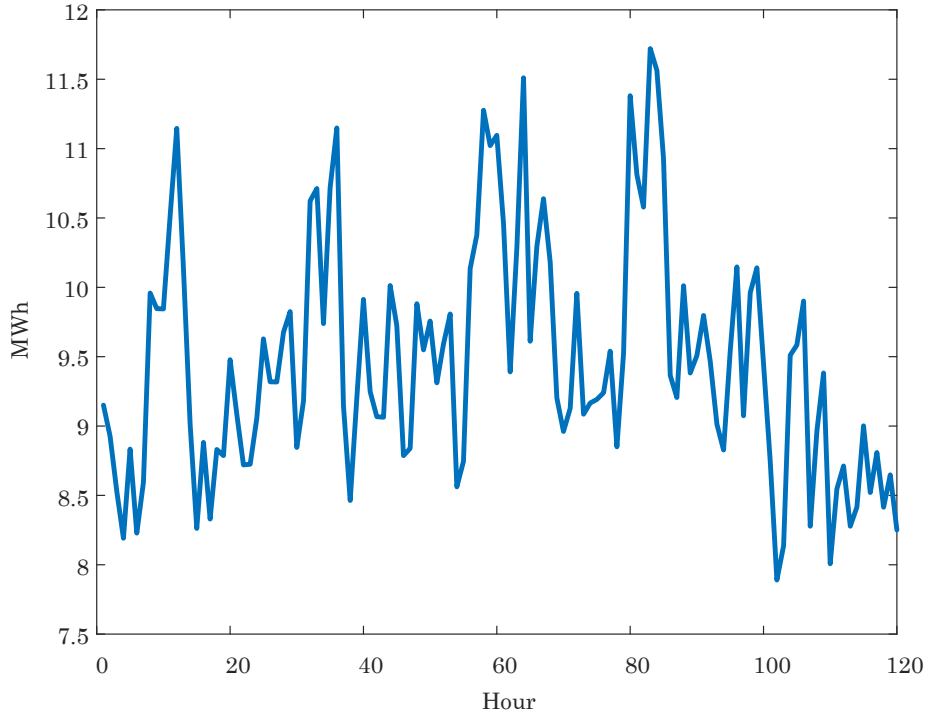


Fig. 2. Non-water electricity demand for 5 sample days in July.

281 The optimization results show that the minimum amount of exchanged electricity
 282 with the grid is 773.1 MWh for these sample days. The obtained wind capacity is 2.6
 283 MW and photovoltaic capacity of 12.9 MW. Photovoltaic and wind electricity
 284 generation accounts for 83% (418.3 MWh) and 17% (86.6 MWh) of total renewable
 285 power production, respectively. Fig. 3 depicts a comparison between the optimal result
 286 and when the model is forced to have 50 percent wind production from the total
 287 renewable power production. For the 50% wind power share, the electricity exchange
 288 with the grid reaches 808.5 MWh for these 5 sample days.

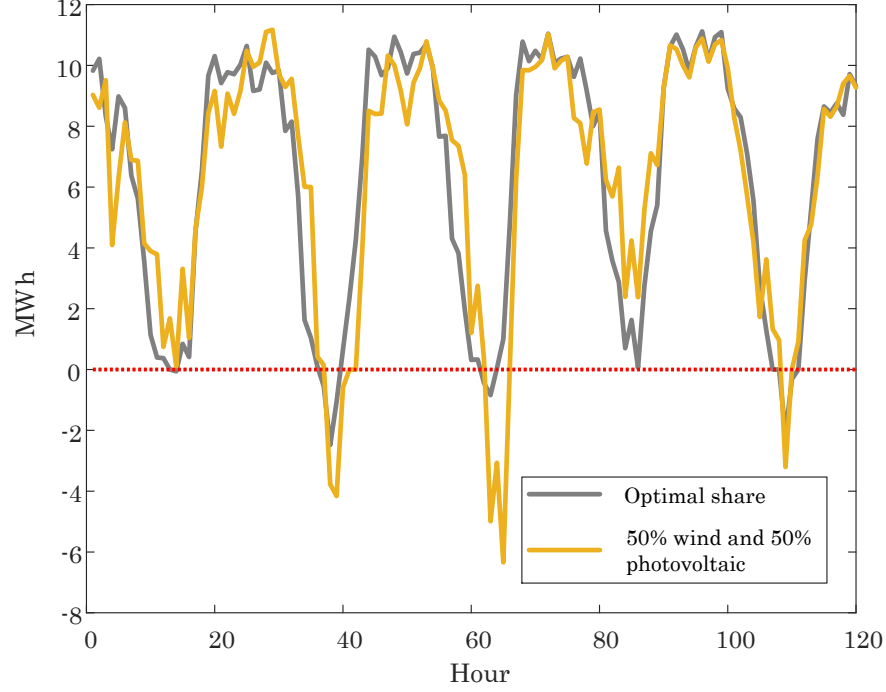


Fig. 3. Electricity exchange with the grid for 5 sample days in July (the integrated system).

2) Energy storage module

The aim of this module is to find the required battery storage unit equivalent to the operational capacity of the flexible water sector. Based on the results of the supply-demand model the new required capacity of battery storage and cost of battery storage for a unit of energy production (MWh) are calculated. The details of this optimization problem are available in Appendix B.

The objective function is finding the minimum required capacity of batteries ($Cap_{bat}(y)$) equivalent to the operational capacity of the flexible water sector which is described as follows:

$$\text{Min} \sum_y Cap_{bat}(y) \quad (2)$$

Using the same 5 sample days in July, the supply-demand model results show that the electricity exchange for the separated scenario is 803.8 MWh (see Fig. 4). The optimization results of the storage model depict that 5.3 MWh battery capacity is required to reach the same performance as the integrated scenario (773.1 MWh electricity exchange with the grid).

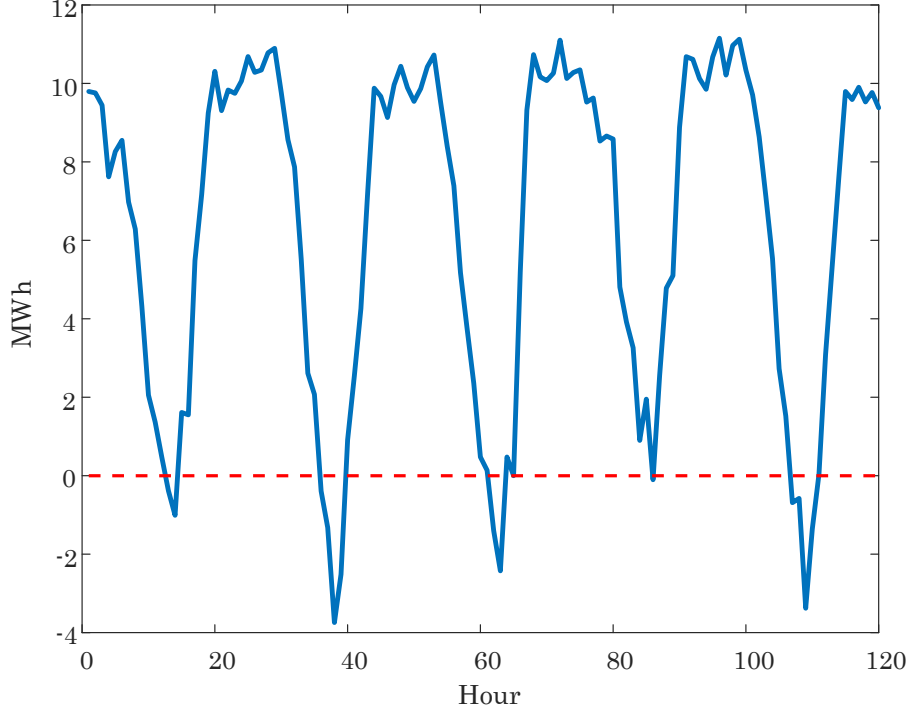


Fig. 4. Electricity exchange with the grid for 5 sample days in July (the separated system).

3) Learning curves

Learning curves have been used as an effective way of looking at technology cost reductions. The basic assumption of the learning curve is that experience, knowledge and other factors can improve technology performance, causing unit cost declines with the accumulation of aforementioned factors. The one-factor learning curve, which reached its popularity in the mid-1970s, is sensitive to the choice in certain cases and only considers the effects from the demand side. Studies have [52] shown that the one-factor model overestimates the learning-by-doing ratio (LDR) because it does not consider the contribution of R&D investment. To overcome these issues, a two-factor learning curve was introduced in 2000 [53]. The one-factor learning curve only considers the cumulative production (experience), whereas the two-factor learning curve reflects both experience and knowledge mechanisms.

For studying synergies in designing both energy systems and water systems together, modeling technology cost just as a function of time ($f(time)$), which is the most common approach among the energy and water transition studies [43], is not practical because it does not allow the consideration of synergistic effects but maintains a separation of the systems due to the assumption of learning based on time. In this study, technology cost is assumed to be a function of experience and knowledge ($f(experience, knowledge)$) and modeled by the two-factor learning curve. The two-factor learning curve is chosen to estimate the future costs of different renewable energy production from the resources and desalinated water from RO units. Eq. (3) describes the two-factor learning curve [53].

$$C_t = C_0 \times CC^{-\alpha} \times KS^{-\beta} \quad (3)$$

Where C_t is the unit cost in year t , C_0 depicts the initial unit cost, CC is the cumulative production, α is the learning-by-doing elasticity, KS describes the knowledge stock, and β is the learning-by-searching elasticity.

Based on this curve, the unit cost decreases from the initial cost by increasing the research and development (R&D) investment as well as the cumulative production. The decreasing cost is illustrated by the learning-by-doing ratio and learning-by-searching (LSR) ratio which denotes the percentage of change in cost as a result of doubling the cumulative production and R&D budget, respectively. The learning-by-doing ratio is obtained as $1-2^{-\alpha}$ and the learning-by-searching ratio (LSR) is calculated as $1-2^{-\beta}$ where α is the learning-by-doing elasticity and β is the Learning-by-searching elasticity.

Because of a lack of data, a new methodology is applied to estimate the Learning-by-searching elasticity and the average research and development budget using particle swarm optimization in MATLAB software. The details of this approach and the two-factor learning curve are described in Appendix C.

4) Economic analysis

To reveal the synergy effect, the results of the previous segments are used to estimate the future costs of renewable energy production and desalinated water for the region of the case study. This section focuses on the difference between the integrated system and the separated system. Two sensitivity analysis are conducted to elaborate the effect of R&D budget scenarios on the future costs and the influence of each learning rate on the systems.

2.1 Case study

The southern coast of Iran, a developing country in the Middle-East, is chosen as a case study. Iran is facing severe water scarcity in the mentioned area of the country [54], which also has ready-access to seawater for desalination. Iran has six main and 31 secondary drainage basins which can be seen in Fig. 5 [54]. The six major basins are the Central Plateau in the middle of the country, the Lake Urmia basin in the north-west, the Persian Gulf and Gulf of Oman basin in the west and south, Lake Hamoon basin in the east, the Kara-Kum basin in the north-east, and the Caspian Sea basin in the north [54]. The Gulf of Oman and Persian Gulf basin has access to seawater, which gives this basin the opportunity to use desalination plants as a source of water. Four provinces inside this water basin are considered as the region of the present case study.



Fig. 5. Iran's main drainage basins. Adapted from Iran Water Statistical Yearbook (2011-2012) [54].

The chosen area as a case study, in the south of Iran, has a great potential for solar and wind power production, based on which solar and wind electricity resources are considered as the variable renewable energy (VRE) supplies in this study. Based on real hourly data in , the daily average solar radiation is equal to $5.63 \text{ KWh/m}^2/\text{day}$, and the hourly average wind speed is 3.26 m/s for this area [55]. Jask is a port town, situated on the Gulf of Oman and is chosen as the sample urban area for this study. Jask has a hot desert climate with very hot summers and little precipitation. At the 2017 census, Jask county's population was 58,884 [56].

3 Results & Discussion

In the current section, first, the results of the technical modules for one urban area as a sample of the case study (Jask, Iran) are explained. In the next step, the results were developed for the region of the case study (southern coastal line of Iran), the outcome of which was the baseline for the economic analysis.

3.1 Supply-Demand model

In 2015 COP21, also known as the 2015 Paris Climate Agreement, Iran voluntarily agreed to reach 7,500 MW capacity of renewable electricity production by 2030 [57]. According to the Sixth Iranian National Development Plan, the Ministry of Energy, Iran's leading electric utility and subsidiaries, and the Renewable Energy Organization are committed to supply 5 percent of total electricity from renewables by 2021 [58]. The Iranian Ministry of Energy has formulated a broad plan to meet these targets such as feed-in tariffs and long-term contracts at guaranteed prices which have been extended from 5 to 20 years in 2015 [59]. Based on the Iranian National Strategic Energy Plan, Iran is planning to reach competitive renewable electricity costs in the electricity sector by 2040 and improve the renewable deployment rate which is currently about one percent yearly growth [60]. In the water sector, according to the Sixth Iranian National Development Plan, the Ministry of Energy is committed to plan for providing financial support and transferring

knowledge to supply 70 percent of the urban water demand on the coast of the Persian Gulf and Gulf of Oman by 2021 [58]. It is assumed that the share of VREs is increasing 2 percent each year (according to government plans) and reaches 42 percent in 2040 [56]. The assumption for expansion of desalination is a linear increase across the period to meet the 70 percent target, meaning a 3.5 percent yearly growth in its share of total water supply. All water, energy and battery related costs were converted to 2018 United States dollars (\$).

A linear programming model is solved for 20 years with an hourly horizon between 2020 to 2040 in GAMS software for the sample urban area (Jask, Iran). The optimal capacity of wind, solar power and RO plant, the hourly operation of RO units, the amount of water stored in the city's water reservoir, the amount of water stored in the desalination unit's reservoir, the water production from conventional water supplies to meet the target share of VRE, the amount of water pumped from the desalination's reservoir and desalination with minimum electricity exchange with the national grid are obtained by this model. Fig. 6 illustrates the amount of renewable electricity production from PV and wind supplies from 2020 to 2040. As can be seen in Fig. 6 and Fig. 7 solar power performs better in following the load demand in this region and is the dominant renewable source with a share of about 80 percent of total renewable electricity production for both the integrated and separated systems. The monthly photovoltaic and wind electricity generation from 2027 to 2029 is available in Appendix A.

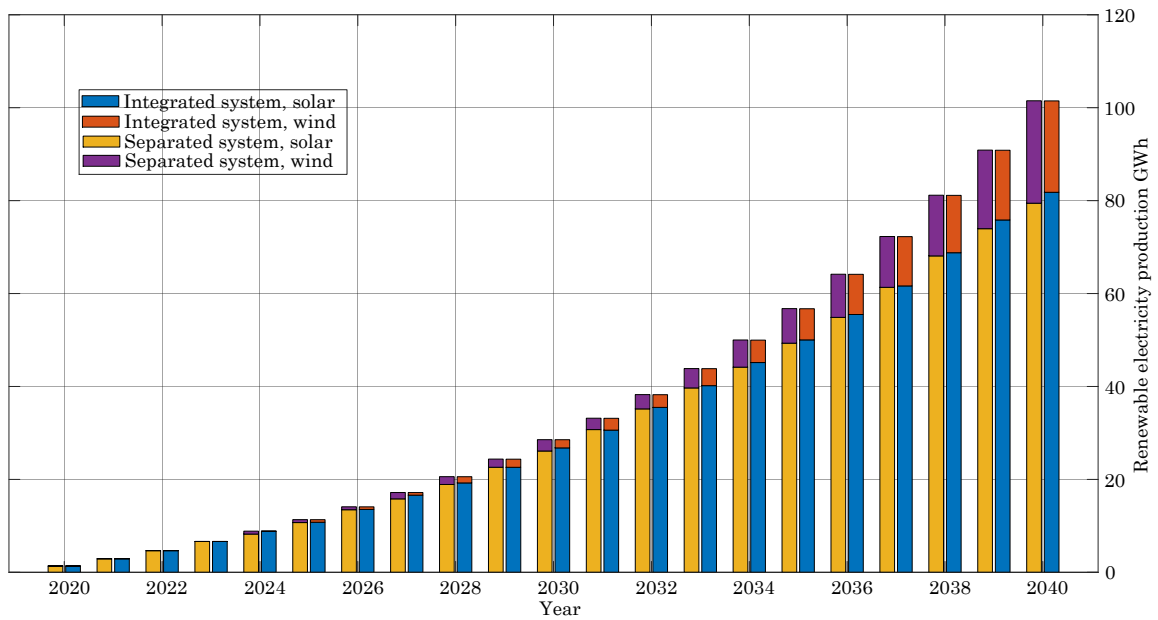


Fig. 6. Renewable electricity production from the PV and wind supplies.

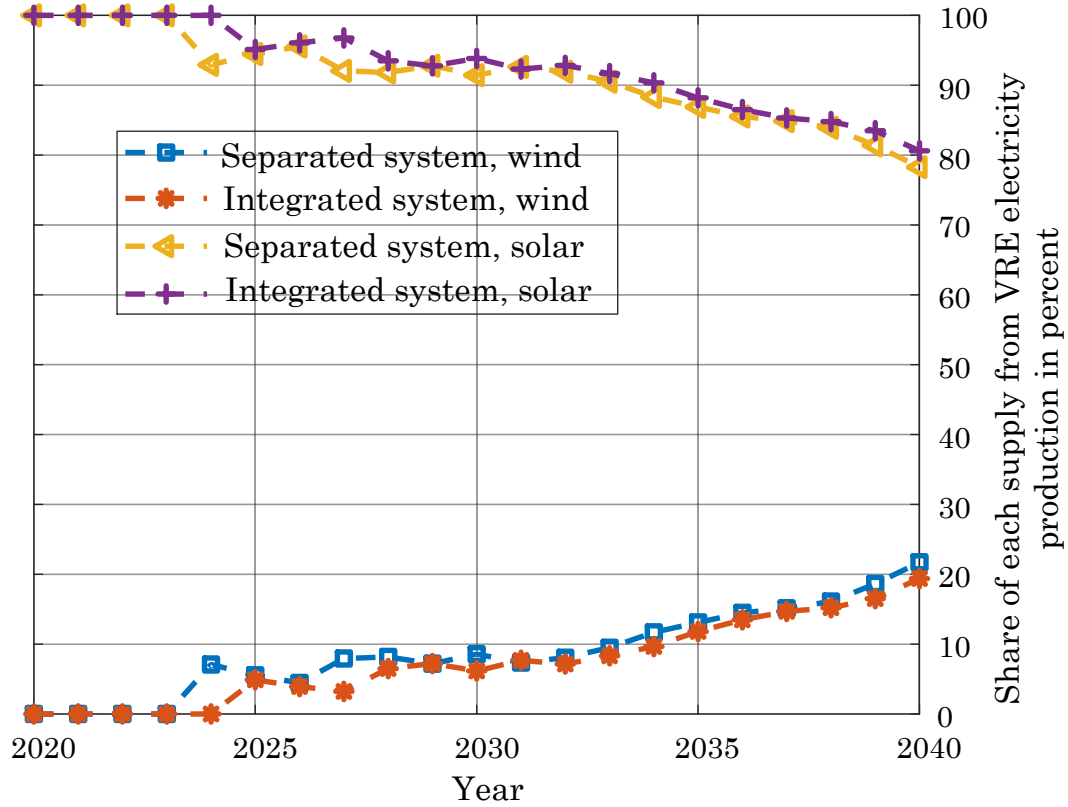


Fig. 7. Share of PV and wind supplies in total VRE electricity production.

The amount of excess electricity production from renewable resources in 2040 reaches about 13 percent of total renewable power production for the separated system, while this excess energy production is around 11 percent for the integrated system. Variability of VRE power generation can cause mismatches between the temporal profiles of VRE electricity production and electric demand. In this study, the excess electricity production is defined as the portion of VRE power production which exceeds electric load. Fig. 8 shows the amount of excess renewable electricity production and share of self-consumption from VRE electricity production in each year for both systems. The self-consumption of VRE refers to electricity that is produced from VREs, and is not fed-into the national grid but is consumed directly by the case study city.

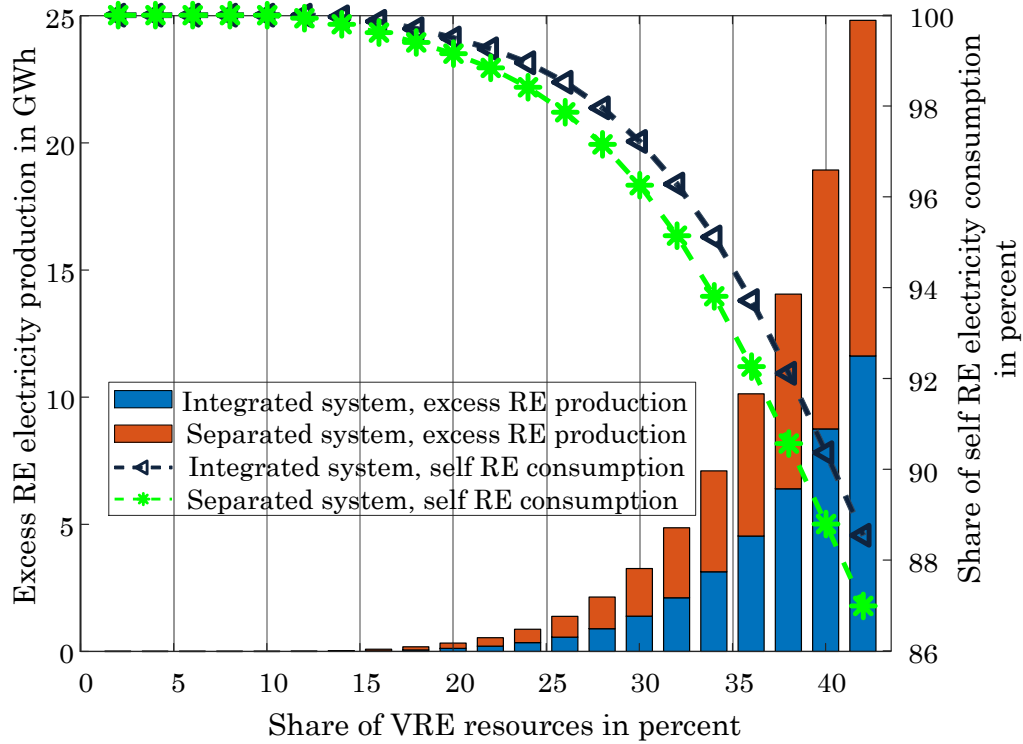


Fig. 8. Share of self-consumption from VRE electricity generation and amount of excess renewable electricity production.

Fig. 9 illustrates the share of the electricity consumption of the water sector of total electricity demand and the amount of electricity consumption in this sector each year. Although the water sector's electricity consumption is increasing due to higher share of desalination (3.5 percent increase for each year) and demand growth (based on Iran's urban population growth [61]), its share of total electricity demand increases from 5.7 percent in 2020 to 6.9 percent in 2030 and then decreases to 6.2 percent in 2040. It comes from the difference between the rate of population growth which directly influences the water demand in this model and the growth rate of electricity demand which is a constant rate based on national data predictions (6.5 percent yearly [56]).

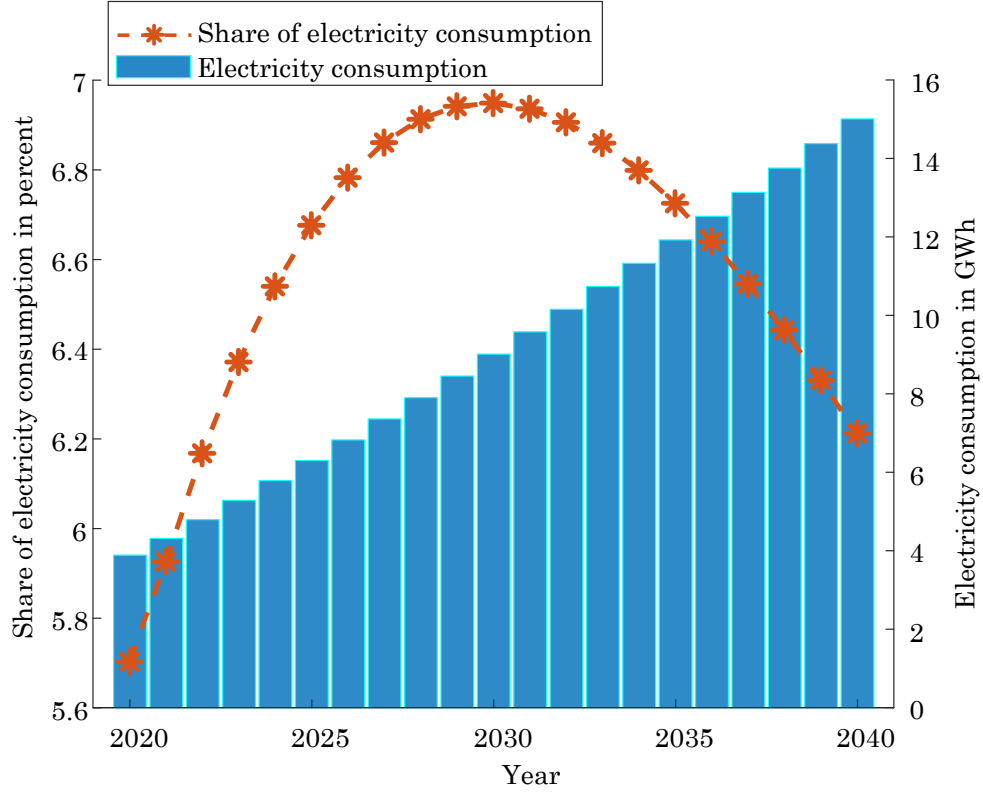


Fig. 9. Electricity consumption of the water sector and its share from total electricity demand.

3.1.1 Statistical model validation

The cumulative distribution functions (CDF) for wind speed and solar irradiance are developed in order to validate the proposed supply-demand module. It is assumed that wind speed is following two-parameter Weibull distribution as follows [62], [63]:

$$F_w(x) = 1 - \exp\left[-\left(\frac{x}{\sigma}\right)^\xi\right] \quad (4)$$

Weibull probability density function (PDF) is

$$P(x) = \frac{\xi}{\sigma} \left(\frac{x}{\sigma}\right)^{\xi-1} \exp\left[-\left(\frac{x}{\sigma}\right)^\xi\right] \quad (5)$$

Where ξ and σ are two parameters of Weibull distribution. ξ is the shape parameter and σ is the scale parameter.

Beta distribution is chosen to develop a distribution curve of solar irradiance in this study [64] as:

$$F_I(x) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \int_0^x (t)^{a-1} (1-t)^{b-1} dt \quad (6)$$

Beta probability density function follows:

$$P(x) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} (x)^{a-1} (1-x)^{b-1} \quad (7)$$

Where a and b are the parameters of Beta distribution and Γ refers Gamma function.

24 Weibull PDFs are obtained by fitting historical data representing PDF of wind speed for each hour of a day (see Fig. 10). Using historical data of solar irradiance, the parameters of 10 Beta probability distribution are estimated representing PDF of solar irradiance from 8 am to 5 pm (see Fig. 11).

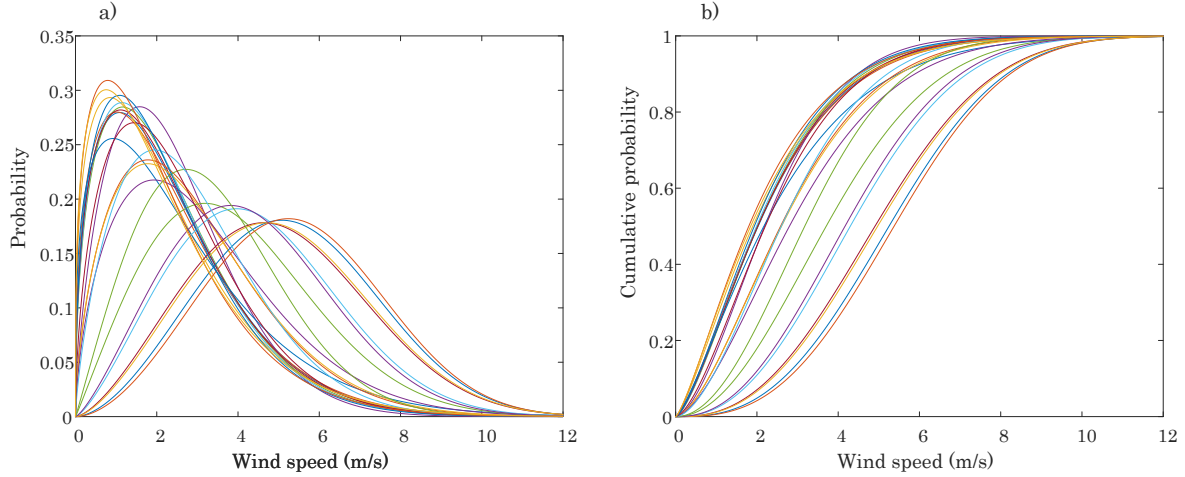


Fig. 10. Wind speed distribution curves for the case study, (a) Weibull probability distribution; (b) Weibull cumulative probability distribution.

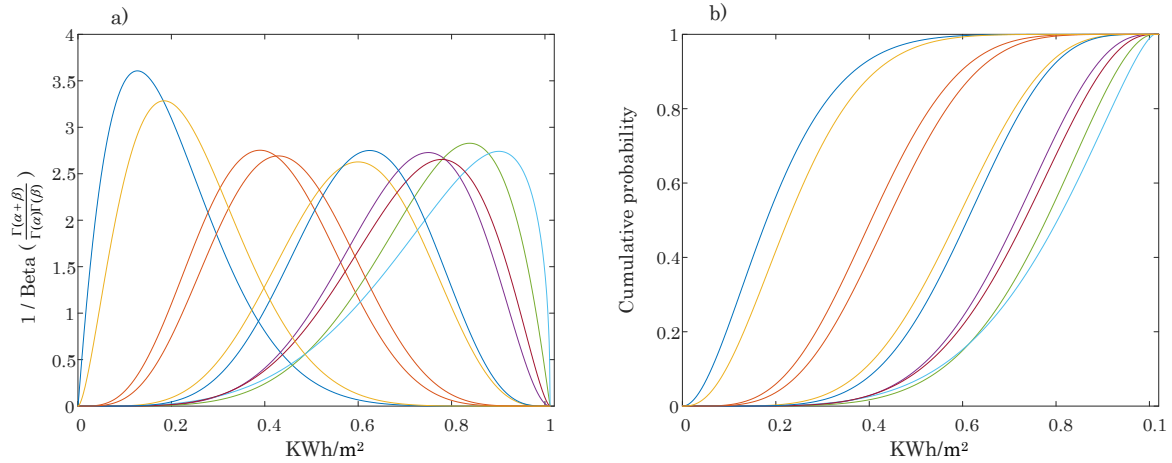


Fig. 11. Solar irradiance distribution curves for the case study, (a) Beta distribution; (b) Beta cumulative probability distribution.

The following representative results in this subsection are evaluated for the separated system. The obtained Weibull cumulative distribution curves show that the probability of wind power generation higher than 93.9 GWh (equal to 90 percent of the result of the proposed model) is 92%. The probability of wind power generation lower than 10.4 GWh (10 percent of the wind power generation in the proposed model) is only 2 percent.

For photovoltaic electricity generation, the obtained Beta cumulative distribution functions estimate that the probability of higher than 601.4 GWh photovoltaic

electricity generation (90 percent of the photovoltaic power generation in the proposed model) is 75%. In the worst scenario possible, photovoltaic electricity generation is more than 26 percent (167.1 GWh) of the photovoltaic electricity generation in the proposed model. As can be seen in Fig. 11 (b), this comes from the fact that for 8 hours during the day, the probability of solar irradiance lower than 100 Wh/m² is zero.

3.2 Energy storage

In the next step, an optimization problem was solved using GAMS software [65] to find the minimum required capacity of batteries to reach the same VRE self-consumption for both systems (integrated and separated). The optimization results (depicted in Fig. 12) indicate that a battery unit with a capacity of 17.4 MWh would be required in 2040. The annual equivalent of the lump sum unit investment cost of the battery unit is calculated to obtain the cost of energy storage for a unit of power production (\$/MWh) which is described in Fig. 12. The annual equivalent of the lump sum unit investment cost of each technology is obtained by calculating the lump sum by a stream of equal annual payments over the lifetime of the technology. The present value of the stream is exactly equal to the lump sum unit investment cost, for each technology. This cost is falling in several periods, from 2025 to 2026, from 2027 to 2033, and 2034 to 2037. This is due to the assumption that the cost of battery technology will decrease by 40 percent by 2040 [66], [67] causing a lowering of costs in these periods while the required capacity of the battery unit is constant or decreasing.

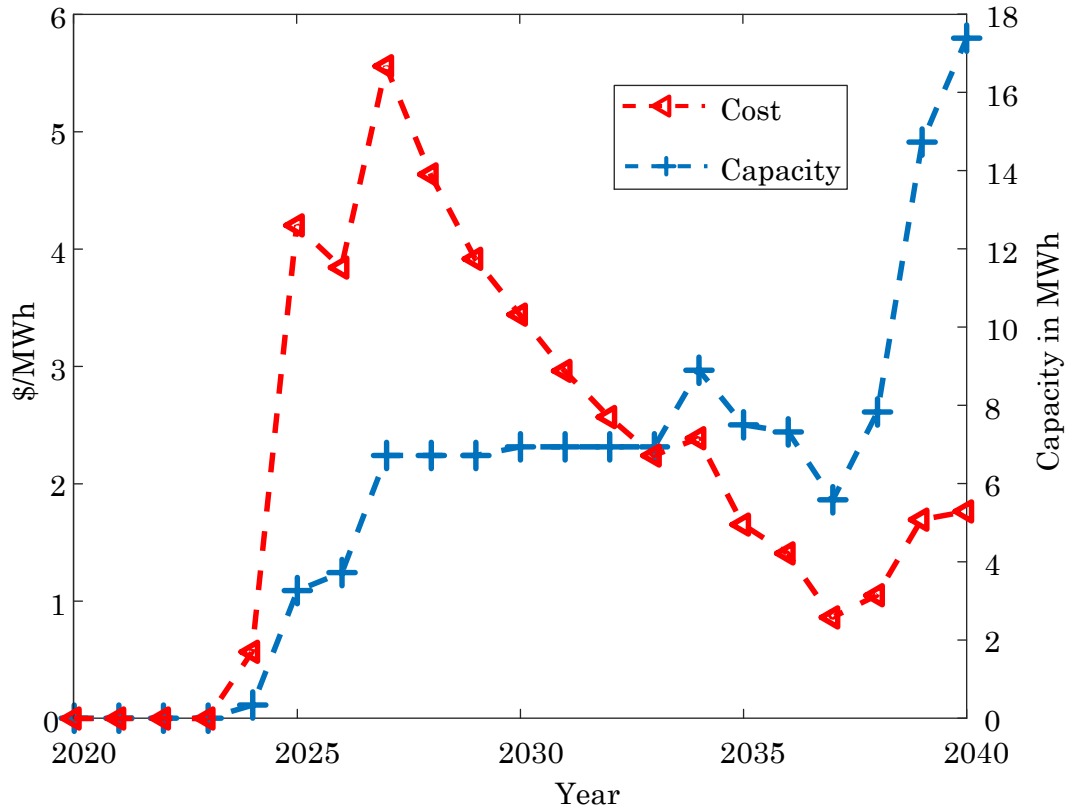


Fig. 12. Capacity and cost of the battery storage to reach same VRE self-consumption for each system.

3.3 Learning curve

The parameters of the two-factor learning curve have been estimated for wind, solar technologies in the Middle East and for worldwide RO desalination technology. The results are depicted in Fig. 13 and Fig. 14. To calculate the LCOE of solar and wind energy, 49 PV projects and 32 wind projects were examined, as explained in detail in Appendix C.

For the Middle East's wind power between 2010 to 2018 the obtained LDR was 13.5% and LSR was 36.6% with a goodness of fit (R^2) of 90.0% based on the average levelized cost of energy and 67.4% based on overall data. Overall LDR rates span a very large range, from -11% to 35% among studies [52]. The predicted levelized cost of wind energy is equal to 34.6 \$/MWh in 2020. Previous studies [53], [68] adopting a similar two-factor learning curve to estimate wind power cost, obtained an LDR of 14.2 percent and an LSR of 18.0% (from 1991-2000) and LDR of 17% and LSR of 37% (from 2009 to 2016).

From 2013 to 2019, the LDR of 15.3% and LSR of 33.9% are the estimated parameters of the two-factor learning curve for solar power in the Middle East with a goodness of fit (R^2) equal to 96.9 percent based on the average and 86.9 percent based on the overall data. The estimation shows the levelized cost of solar energy will reach 55.2 \$/MWh in 2020. LDR is calculated as 18% with the one-factor learning curve for 26 regions in North Africa, South America, and Australia [69] to estimate the LCOE of PV technology. Authors in previous studies [70] found an LDR of 17% and an LSR of 10% by developing the two-factor learning curve for PV systems. Other studies [68] (using data from 1975 to 2000 using worldwide data) and [53] (using data from 2009 to 2016 for US) also include a time lag between investment in R&D and subsequent declines in cost, and report rates of 18.4% and 6.7% for LDR and 14.3% and 75.2% for LSR, respectively.

The learning rates that have been obtained in this study, by applying the two-factor learning curve, were higher than the previous studies, indicating that, in the Middle East, with large-scale investments and commercialization, the learning ability of PV and wind power technologies have substantially improved. Furthermore, for these technologies, LSR was higher than LDR which indicates that wind and photovoltaic industries are both experiencing an explosion of knowledge-driven technology cost reductions, which is ensuring R&D investment can play an important role in the development of these industries.

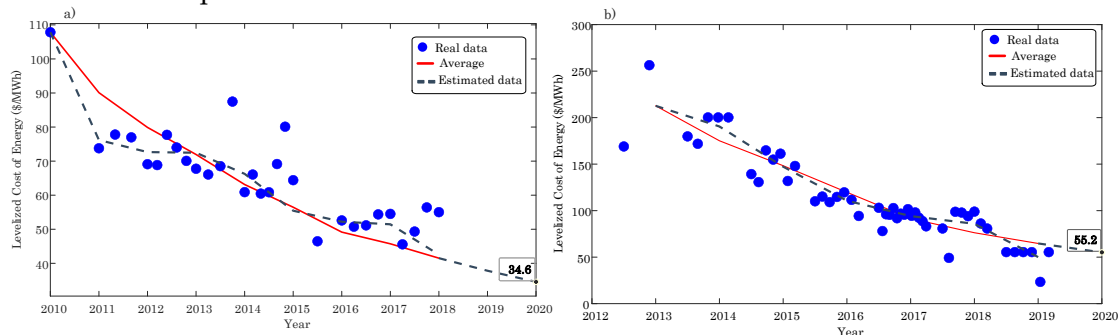


Fig. 13. Learning-curve model fitting: (a) wind-power investment-cost reduction; (b) photovoltaic investment cost reduction.

For RO technology in 2012 to 2020 [71], the obtained LDR is 9.1%, LSR is 49.6 percent with a goodness of fit (R^2) of 98.8% and the estimated average is 0.177 \$Billion. The result for RO technology is illustrated in Fig. 14. A one-factor model was developed by authors previously [72] to estimate the learning rate for the CAPEX of RO technology using worldwide empirical data. This study found an LDR of 15 percent for RO technology. Another study [73] proposed a range of 6 to 20 (high learning scenario) percent for LDR of RO. The learning rates which have been obtained in this sector are applied to estimate future costs in the next section.

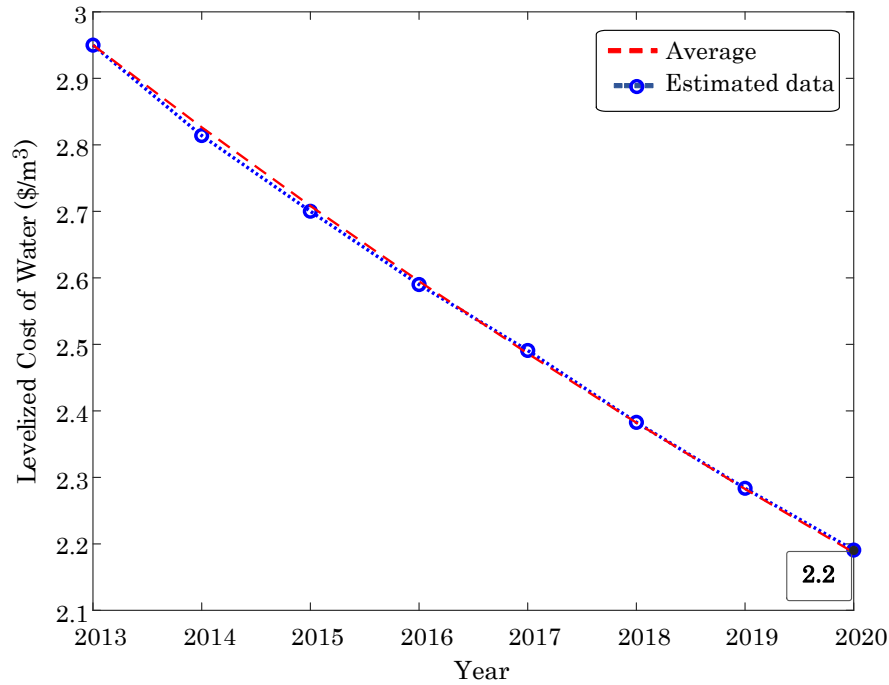


Fig. 14. Learning-curve model fitting of RO desalination industry investment cost.

3.4 Economic analysis

Based on the previous results, the future LCOE for wind and solar energy and the LCOW for RO technology are estimated for the coastal area in the southern part of Iran. The future electricity and water demand for this area have been obtained based on national predictions [56] and the World Bank's population estimation [61].

Ten percent of the saved budget (from a lower capacity of batteries for the integrated system) is assumed to be invested in the R&D of wind and solar industries in proportion to the share of each technology in renewable electricity generation (see Fig. 7). The rest of the saved budget (90 percent) is assumed to be invested in producing wind and solar power, also in proportion to the share of each technology in renewable electricity over 20 years. This means that the new installed capacity is producing energy for the next 20 years which is considered as the life-time of the wind, PV and RO units in this study.

Based on previous studies [1], [74], [75] around 40 percent of the LCOW of RO technology goes to energy, causing a cost-saving in water desalination for the integrated system compared to the separated system (due to lower LCOE). Moreover, the difference between the LCOW of the integrated and the separated systems is another source of budget savings for the water sector. These savings are invested in

RO industry R&D (10 percent of the saved budgets) and RO water production (90 percent of the saved budgets) over the period of 20 years to increase the share of desalination in the region of the case study. Table 2 summarizes the LCOE of renewable supplies and LCOW of RO technology for 20 years from 2020 to 2040 in Iran.

Table 2. Estimated future LCOE of VRE and LCOW of RO.

Year	Separated system, wind energy, \$/MWh	Integrated system, wind energy, \$/MWh	Separated system, solar energy, \$/MWh	Integrated system, solar energy, \$/MWh	Separated system, desalinated water, \$/m ³	Integrated system, desalinated water, \$/m ³
2020	34.6	34.6	55.2	55.2	2.19	2.19
2021	34.6	34.6	48.3	48.3	2.05	2.05
2022	34.6	34.6	43.9	43.9	1.94	1.94
2023	34.5	34.5	40.7	40.7	1.84	1.84
2024	30.5	34.5	38.8	38.2	1.75	1.75
2025	30.4	30.8	36.6	36.5	1.67	1.67
2026	30.4	30.7	34.7	34.3	1.60	1.60
2027	27.8	30.6	33.4	32.3	1.54	1.53
2028	27.0	27.7	32.0	30.6	1.48	1.47
2029	26.7	26.6	30.7	29.0	1.42	1.42
2030	25.4	26.5	29.7	27.4	1.37	1.36
2031	25.4	24.9	28.5	26.1	1.32	1.31
2032	24.4	24.6	27.6	24.8	1.28	1.27
2033	23.1	23.3	26.8	23.7	1.24	1.22
2034	21.7	22.1	26.1	22.7	1.20	1.18
2035	20.7	20.7	25.4	21.7	1.16	1.14
2036	19.8	19.7	24.7	20.9	1.13	1.10
2037	19.2	18.8	24.0	20.1	1.09	1.07
2038	18.5	18.2	23.4	19.4	1.06	1.03
2039	17.5	17.4	22.9	18.8	1.03	1.00
2040	16.6	16.4	22.5	18.1	1.01	0.97

Table 2 shows that the levelized cost of PV electricity will reach 22.5 \$/MWh for the separated system and 18.1 \$/MWh for the integrated system. This means that solar electricity production will remain more expensive than natural gas power plants in 2040 (natural gas plants produce electricity with an LCOE of 10 \$/MWh in Iran [57], [76]). The obtained LCOE for the integrated system is 20 percent lower than the LCOE for the separated system while the required budget is 13 percent lower than the separated system. It was calculated that 74% of the cost reduction of solar power in 2040 compared with 2020, is driven by the influence of cumulative production, and 26% is driven by the effect of the knowledge stock of the cumulative increase in R&D spending for the integrated system. These shares for the separated system are 96% of cost reduction by the experience effect of cumulative production, and 4% by the cumulative increase in R&D spending. Although LSR is higher than LDR, the main share of the cost reduction comes from the experience of cumulative production which shows the inadequate solar industry R&D budget (wind industry is also facing this inadequate budget).

For the wind industry, the LCOE in 2040 is equal to 16.6 \$/MWh for the separated system and 16.4 \$/MWh for the integrated system. About 89% of this cost reduction in 2040 as compared with 2020 is caused by the experience of cumulative production, and 11% comes from the knowledge stock of the cumulative increase in R&D spending for the integrated system. The cost reduction for the separated system is caused by 94 percent due to the cumulative production experience and only 6 percent because of the R&D budget. The cost reduction of wind power is much lower than the cost reduction of solar power. There are several factors that cause this difference. First, the wind power production share of total VRE power production reaches around 20 to 22 (see Fig. 7) percent in 2040 which affects the cost reduction by the experience of cumulative production. In the proposed model in this study, the technology with a higher share of power production gains more budget for R&D and new capacity because it's more attractive based on the technical model.

The LOCW for RO technology will reach 1.01 \$/m³ for the separated system and 0.97 \$/m³ for the integrated system. For RO technology in the integrated system, about 64% of the cost reduction caused by the effect of knowledge stock in 2040 as compared with 2020 and around 36 percent is driven by the experience effect of cumulative production which means the RO technology received more adequate R&D budget compared to wind and solar industry. The cost reduction for the separated system is about 62 percent due to the production experience and 38 percent of caused by the R&D knowledge stock. Around 44 percent of worldwide desalination capacity is located in the Middle East [4] which explains the share of knowledge stock and R&D budget for RO technology in this region.

Above the lower LCOE for wind and solar power and LCOW for RO technology, the share of renewable electricity production in 2040 will be 1.2 percent (2,443 GWh) more than the VRE share for the separated system with 13 percent lower budget compared to the separated system. Furthermore, with one percent lower budget compared to the separated system, the integrated system desalinates 0.4 percent more water than the separated system in 2040 which is equal to 8.0 million m³.

3.4.1 Sensitivity analysis

Two sensitivity analyses are developed in this subsection. First, a sensitivity analysis has been conducted to explore the role of R&D budget share in the future costs of wind, solar and RO technologies. To this end, the share of research and development investment from the saved budget is assumed to differ by up to 20 percent. The results in 2040 are summarized in Table 3. Because of the higher effect of cumulative production and receiving a higher share of the research and development budget, the LCOE for solar power has been affected the most (about 30 percent cost reduction) by increasing the share of R&D budget compared to the LCOE of wind power (around 6 percent cost reduction) and LCOW of RO technology (around 12 percent cost reduction). As expected, the share of VRE is decreased by increasing the share of R&D investment, because the budget for VRE production is decreased and invested in R&D. The share of desalinated water reaches 71.4% by raising the share of the R&D budget to 20 percent. Although the share of RO water production decreases to 80 percent, the total saved budget is increasing because of the high cost reduction of PV energy (around 30 percent). This shows the role of LCOE in the cost of water desalination which is considerable and with 5 percent lower budget compared to the budget for no share of R&D (see Fig. 15), the RO water production rises about 1.4 percent.

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Table 3. Sensitivity analysis on the share of research & development from the budget savings.

Share of R&D in percent	Solar energy, \$/MWh	Wind energy, \$/MWh	Desalinated water, \$/m ³	VRE share in percent	Desalination share in %
0	22.2	16.9	1.01	43.3	70.0
2	21.2	16.8	1.00	43.3	70.1
4	20.3	16.7	1.00	43.3	70.1
6	19.5	16.6	0.99	43.2	70.2
8	18.8	16.5	0.98	43.2	70.4
10	18.1	16.4	0.97	43.2	70.5
12	17.5	16.3	0.96	43.2	70.7
14	17.0	16.2	0.94	43.1	70.8
16	16.5	16.1	0.93	43.1	71.0
18	16.0	16.0	0.91	43.1	71.2
20	15.6	15.9	0.89	43.1	71.4

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In this study, it is assumed the share of the saved budgets goes into production, adding new capacity to the supply side. In other words, these shares of the budget are spent to cover the overall cost of production for the life-time of each technology which is equal to 20 years in this study. Fig. 15 depicts the share of the total production of these new capacities during their lifetime. The results indicate that with just the new capacity from the saved budgets in the integrated system by 2040, these new capacities during their lifetime will produce 6 percent more VRE electricity and 5 percent more desalinated water (for 20 percent share of R&D) compared to the production of the separated system by 2040. Fig. 15 also illustrates the role of R&D in the share of desalination in the integrated system. The obtained LSR of the RO technology (around 50 percent) in this study is higher than VRE technologies (around 34 to 37 percent) causing the rise in the share of R&D budget influences the RO water production much more than the VRE electricity production.

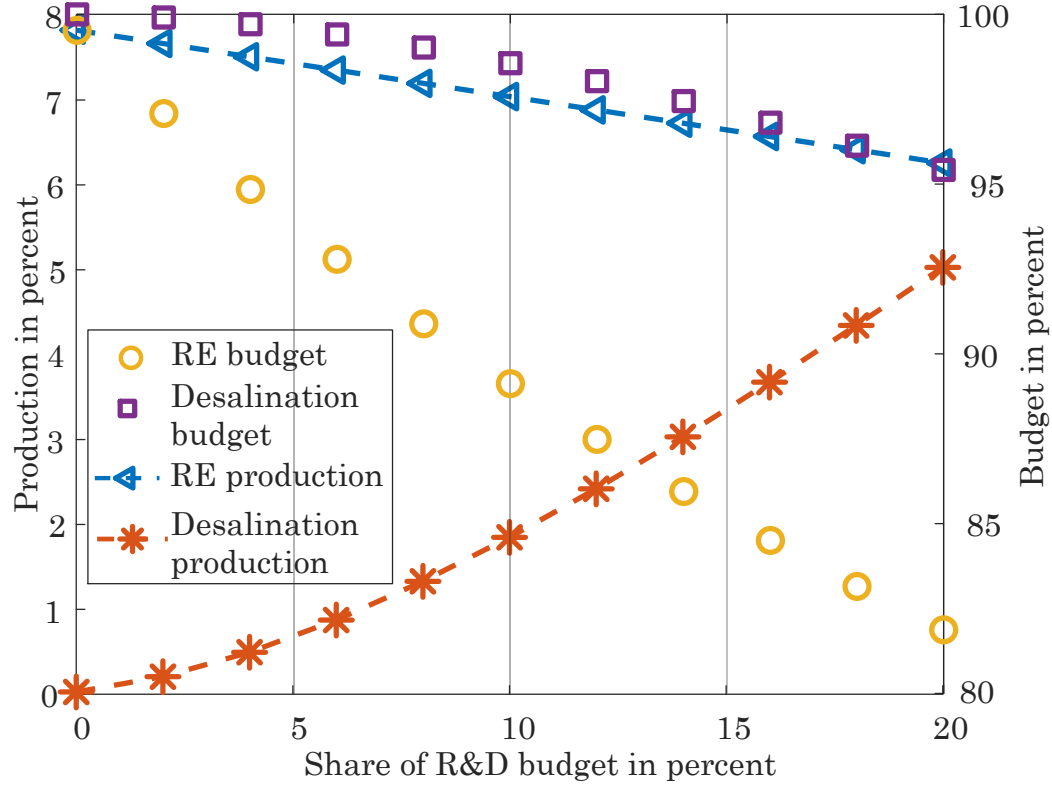


Fig. 15. Share of lifetime VRE electricity generation from the saved budgets out of the total VRE electricity generation of the separated system and required budget compared to the separated system. Share of lifetime RO water generation from the saved budgets out of the total RO generation of the separated system and required budget compared to the separated system.

A further sensitivity analysis has been conducted to study the influence of learning rates of each technology on systems with a fixed 10 percent share of R&D. Fig. 16 illustrates the results of this sensitivity analysis. Despite the higher rate of LSR compared to LDR, the results indicate that wind and PV technologies are more sensitive to changes in LDR compared to LSR causing as an example, 45 percent rise in LCOE of PV (for the integrated system) by decreasing 0.1 of learning by doing elasticity (α PV) while reducing 0.1 of learning by searching elasticity (β PV) increase the LCOE only 4 percent in Fig. 16(b). As mentioned, more investments on R&D in wind and PV industry must be spent to promote the stock of knowledge of these technologies.

Similar to the previous sensitivity analysis, RE share depicts the percentage of lifetime variable renewable electricity generation from the saved budgets out of the total VRE electricity generation of the separated system. As expected, this RE share surges by increasing the VRE learning elasticities because of lower LCOE of VRE causing higher VRE capacity (see Fig. 16(e)). With limited renewable financing being one of the challenges that renewable projects are facing [77], especially in developing countries, these lower costs could accelerate the development and uptake of renewable energy.

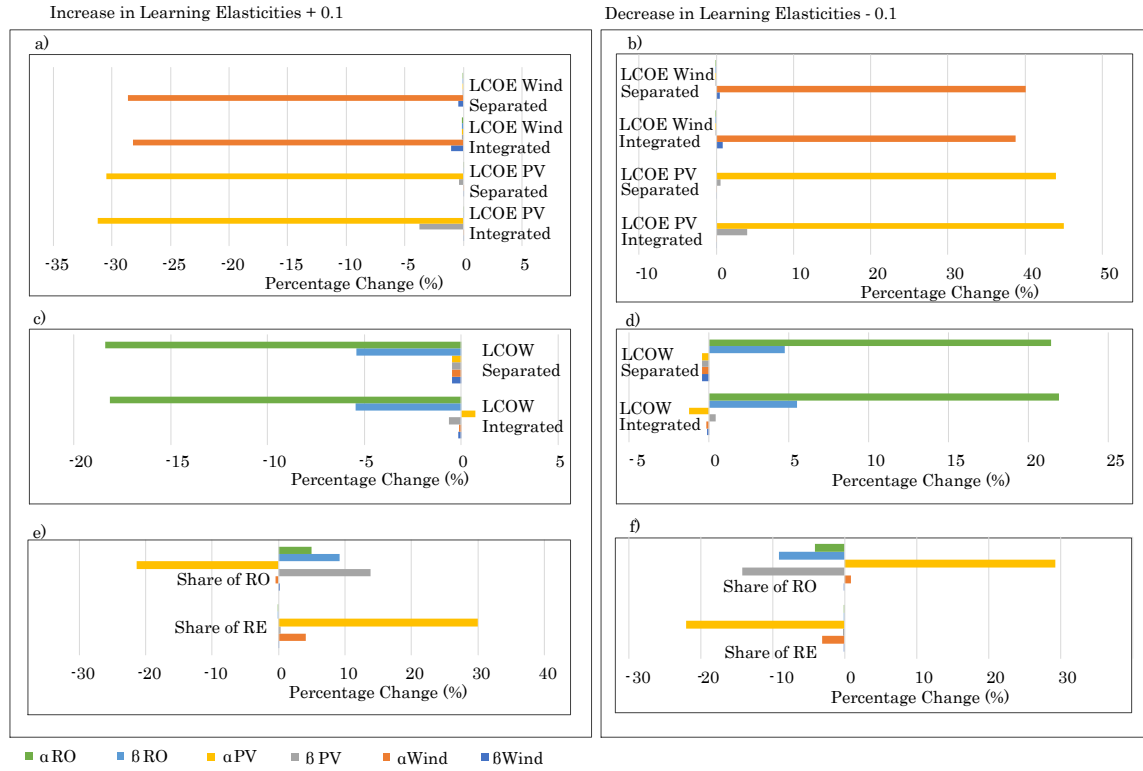


Fig. 16. Sensitivity analysis on the influence of the learning elasticities (depicts the variations in percent) on: (a) increase (b) decrease in levelized cost of renewable energy; (c) increase (d) decrease in levelized cost of desalinated water; (e) increase (f) decrease in share of VRE and RO production for the integrated scenario.

The share of RO illustrates the percentage of life-time RO water production from the saved budgets out of the total reverse osmosis water production of the separated system. In Fig. 16(f), although the learning by doing elasticity of PV (α_{PV}) diminishing 0.1 (lower LDR and higher LCOE), the RO share rises 29 percent and LCOW declines 1.3 (see Fig. 16(d)) percent. It comes from a higher saved budget due to a different growth in LCOE of PV between the separated system and the integrated system. For the integrated system, this cost rises from 18.1 \$/MWh and reaches 26.2 \$/MWh while for the separated system surges 44 percent from 22.5 \$/MWh and reaches 32.4 \$/MWh (see Fig. 16(b)). This means the difference of cost increases from 4.4 to 6.2 \$/MWh. Because of the same reason, the RO share rises 0.8 percent and LCOW declines 0.2 percent by falling 0.1 the learning by doing elasticity of wind (α_{wind}).

4 Conclusions

The water and energy sectors are experiencing a transition to deploying desalination water supplies and renewable resources in the Middle East. A novel nexus methodology is proposed to model the synergies of integrated planning of interlinked sectors.

In this study, the results showed that designing the water and energy sectors as endogenous parts of one system has the potential to decrease the cost of mitigating the fluctuation of variable renewable power production. This reveals the necessity of an integrated planning of the energy sector and water sector and also considering the

operational aspects (especially the fluctuations of variable renewable power) in long-run planning.

The synergy results indicate that by planning the water and energy sectors at the same time, the renewable power production increased about 6 percent and the desalinated water production rises around 5 percent for a 20 percent share of R&D from the saving budget while the VRE and desalination budgets are 18% and 5% lower compared to the budgets for the separated system, respectively. Furthermore, in 2040, the RO LCOW and levelized cost of photovoltaic energy reach 0.97 \$/m³ and 18.1 \$/MWh which are 4% and 20% lower than the costs for the separated models of water sector and energy sector. Although the levelized cost of wind energy for the separated system (16.6 \$/MWh) is close to the cost for the integrated system (16.4 \$/MWh), the overall LCOE of VRE of the integrated system (17.8 \$/MWh) is 20 percent less than the cost for the separated system (21.2 \$/MWh) in 2040 due to higher share of PV system from the total VRE electricity production.

Furthermore, in this study, technology cost is assumed to be a function of experience and knowledge in order to capture the synergies of integrated planning of inter-connected sectors (instead of modeling technology cost just as a function of time, which is the most common approach in the literature). Therefore, the two-factor learning curves are developed to estimate the pace of technology deployment and the path of cost reduction which showed a good fit for the decline in investment costs in the Middle East over the past decade. The calculated learning rates showed that solar, wind and RO technologies are rapidly developing technologies, with higher LSR rates comparing to LDR. In other words, the R&D investment has a significant role in deployment and cost reduction for these technologies in the future. For the integrated system by 2040, driver analysis found that the experience effect of cumulative production accounts for 74%, 89%, and 64% of the total cost reduction for solar power, wind power, and RO technologies, respectively. While for the separated system, the experience effect of cumulative production causes 96%, 94% and 62% of the cost reduction for solar power, wind power, and RO technologies, respectively by 2040. Despite LSR being higher than LDR for all industries, the main share of the cost reduction comes from the experience of cumulative production for wind and solar power which depicts the inadequate R&D budget. However, in the integrated system, investing a portion of the saved budgets on R&D solved this issue to some extent.

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Appendices Nomenclature

Subscripts	Description
t	Set of time, hour
d	Set of time, day
y	Set of time, year
$city$	City
r	Reservoir
pmp	Pump
des	RO desalination
$conv$	Conventional
w	Water
i	Integrated system
s	Separated system
Variables	Description
$w_{r,city}(d, y)$	Amount of water in the city's reservoir
$w_{conv}(t, y)$	Water extraction from conventional water supplies
$w_{pmp,des}(t, y)$	Pumped water from the desalination plant's reservoir
$w_{r,des}(t, y)$	Amount of water in the desalination reservoir
$w_{des}(t, y)$	Water production by the desalination plant
$Cap_{conv}(y)$	Water production capacity of conventional water supplies
$Cap_{des}(y)$	Water production capacity of desalination plant
$Cap_{wind}(y)$	Wind energy capacity
$Cap_{pv}(y)$	Capacity of the photovoltaic panels
$Cap_{bat}(y)$	Capacity of battery unit
$p_{dch}(t, y)$	Electricity discharge of battery unit
$C_{new}(y)$	Unit cost
$Prd_{new}(y)$	Cumulative production
$K_{new}(y)$	Cumulative investment
Parameters	Description
$w_d(d, y)$	Water demand
$Cap_{r,city}(y)$	Capacity of the city's water reservoir
$Cap_{r,des}(y)$	Capacity of the desalination unit's reservoir
$Cap_{pmp,des}(y)$	Pumping capacity of the desalination's reservoir
$RO_{share}(y)$	Share of desalination from total water demand
p_{des}	Required energy for producing unit of desalinated water
p_{pmp}	Required pumping electricity for unit of water from desalination plant to the city's reservoir
p_{conv}	Required electricity to extract and transfer unit of water from conventional water resources
$p_{wind}(t, y)$	Wind electricity production
$v(t)$	Wind speed

$p_{pv}(t, y)$	Electricity production from photovoltaic panels
$I(t)$	Solar radiation
$p_{RE}(t, y)$	Renewable energy production
$RE_{share}(y)$	Target share of renewable energy production
$p_d(t, y)$	Electricity demand
$p_w(t, y)$	Electricity consumption of water sector
$p_{grid}(t, y)$	Electricity exchange with national grid
$p_{ch}(t, y)$	Electricity charge of battery unit
$E_{bat}(t, y)$	Energy stored in the battery unit
$C_{initial}$	Initial unit cost
α	Learning-by-doing elasticity
β	Learning-by-searching elasticity
$Prd_{initial}$	Initial cumulative production
KS	Knowledge stock
In	Investment expenditures
OM	Operations and maintenance expenditures
F	Fixed expenditures
C_f	Capacity factor
d_r	Discount rate
Lf	Lifetime of the technology

Appendix A: Supply-Demand Model

Water Model

Integrated system

To meet the water demand, the amount of water in the city's water reservoir at the end of each day need to be more than the water demand for the next day.

$$w_d(d, y) \geq w_{r,city}(d-1, y) \quad (A.1)$$

Where w_d is the daily water demand and $w_{r,city}$ is the amount of water in the water reservoir.

The hourly amount of stored water in the water reservoir is calculated as Eq. (A.2).

$$w_{r,city}(t, y) = w_{r,city}(t-1, y) + w_{conv}(t, y) + w_{pmp,des}(t, y) \quad A. (2)$$

Where w_{conv} is the amount of water extraction from conventional water resources (underground and surface water) and $w_{pmp,des}$ depicts the amount of pumped water from the desalination plant's reservoir. The amount of water in the desalination reservoir is obtained from Eq. (A.3).

$$w_{r,des}(t, y) = w_{r,des}(t-1, y) + w_{des}(t, y) - w_{pmp,des}(t, y) \quad (A.3)$$

Where w_{des} is the hourly amount of water production from the desalination plant. The amount of stored water in the reservoirs cannot exceed the capacity of them which can be defined as (A.4, A.5).

$$w_{r,city}(t, y) \leq Cap_{r,city}(y) \quad (A.4)$$

$$w_{r,des}(t, y) \leq Cap_{r,des}(y) \quad (A.5)$$

The amounts of water production from the desalination plant, conventional resources and pumped water are limited based on (A.6, A.7 and A.8).

$$w_{conv}(t, y) \leq Cap_{conv}(y) \quad (A.6)$$

$$w_{des}(t, y) \leq Cap_{des}(y) \quad (A.7)$$

$$w_{pmp,des}(t, y) \leq Cap_{pmp,des}(y) \quad (A.8)$$

The amount of water demand is provided by the desalination plant needs to meet to target each year which is considered as Eq. (A.9).

$$\sum_t w_{des}(t, y) = RO_{share}(y) \times \sum_d w_d(d, y) \quad (A.9)$$

Desalination plants need to operate more than 80 percent of their capacity during a year, to become economically and technically feasible. This limitation is imposed on the model based on (A.10).

$$\sum_t w_{des}(t, y) \geq Cap_{des}(y) \times 365 \times 0.8 \quad (A.10)$$

766 The hourly electricity consumption of the water sector for the integrated system is
 767 obtained from Eq. (A.11) for each year.

$$p_w(t, y) = \sum_t p_{conv} \times w_{conv}(t, y) + p_{pmp} \times w_{pmp,des}(t, y) + p_{des} \times w_{des}(t, y) \quad (A.11)$$

768 Where p_w is the hourly electricity consumption of water sector, p_{des} is the
 769 required energy for producing unit of desalinated water, p_{pmp} is the required
 770 electricity for pumping unit of water from the desalination plant to the city's reservoir,
 771 and p_{conv} is the amount of energy needed to extract and transfer unit of water from
 772 conventional water resources.

773 **Separated system**

774 The amount of hourly electricity which the water sector consumes is constant for
 775 the separated system and obtained from Eq. (A.12).

$$p_w(t, y) = \left[RO_{share}(y) \times (p_{pmp} + p_{des}) + (1 - RO_{share}(y)) \times p_{conv} \right] \times w_d(d, y) \times \frac{1}{24} \quad (A.12)$$

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777 **Energy Model**

778 In the proposed model, the amount of hourly wind power production is calculated
 779 as Eq. (A.13).

$$p_{wind}(t, y) = Cap_{wind}(y) v(t)^3 \quad (A.13)$$

780 Where p_{wind} is the hourly wind electricity production, Cap_{wind} is the wind energy
 781 capacity, and v describes the hourly wind speed which is normalized based on
 782 maximum wind speed during the year ($0 \leq v^3 \leq 1$).

783 The amount of solar electricity production is obtained from Eq. (A.14).

$$p_{pv}(t, y) = Cap_{pv}(y) I(t) \quad (A.14)$$

784 Which p_{pv} depicts the hourly electricity production from photovoltaic panels, Cap_{pv}
 785 is the capacity of the photovoltaic panels, and I is the hourly solar radiation during
 786 the year which is normalized based on the maximum solar radiation during the year
 787 ($0 \leq I(t) \leq 1$).

788 As a result, the hourly renewable electricity production is obtained from (A.15).

$$p_{RE}(t, y) = p_{pv}(t, y) + p_{wind}(t, y) \quad (A.15)$$

789 Where, p_{RE} is the hourly renewable energy production.

790 Inequation (A.16) ensures to meet the share of renewable energy production which
 791 is targeted to reach in each year in percent of the whole electricity demand during
 792 each year.

$$\sum_t p_{RE}(t, y) = RE_{share}(y) \times \sum_t [p_d(t, y) + p_w(t, y)] \quad (A.16)$$

Where RE_{share} is the target share of renewable energy production in each year and $p_d(t, y)$ depicts the hourly electricity demand. Eq. (A.17) shows the electricity balance to meet hourly demand.

$$p_d(t, y) + p_w(t, y) = p_{grid}(t, y) + p_{RE}(t, y) \quad (A.17)$$

Where p_{grid} is the amount of hourly electricity exchange with the national grid getting both negative (for feeding electricity into the grid) and positive values (for injecting electricity from the grid).

The objective function is to minimize the exchange of electricity with the grid which is explained in Eq. (A.18).

$$\text{Min} \sum_{t,y} |p_{grid}(t, y)| \quad (A.18)$$

For the separated system, the capacity of PV units and wind units and hourly electricity exchange with the grid are the variables of the optimization problem. For the integrated system, the capacity of PV units, wind units and desalination unit, hourly water production of desalination unit, hourly water extraction from the conventional water resources, hourly pumped water from the desalination unit's reservoir to the city's water reservoir and hourly electricity exchange with the grid are the variables of the optimization problem.

The monthly photovoltaic and wind electricity generation from 2027 to 2029 are depicted in Fig. A.1 and Fig. A.2 for the separated system. The maximum wind power generation accrues during June. Photovoltaic supply generates its maximum power in May. The database that has been used in this study is from a weather station at Jask [55] providing real hourly wind speed and solar irradiance data for two years. For further investigation, daily solar irradiance data from NASA database [78] through 01/01/2019 to 01/01/2020 for this case study (Jask, latitude: 25°38'N, longitude: 57°46'E) are depicted in Fig. A.3. As can be seen in this Fig. A.3, the month of May has the maximum solar irradiance during 2019. These results revealed that the monthly variability of wind power is higher than the variability of photovoltaic power for the case study.

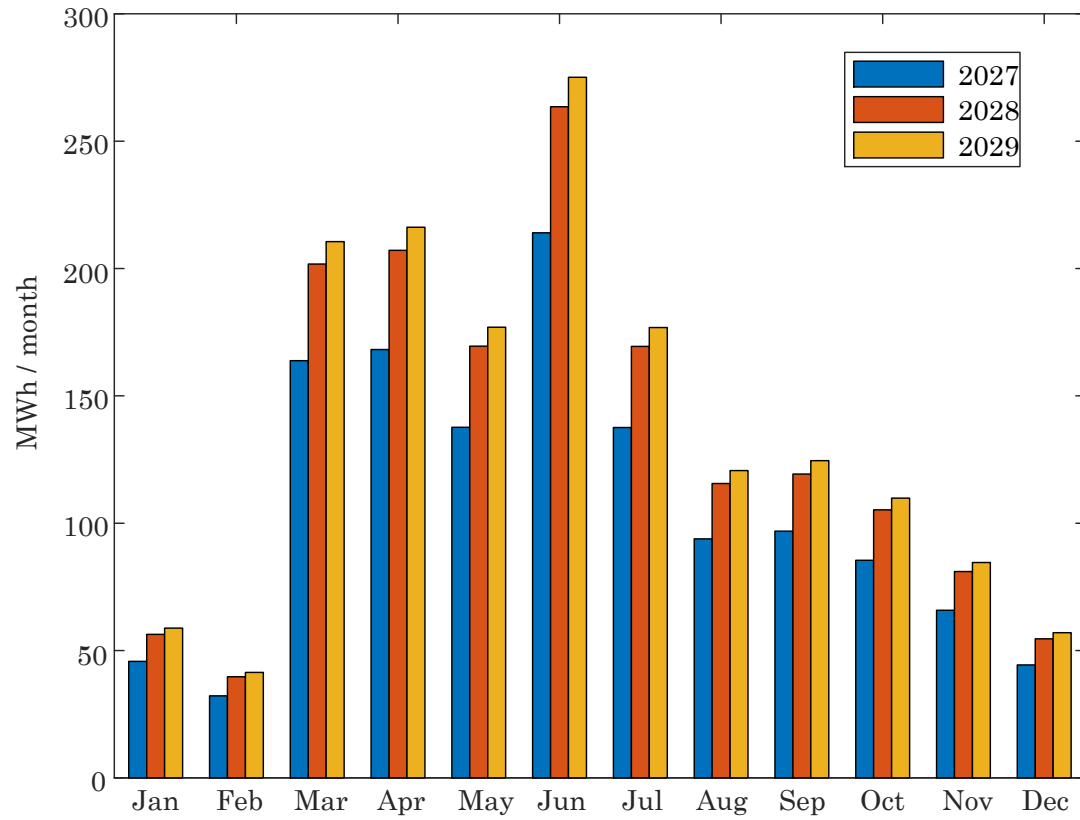


Fig. A.1. Monthly photovoltaic power generation between 2027-2029 for the separated system.

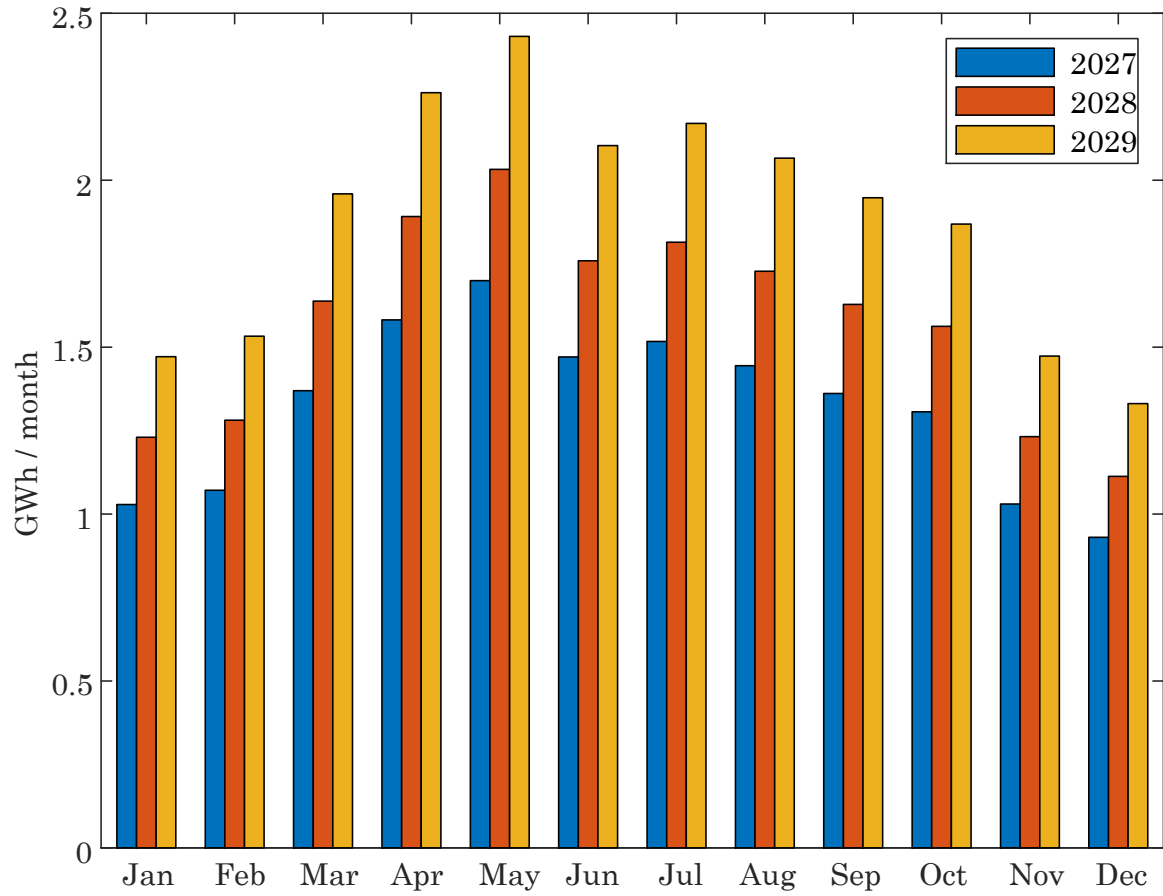


Fig. A.2. Monthly wind power generation between 2027-2029 for the separated system.

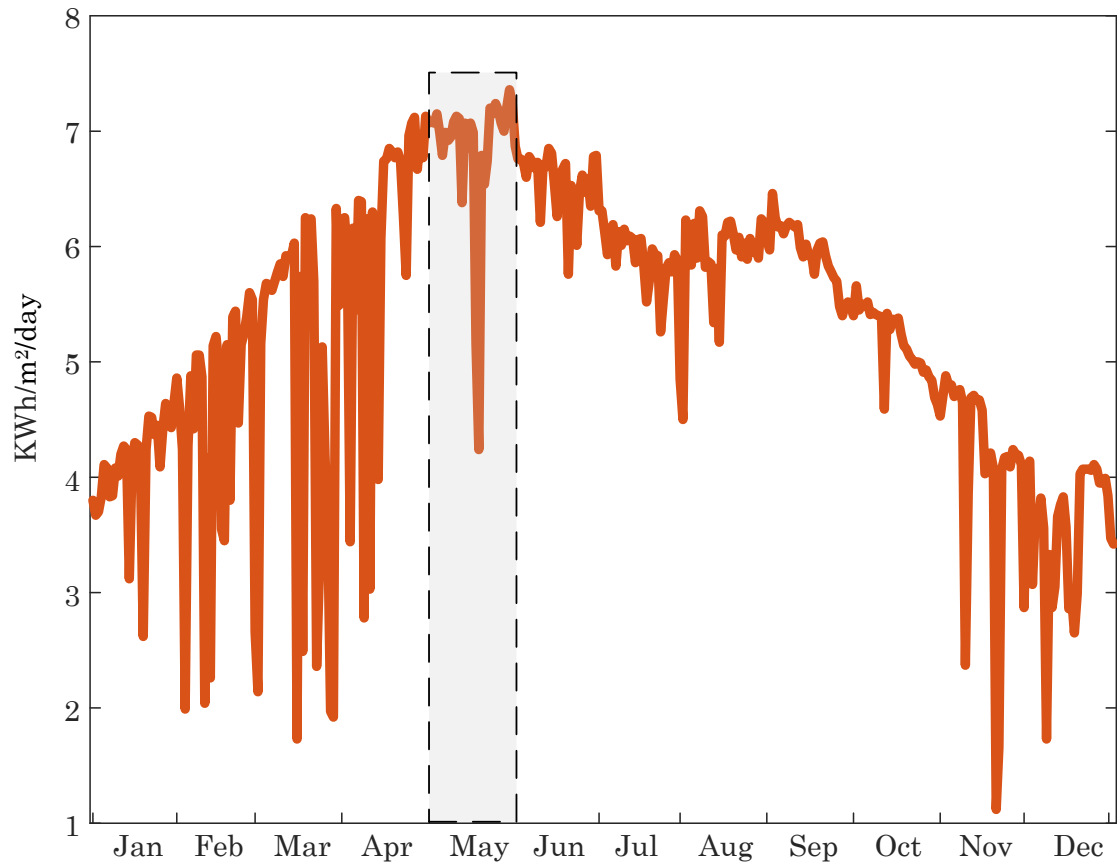


Fig. A.3. Daily solar irradiance in 2019 from NASA database.

Appendix B: Energy Storage Model

The section aims to find the required battery storage unit to reach the same operation as the flexible water sector. To this aim, the electricity exchange with grid of the separated system and the integrated system are compared and obtained from Eq. (B.1).

$$\begin{aligned} & \text{if } p_{grid}(t, y) < 0 \\ & p_{ch}(t, y) = p_{grid,s}(t, y) - p_{grid,i}(t, y) \end{aligned} \quad (B.1)$$

Where p_{ch} depicts the amount of hourly electricity charge of the energy storage unit, $p_{grid,s}$ is the excess renewable electricity production of the separated system and $p_{grid,i}$ shows the excess renewable electricity production of the integrated system. Inequation (B.2) limits the hourly amount of charged or discharged energy based on charge and discharge rate limitation of each energy storage.

$$\begin{aligned} p_{ch}(t, y) & \leq Cap_{bat}(y) \times R_{bat} \\ p_{dch}(t, y) & \leq Cap_{bat}(y) \times R_{bat} \end{aligned} \quad (B.2)$$

p_{dch} is the amount of hourly electricity discharge of the energy storage unit and R_{bat} depicts the maximum rate of the charge or discharge for each energy storage system in percent (share of the total capacity). The amount of stored electricity in the battery unit is obtained from the Eq. (B.3).

$$E_{bat}(t, y) = E_{bat}(t-1, y) + p_{ch}(t, y) - p_{dch}(t, y) \quad (B.3)$$

Where E_{bat} shows the amount of hourly energy stored in the battery unit. This amount can not exceed the capacity of the battery unit which is considered in (B.4).

$$E_{bat}(t, y) \leq Cap_{bat}(y) \quad (B.4)$$

Eq. (B.5) depicts the electricity balance to meet hourly demand, including energy storage system.

$$p_d(t, y) + p_w(t, y) + p_{ch}(t, y) = p_{grid}(t, y) + p_{RE}(t, y) + p_{dch}(t, y) \quad (B.5)$$

The objective function is to find the minimized required capacity of the battery unit to operate as the flexible water sector which is described in (B.5).

$$\text{Min} \sum_y Cap_{bat}(y) \quad (B.5)$$

The hourly electricity discharge of the battery unit, the capacity of the battery unit and hourly exchange electricity with the national grid are the variables of this optimization problem.

Appendix C: Learning Curve

Two-factor learning curve is chosen to estimate the future costs of different renewable energy production from the resources and desalinated water in this study which follow Eq. (C.1).

$$C_{new}(y) = C_{initial} \times \left(\frac{Prd_{new}(y)}{Prd_{initial}} \right)^{-\alpha} \times \left(\frac{K_{new}(y)}{KS} \right)^{-\beta} \quad (C.1)$$

Where C_{new} is the unit cost in year y , $C_{initial}$ depicts the initial unit cost, $Prd_{initial}$ is the initial cumulative production, Prd_{new} is the historical cumulative production in year y (obtained from Eq. (C.2)), α is the learning-by-doing elasticity, KS depicts the knowledge stock which is the initial cumulative investment on R&D, K_{new} is the historical cumulative investment on R&D in year y (described in Eq. (C.3)), and β is the learning-by-searching elasticity.

$$Prd_{new}(y) = \sum_{Y=0}^y Prd(Y) \quad (C.2)$$

Where Prd is the amount of new production each year and $Prd(0)$ depicts the starting year of applying the technology.

$$K_{new}(y) = \sum_{Y=0}^y K(Y) \quad (C.3)$$

Where K is the amount of new investment in R&D in each year and $K(0)$ depicts the R&D investment in the starting year of applying the technology.

The decreasing rate is illustrated by the learning-by-doing ratio (LDR) is obtained as $1 - 2^{-\alpha}$ and Learning-by-searching ratio (LSR) is calculated as $1 - 2^{-\beta}$ which denote the percentage of change in cost as consequence of doubling the cumulative production and R&D budget, respectively.

Because of a lack of data, a new approach is applied to estimate the Learning-by-searching elasticity and the average research and development budget using particle swarm optimization in MATLAB software. To validate this approach, the results for US residential photovoltaic [79] and wind resources [80] are compared with reference [53] and the IEA R&D budget database. For residential PV for 17 years between 2000 to 2016, with time delay of one year for investment R&D, the obtained LDR was 9.52%, LSR was 18.77% and a goodness of fit (R^2) of 94.04%. Reference [53] has reached 94.9% of goodness of fit (R^2) for the US residential PV in 2009 to 2016 based on real data. The real yearly average investment on research and development of US residential PV [81] is equal to 0.128 \$Billion (2018 prices and exch. rates) and the estimated average by PSO approach is 0.124 \$Billion (2018 prices and exch. rates).

For US wind power in 2009 to 2018, with a time delay of three years for invested R&D, the obtained LDR was 17.07%, LSR was 38.68% and a goodness of fit (R^2) of 92.21%. Reference [53] has reached 97.4 of goodness of fit (R^2) for the US wind power in 2009 to 2016 based on real data. The actual yearly average investment on R&D of US residential PV [81] is equal to 0.059 \$Billion (2018 prices and exch. rates) and the estimated average by PSO approach was 0.056 \$Billion (2018 prices and exch. rates) in this study.

By considering the decay factor between 2.5 to 10.5 percent for invested R&D on PV and wind technologies based on literature, the proposed approach is applied for this study. As a result, the parameters of two-factor learning curves for the levelized cost of water (LCOW) of RO desalination technology and the levelized cost of energy (LCOE) for utility-scale solar and wind technologies are estimated using the proposed approach in the Middle East.

Due to a lack of data for LCOE of wind and photovoltaic supplies in the Middle East, 32 wind projects and 49 PV projects have been studied to estimate the LCOE for wind and PV resources in the Middle East. These projects are summarized in Tables C.1 and C.2. The levelized cost of electricity (LCOE) is calculated as (C.4) in this study.

$$\frac{\sum_{y=0}^{L_f-1} In(y) + OM(y) + F(y)}{\sum_{t=1}^n Cap(y) \times C_f(y) \times 8760} \times \frac{1}{(1+d_r)^y} \quad (C.4)$$

Where In is the investment expenditures in year y , OM is the operations and maintenance expenditures in year y , F depicts the fixed expenditures in year y , C_f describes the capacity factor of the supply technology in each year and Cap is the installed capacity of the technology in each year, d_r is the discount rate and L_f describes the life of the technology.

The investment costs, fixed and variable costs and the average capacity factor of wind and PV electricity resources in the Middle East have been obtained through overall VRE electricity production of the countries [82]–[84] and the studied mentioned projects in Tables C.1 and C.2 which is depicted in Fig. C.1. The capacity of wind and photovoltaic resources from 2000 to 2018 in the Middle East is depicted in Fig. C.2. Middle East in this study refers to these countries: Oman, Qatar, Islamic Republic of Iran, Bahrain, Egypt, Iraq, Palestine, Turkey, Israel, Jordan, Kuwait, Lebanon, Kingdom of Saudi Arabia, Syrian Arab Republic, United Arab Emirates, Yemen.

Table C.1. List utility-scale wind projects for obtaining LCOE.

Year	Project	Capacity in MW	Investment M\$ 2018	LCOE (\$/MWh)
2010	Bahce Wind Farm	135	230.31	107.8
2011	Kozbeyli Wind Power Plant	29.9	47.97	77.0
2011	Sayalar Wind Power Plant	23	32.93	73.8
2011	Samurlu Wind Power Plant	30	49.45	77.8
2012	Usak Wind Power Plant	54	62.14	69.1
2012	Edincik Wind Power Plant	30	52.43	74.0
2012	Sadilli Wind Power Plant	38.5	54.75	68.8
2012	Gunaydin Wind Power Plant	12.5	18.75	70.1
2012	Karadere Wind Power Plant	15	29.75	77.7
2013	Geres Wind Power Plant	27.5	38.156	67.8
2013	Mocha Wind Park Project	60	155.22	87.5
2013	Soke Wind Power Plant	45	57.79	66.1
2013	Salman Wind Power Plant	27.5	39.43	68.5
2014	Geres Wind Power Plant	27.5	37.57	60.9
2014	Ova Wind Power Plant	18	24.09	60.5
2014	Tafila Wind Farm	117	304.06	80.1
2014	Edincik Ii Wind Power Plant	26.4	36.01	60.9
2014	Bozyaka Wind Power Plant	4.8	8.64	66.1
2014	Pitane Wind Power Plant	4.8	9.10	69.2
2015	Amasya Wind Power Plant	42	76.77	64.4
2015	Bozyaka Wind Power Plant	12.5	8.66	46.5
2016	Umurlar Ext Power Plant	26.4	35.81	52.6
2016	Incesu Wind Power Plant	14	20.85	54.4
2016	Edincik Iii Wind Power Plant	21	26.20	51.2
2016	Soma Wind Power Plant	30	36.55	50.8
2017	Cakil Wind Power Plant	31.55	50.53	54.5
2017	Gulf Of El Zayt Farm, El Zayt	200	348.30	56.4
2017	Alibey Adası Wind Power Plant	30	36.64	49.3
2017	Camseki Plant (Extension)	42.3	39.98	45.6
2018	Egypt - Development Project	250	409.77	55.0
2018	Lekela Egypt Power Boo S.A.E	252	339	30.1
2018	Yahselli Wind Power Plant	20	31.4	30.1

Table C.2. List of photovoltaic projects for obtaining LCOE.

Year	Project	Capacity in MW	Investment M\$ 2018	LCOE (\$/MWh)
2013	Belectric And Solel Boneh	10	-	169.0
2013	Talmei Bilu Solar Power Plant	21	48.39	256.4
2014	Al-Zanbaq For Energy Generation Psc	10	31	200.2
2014	Falcon Ma An For Solar Energy	10	50	179.8
2014	Zahrat Al-Salam For Energy	10	31	200.2
2014	Al-Ward Al-Joury For Energy Generation PSC	40	31	200.2
2014	Shamsuna Power Company Llc.	10	21	171.9
2015	Ketura Solar Facility	200	83.7	139.3
2015	Scatec Solar Asa	43	50.3	131.9
2015	Mohammed Bin Rashid Almaktoom Solar- Park-Phase 2	10	345.4	130.7
2015	Maan Development Area	10	31.78	164.8
2015	First Solar	28.3	158.92	161.2
2015	Sunedison	12.9	105.94	148.0
2015	Martifer Solar	52.5	27.55	154.8
2016	Zaatari Syrian Refugee Camp	50	15.69	110.1
2016	Mohammed Bin Rashid Al Maktoum	29.7	327.8	119.7
2016	Akfen Solar Power Project	17.9	100	109.2
2016	Al Sharika Al Mahaliya	85	72	115.1
2016	MGES Power	200	261.56	94.3
2016	Soho Solar PV Power Plant	200	25.46	114.8
2016	Hipot Solar PV Power Plant	500	38.07	111.6
2017	Baynouna Solar Energy Company Psc	66.6	266.35	103.1
2017	Caba Solar PV Power Plant	7	23.77	95.5
2017	Alsafawi For Green Energy PSC	5.814	35	78.1
2017	Stars Solar PV Power Plant	48.946	11.56	102.8
2017	Zen Solar PV Power Plant	15.25	57.37	101.6
2017	Çiftay Solar PV Power Plant	10.3	47.48	96.7
2017	Zigana Solar PV Power Plant	8.15	15.23	98.1
2017	Mohammed Bin Rashid Al Maktoum Park	1177	962.96	88.8
2017	İven Solar PV Power Plant	17.988	7.84	96.1
2017	Noor Abu Dhabi	100	891.3	83.1
2017	Koyuncu Nevsehir Solar PV Power Plant	950	9.62	92.4
2017	Aktas Solar PV Power Plant	10.59	19.40	94.4
2017	Basari Solar PV Power Plant	35.9	13.65	95.6
2017	Met-Gun Solar PV Power Plant	34.5	56.49	91.8
2018	Pdo Amin PV Plant	100	100.00	80.8
2018	Mt Dogal Solar PV Power Plant	9.95	18.93	98.8
2018	Me - Se Solar PV Power Plant	9.98	16.46	94.1

2018	Sunfarming Eurasia Asset Enerji Yat	500	16	86.2
2018	Askar Landfill	9.98	-	49.2
2018	Ibri PV Plant	9.95	500.00	80.8
2018	Omicron Engil Solar PV Power Plant	9.9	18.45	97.9
2018	Yaysun Solar PV Power Plant	12.2	19	99.0
2019	Omicron Ercis Solar PV Power Plant	9.95	17.47	55.4
2019	Sakaka Project	200	300.00	23.4
2019	Psi Engil Solar PV Power Plant	26	17.80	55.4
2019	Iota Solar PV Power Plant	9.95	17.91	55.4
2019	Cingilli Solar PV Power Plant (Licensed)	-	38.35	55.4
2019	Al-Muwaqqar Solar Energy Project	10	253.83	55.4

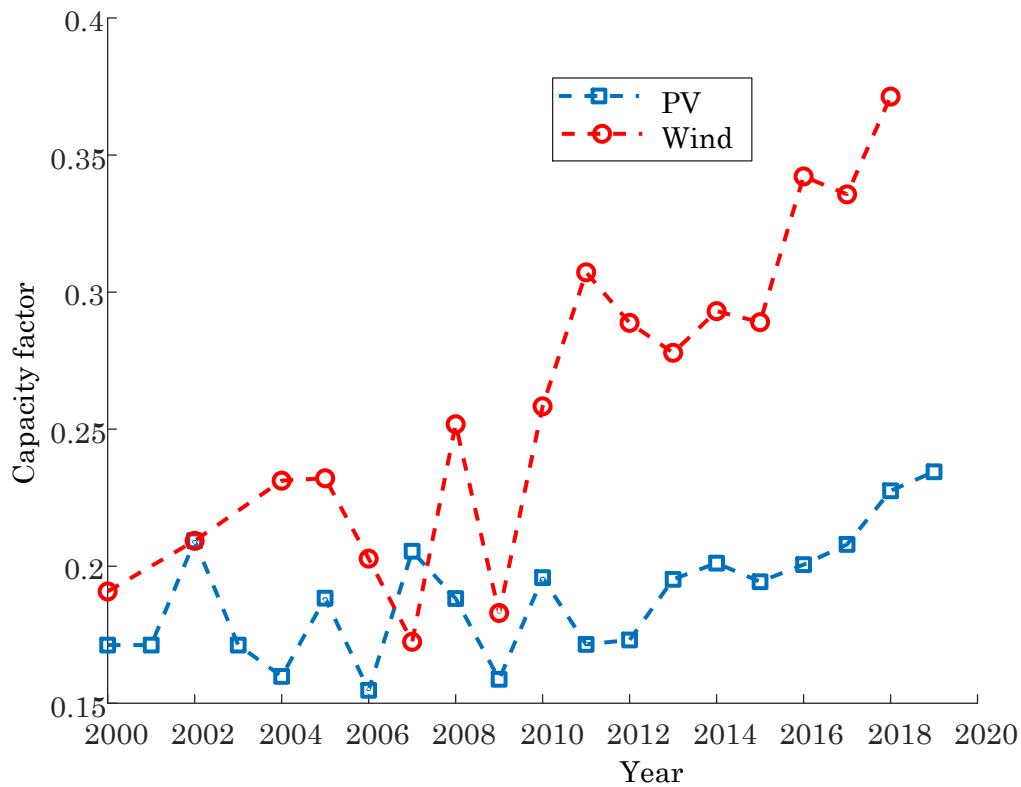


Fig. C.1. Average capacity factor of wind and PV electricity resources in the Middle East.

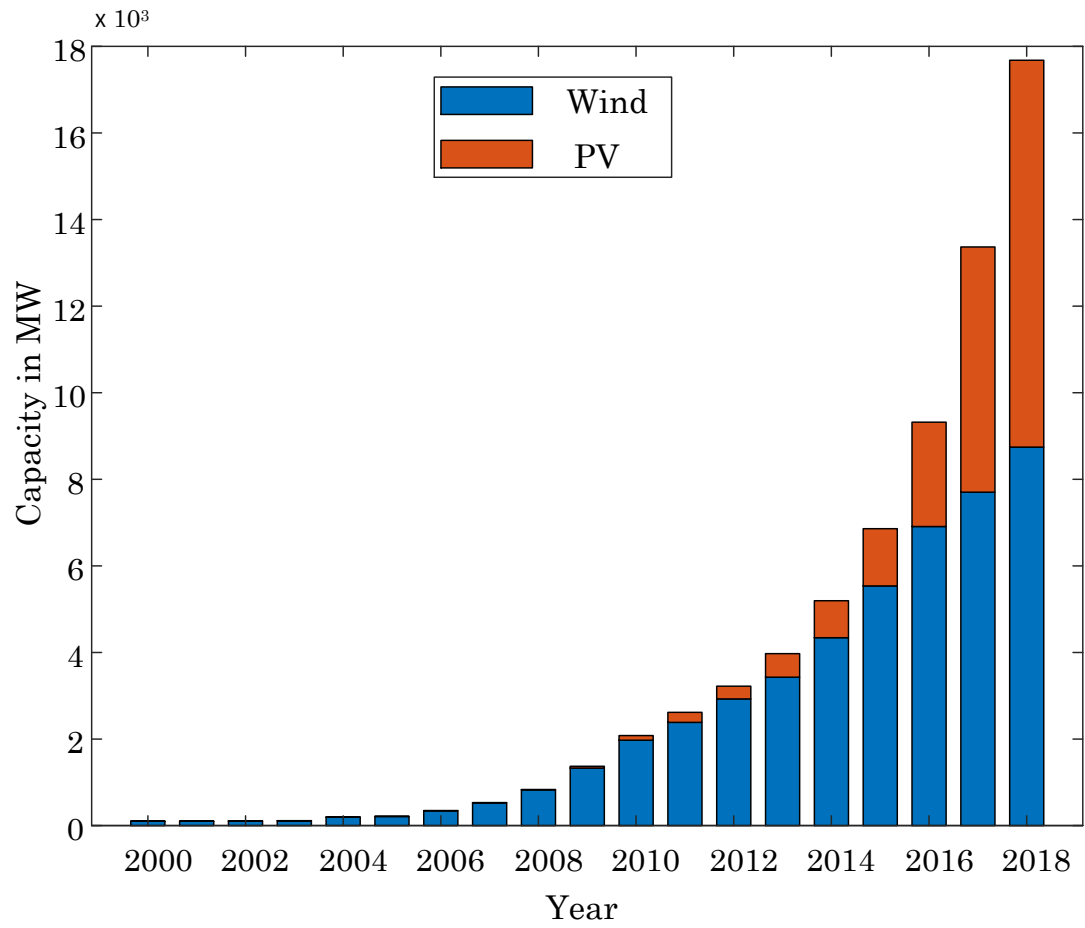


Fig. C.2. Capacity of wind and photovoltaic electricity resources from 2000 to 2018 in the Middle East.

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