5 The roadmap to energy security in Egypt

Mostafa Shaaban

S. 83–102

aus:

Climate Change, Security Risks, and Violent Conflicts

Essays from Integrated Climate Research in Hamburg

Edited by Michael Brzoska and Jürgen Scheffran

Hamburg University Press
Verlag der Staats- und Universitätsbibliothek Hamburg
Carl von Ossietzky

Impressum

BIBLIOGRAFISCHE INFORMATION DER DEUTSCHEN NATIONALBIBLIOTHEK
Die Deutsche Nationalbibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über https://portal.dnb.de abrufbar.

ONLINE-AUSGABE
Die Online-Ausgabe dieses Werkes ist eine Open-Access-Publikation und ist auf den Verlagswebseiten frei verfügbar. Die Deutsche Nationalbibliothek hat die Online-Ausgabe archiviert. Diese ist dauerhaft auf dem Archivserver der Deutschen Nationalbibliothek (https://portal.dnb.de) verfügbar.
DOI https://doi.org/10.15460/HUP.208

ISBN 978-3-943423-81-5

COVERABBILDUNG
Coverabbildung: Alexas_Fotos (https://pixabay.com/de/photos/sonnenuntergang-abend-romantisch-2180346/) auf Pixabay (https://pixabay.com/de/)

SCHRIFT
Alegreya. Copyright 2011: The Alegreya Project Authors (https://github.com/huertatipografica/Alegreya). This Font Software is licensed under the SIL Open Font License, Version 1.1. This license is also available with a FAQ at: http://scripts.sil.org/OFL

DRUCK UND BINDUNG
Books on Demand – BoD, Norderstedt

VERLAG
Hamburg University Press, Verlag der Staats- und Universitätsbibliothek Hamburg Carl von Ossietzky, Hamburg (Deutschland), 2020
http://hup.sub.uni-hamburg.de

Table of Contents

---

5 The roadmap to energy security in Egypt

Mostafa Shaaban

Abstract

In response to the increasing demand of electricity in Egypt, I introduce a new approach to dynamic temporal and spatial sustainability assessment modeling of technologies for electricity planning with an analysis of the decision-making process of multiple actors in the energy sector and its impact on climate change. I use a novel approach of integrating multi-criteria decision analysis, spatial geographic information system data analysis and agent-based modeling.

KEYWORDS: *Electricity, multi-criteria decision analysis, GIS, agent-based modeling, GHG emissions.*

Introduction

With growing concern about the consequences of environmental change and their close relationship to energy development, the concept of sustainable development has been introduced, in addition to the need to involve key stakeholders, including end users, in the decision making process. Throughout the last three decades, there has been a major worldwide concern about sustainable development and the identification of indicators for sustainable energy assessment by many national and international organizations. The International Atomic Energy Agency defines sustainable energy development as "provision of adequate and reliable energy services at affordable costs, in a secure and environmental manner, and in conformity with social and economic development needs" (Vera and Langlois 2007).

In 2011, the ex-UN Secretary-General Ban Ki-moon launched the Sustainable Energy for All (SE4A) Initiative and shared his vision for how governments, businesses, and civil society can make sustainable energy for all a reality by 2030 if working in partnership. "Energy is the golden thread that connects economic growth, increased social equity, and an environment that allows the world to thrive", said Ban Ki-moon (SE4All 2011). The initiative is concerned with renewable energy sources as a key technology offering clean electricity, heating, and lighting solutions to people who mainly depend on conventional energy sources. Nevertheless, these technologies still face a range of social, economic, and structural challenges, requiring not only further technological development but also a deeper understanding of both the success factors and the barriers to accomplish a widespread dissemination (Terrapon-Pfaff et al. 2014). In 2015, world leaders, at a historic UN Summit, have adopted 17 Sustainable Development Goals (SDGs) of the 2030 Agenda for Sustainable Development. These goals came into force on 1 January 2016, aiming at accelerating efforts worldwide to end all forms of poverty, fight inequalities, and tackle climate change while ensuring that no one is left behind. The SDGs extend the success of the Millennium Development Goals (MDGs) and look to go further to end all forms of poverty in all countries while protecting the planet. The seventh goal of these SDGs is to ensure access to affordable, reliable, sustainable, and modern energy fostering the objectives of the SE4A-Initiative (United Nations 2016).

Energy security implies a concept of ensuring the availability of supply that could meet the demand. Some studies support the concept of separating the term security of supply from other policy objectives, e. g. economic efficiency and sustainability, and to restrict the definition to the continuity of supply relative to demand (Winzer 2012). However, in this study it is crucial to link the term security to sustainability. In a dynamic complex system, it is not wise to focus on a single dimension of an alternative while performing applicability assessment of that alternative. A negative impact on other neglected dimensions would hinder the continuity of the provision of the resource. Thus, I identify energy security as a provision of relatively efficient, harmless to human beings and the environment, affordable, and socially acceptable supply that covers the basic demands of the community. In this study, I focus on electricity security as one of the most vital forms of energy in this era.

Egypt has experienced frequent electricity blackouts during the last eight years because of a growing demand, natural gas supply shortages, aging infrastructure, and inadequate generation and transmission capacity. About 70 % of the electricity in Egypt is fueled by natural gas, 19 % by petroleum, and 11 % by renewable energy, which is mostly hydroelectricity (9 %). Recently, Egypt suffered from natural gas shortages, particularly during the summer months. As a result, it imports fuel oil and diesel fuel to cover the shortages (US EIA 2015, EEHC 2014). So far, no previous studies of the sustainability of electricity technologies in Egypt have been conducted. Based on interviews with energy experts in Egypt during February and April 2015, most of the electricity planning is pursued by assessing only the technical and economic aspects as outlined by the study project "Technical Assistance to support the Reform of the Energy Sector" (TARES).

Literature review

Going through the literature, I found that different methodologies have been applied to evaluate the complex energy system from different perspectives. Liu (2014), Singh et al. (2009), and Ness et al. (2007) provide an overview of various approaches to sustainability assessment including a composite index and a general sustainability indicator for renewable energy systems, as well as approaches to apply formulation strategies, scaling, normalization, weighing, and an aggregation methodology. Pohekar and Ramachandran (2004), Wang et al. (2009), and Abu Taha and Daim (2013) evaluate different multi-criteria decision making (MCDM) models for sustainable energy planning and analysis (see Section 3). Doukas et al. (2012) assesses energy sustainability of rural communities using the principal component analysis (PCA), which is one of the MCDM models. Troldborg et al. (2014) develop and apply a multi-criteria analysis (MCA) to a national-scale sustainability assessment and ranking of eleven renewable energy technologies in Scotland and critically investigate how the uncertainties in the applied input information influence the result. Evans et al. (2009) assess renewable electricity generation technologies with respect to sustainability indicators. Islam et al. (2014) examine the current energy-mix, present energy crisis, and possibilities to overcome such scenario by utilizing alternative energy sources such as biomass, solar, wind, and small-scale hydropower energy in the context of Bangladesh. Góralczyk (2003), Pehnt (2006), and Varun et al. (2009a) investigate a dynamic approach towards the life cycle assessment (LCA) of renewable energy technologies. Scheffran (2010) discusses principles and criteria for establishing and evaluating a sustainable bioenergy lifecycle covering all dimensions of sustainability. Demirtas (2013) studies the best selection of renewable energy technology for sustainable energy planning using the analytical hierarchy process (AHP) methodology, another MDCM method. There are many other studies that are concerned with the evaluation of the sustainability of energy systems for future energy planning and decision-making processes.

Research approach

This study aims at answering the following research question: What would be the rational future energy-mix scenario that could secure a sustainable electricity supply in Egypt until 2100? In order to answer this question, this study investigates conditions, scenarios, and strategies for future planning of energy in Egypt, with an emphasis on alternative energy pathways and a sustainable electricity supply mix as part of an energy roadmap until 2100. A novel approach is developed of integrating multi-criteria decision analysis (MCDA) with agent-based modeling (ABM) and geographic information system (GIS) visualization to integrate the temporal and geographic factors to assess the transformation of energy landscapes in Egypt. Different electricity supply technologies are investigated and compared regarding multiple assessment criteria and multiple agents to achieve a comprehensive sustainability assessment covering technical, social, economic, and environmental aspects of these technologies (Shaaban 2017).

The research is guided by the underlying hypothesis that a comprehensive sustainability assessment supports a transformation from the fossil-based energy system in Egypt towards alternative pathways developing the enormous renewable energy potentials of North Africa. Starting from an understanding of the obstacles and lock-in effects of the current energy situation, the assessment aims at going beyond technical and economic fixes of established structures towards expanding the range of criteria and agents to reflect sustainable development in its multiple dimensions. Scenario-based modeling and simulation represent the shifting priorities of agents that shape the evolving energy landscape in Egypt.

I use the open source ABM software “NetLogo” to explicitly represent spatial agents across space and time as they decide on different energy pathways, taking into consideration environmental factors that vary across the landscape and create non-uniform environments for each energy type. I selected seven principal technologies based on their potential resources in Egypt and the intention of the government to involve them in their future planning. These technologies are coal-fired power plants, natural gas-fired power plants, wind, concentrated solar power (CSP), photovoltaics (PV), biomass, and nuclear power plants.

Exploring previous studies, I found numerous energy indicators that have been used for the sustainable development assessment. The United Nations Commission on Sustainable Development (UNCSD) derived 58 indicators from a working list of 134 indicators for applications worldwide (Singh et al. 2009). Neves and Leal (2010) proposed a framework of 18 local energy sustainability indicators to be used both as an assessment and as an action-planning tool. I collected a list of 72 indicators from a sample of 30 studies to be used as a pool of indicators, from which I then selected the most suitable ones for my case study. Based on a particular selection procedure (Shaaban and Scheffran 2017), I selected 13 indicators as shown in Table 1 for the sustainability assessment of the technologies.

Since the indicators have different measuring units, I apply a min-max normalization method as shown in the formulas below to obtain normalized values of the indicators while having the same relation of evaluation with regard to sustainability, for which some indicators are directly proportional to sustainability while others are inversely proportional to sustainability, where v is the value of the indicator, v_{max} and v_{min} are the maximum and minimum value of the indicator across the technologies, respectively. In order to avoid zero values of the indicator, the formula has been modified by reducing v_{min} by 10 % in the first equation and increasing v_{max} by 10 % in the second equation.

$$\frac{(v-(0.9 \times v_{\mathrm{min}}))}{(v_{max}-(0.9 \times v_{min}))} \tag{1}$$

$$\frac{((1.1 \times v_{max})-v)}{\left((1.1 \times v_{max})-v_{min}\right)} \tag{2}$$

The initial input data of the model have been identified through a questionnaire that has been communicated to stakeholders in the energy sector through interviews with the objective to determine the initial preference of different electricity supply technologies and the preference order of the sustainability assessment indicators in the evaluation of these technologies. Then I used these input data to deduce the weights of the indicators. The initial preference values of the technologies by each actor represent the setup values of the priorities of the technologies. I categorized the participants into four groups of actors representing experts, policy-makers, investors, and young-researchers according to their affiliations. Another virtual actor that I use in this study is based on a sustainable scenario, in which it represents equal initial preferences of all technologies and its progress while using equal weights of the sustainability dimensions.

Category	**Indicator**	**Measuring Unit**	**Sustainability target**
Economic	investment cost	USD/kW	minimize
	job creation	jobs/MW	maximize
	cost of electricity	USD/kWh	minimize
	operation and maintenance cost	USD/kW	minimize
Environmental	CO2 emission	g/KWh	minimize
	NOx emission	g/KWh	minimize
	SO2 emission	g/KWh	minimize
Social	safety risks	fatalities/GWeyr	minimize
	social acceptability	ordinal scale	maximize
Technical	efficiency of energy generation	%	maximize
	resource potential	TWh/year	maximize
	reliability of energy supply	%	maximize
	water consumption	kg/kWh	minimize

Table 1: The selected assessment criteria. Source: Based on Shaaban and Scheffran 2017.

Methodology

The multi-criteria decision analysis

The multi-criteria decision analysis MCDA is based on comparing different alternatives by identifying a set of evaluation criteria that are applicable to all of these alternatives. The values of these criteria are then normalized and their weights are determined according to the relative importance of the criteria. The main objective of MCDA is to integrate the weights and the normalized values of the criteria so that each alternative is associated with an integrated value that reflects its ranking (Wang et al. 2009). It plays an important role in energy systems planning, especially since the concern about environmental protection has increased. I apply two MCDA approaches in the sustainability assessment of the technologies, the analytical hierarchy process (AHP) and the weighted sum method (WSM).

The analytical hierarchy process (AHP) is based on the decomposition of a complex problem into a hierarchy with an objective at the top of the hierarchy, indicators and sub-indicators at levels and sub-levels of the hierarchy and decision alternatives at the bottom of the hierarchy as shown in Figure 1 (Pohekar and Ramachandran 2004).

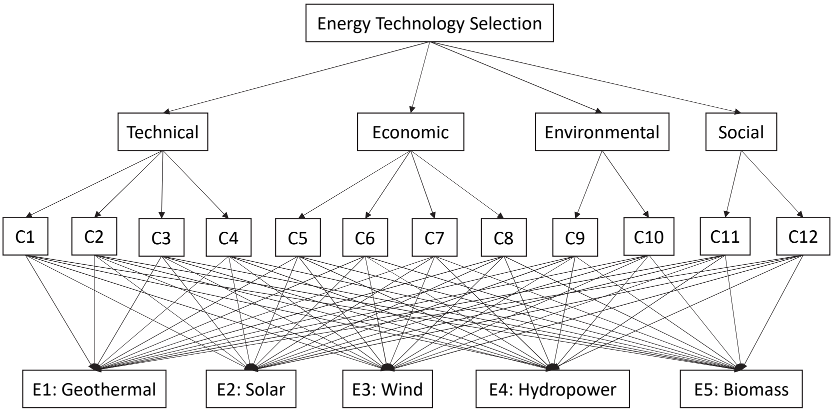


Figure 1: Illustrative scheme of the AHP network. Source: Demirtas 2013.

Scale	**Degree of preference**
1	equal importance
3	weak
5	strong
7	very strong
9	extreme importance
2, 4, 6, 8	intermediate values

Table 2: Scoring scale of AHP and its interpretation. Source: Wang et al. 2009.

I evaluate the weight of the indicators in a pairwise comparison using the scoring system presented in Table 2, based on their importance regarding energy technology selection according to the perspectives of the stakeholders who have been interviewed.

The weighted sum method (WSM) is the most commonly used approach in sustainable energy systems (Wang et al. 2009) that satisfies the following expression:

$$A_i = \sum_{j=1}^{n} \left(a_{ij} w_j\right), \text{ for } i = 1,2,3,\ldots\text{m} \tag{3}$$

where A_i is the WSM score of alternative i, n is the number of decision indicators, m is the number of alternatives, a_{ij} is the normalized value of the jth indicator in terms of the ith alternative and w_j is the weight of the jth indicator that has been obtained from the AHP. The total value of each alternative is equal to the sum of products, which is ultimately used to rank, screen, or select the alternative with the maximum score. From this step, I can obtain the ranking of the technologies, which corresponds to the general integrated sustainability index as calculated through the WSM.

GIS-based spatial data analysis

The second part of the model evaluates the influence of some important spatial factors that represent the local conditions on the selection of an energy pathway. I selected seven spatial factors: resource potential, population density, primary roads availability, water availability, grid availability, political stability, and the negative impact potential on crops. I designed these data sets as layers of raster data. Then I applied the WSM to get an integrated value for each site location for ranking.

Agent-based modeling (ABM)

The third component of the model is the agent-based model reflecting the temporal dynamics of the decision-making process based on cost benefit analysis. In comparison with variable-based approaches using structural equations or system-based approaches using differential equations, agent-based simulation is a bottom-up modeling approach that offers the possibility of modeling individual heterogeneity, representing explicit agent decision rules, and situating agents in a geographical or other type of space (Billari et al. 2006, Gilbert 2008). An agent-based model consists of a set of agents, their relationships, rules of behavior, and a framework for simulating agent behaviors and interactions. Here, the ABM consists agents who act by adjusting their priorities (p) for action pathways (A) in response to the change in the marginal values of the pathways as a function of costs (C) and value preferences (V) as well as environmental conditions (E) that change in space and time as shown in Figure 2 (for a description of the VCX model framework see Scheffran and Hannon 2007). I modified and expanded this ABM approach by including value functions based on the MCDA assessment models as well as expert evaluations and the projected future electricity demand to compare different energy pathways used in electricity mix scenarios and scenarios of sustainable land use.

The multi-criteria assessment is applied to classify typical agents characterized by weighted priorities for certain criteria sets. These types of agents are then used in

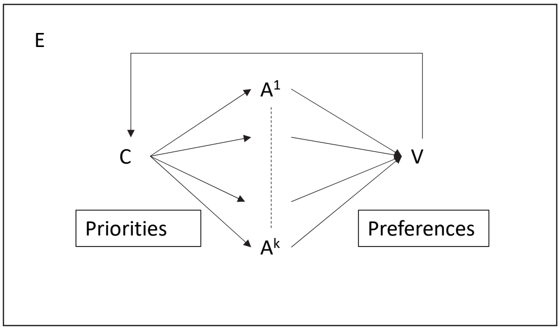


Figure 2: An illustrative diagram of the agent-based model. *Note: The figure describes the allocation of priorities (p) of investment (C) to action pathways (A), affecting value preferences (V) under changing environmental conditions (E). Source: Based on Scheffran and Hannon 2007.*

agent-based models where agents follow these priorities to select energy pathways that meet the desired criteria. Agent decision-rules are applied to a GIS-based spatial (cellular) model landscape, taking into account spatially specific environmental and socio-economic conditions.

The dynamics of changing action priorities for energy pathways describes agents that iteratively shift their action pathways towards large marginal value-cost preferences by comparing the marginal value of one pathway with the weighted average marginal value including all pathways. This is given by the following evolutionary equation of shifting priorities for action pathway k of actor type q in spatial cell (agent) i:

$$\frac{\Delta p_{iq}^{k}}{\Delta t} = \alpha_{iq} p_{iq}^{k} \left(v_{iq}^{k} - \sum_{l} p_{iq}^{l} v_{iq}^{l} \right) \tag{4}$$

- $\frac{\Delta p_{iq}^{k}}{\Delta t}$ is the change in action priority p of actor q for energy pathway k in spatial cell i for time period Δt, which is one year in my case.
- α_{iq} is the adaptation rate of actor q in spatial cell i (in this study I apply the same adaptation rate for all actors).
- v_{iq}^{k} is the marginal value of energy pathway k for actor q in spatial cell i, which is a function of the value and the weight of the spatial factors and the assessment indicators.
- $\sum_{l} p_{iq}^{l} v_{iq}^{l}$ is the sum of weighted marginal values (average) including all energy pathways l.

$$v_{iq}^{k}=\frac{\left(\frac{(\sum_{m=1}^{o}s_{mi}^{k}\times h_{m})}{\sum_{i=1}^{z}(\sum_{m=1}^{o}s_{mi}^{k}\times h_{m})}\right)\times(\sum_{j=1}^{n}a(t)_{kj}\times w_{jq})}{\sum_{k=1}^{l}[\left(\frac{(\sum_{m=1}^{o}s_{mi}^{k}\times h_{m})}{\sum_{i=1}^{z}(\sum_{m=1}^{o}s_{mi}^{k}\times h_{m})}\right)\times(\sum_{j=1}^{n}a(t)_{kj}\times w_{jq})]} \tag{5}$$

- s_{mi}^{k} is the value of spatial factor m influencing spatial cell i, which is for some factors specific to energy pathway k as in case of the resource potential, where z is the number of spatial agents.
- h_m is the weight of the spatial factor m, where o is the number of spatial factors.
- $a(t)_{kj}$ is the value of the assessment indicator j for energy pathway k, which is a function of time for some indicators.
- w_{jq} is the weight of the assessment indicator j of actor q, where n is the number of the assessment indicators.

In this study, I am concerned with the interaction between four categories of actors who represent energy planners selecting from energy system technologies that could meet the growing electricity demands. In one of the investigated scenarios, which I call the game scenario, as well as in the sustainable scenario, each of the four types of actors (experts, policy-makers, investors, and young-researchers) jointly ranks the technologies in each spatial location. The dominant actor is the one with the maximum priority of technologies following their marginal value preferences. The other actors can modify their evaluation preferences afterwards to get the maximum priority technology in future time steps. Figure 3 shows a schematic diagram summarizing the principle of integrating the three methodologies in this technology assessment. Further details about the model can be found in Shaaban et al. (2019) and Shaaban et al. (2018).

Results and discussion

Comparison of energy landscapes transitions

Figure 4 compares the adaptive changes in the average priorities of the technologies over all spatial cells for the four simulated kinds of actors (experts, investors, policy makers and young researchers), the sustainable scenario and the game scenario for the time period 2015 – 2100 (i. e. time steps 0 – 85 in NetLogo). In the scenario of "experts", the model starts with the highest average priority for CSP, followed by PV, wind, and NG. Nuclear and coal are of almost zero priority throughout the simulation period of the model for both experts and investors. However, in the policy

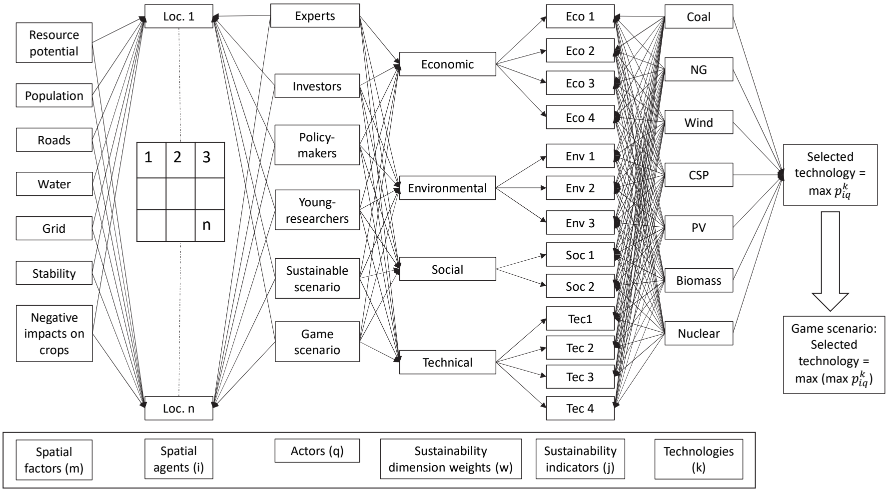


Figure 3: A schematic diagram describing the principle of the integrated assessment.

makers and young researchers' scenario these energy sources are initially at a small level above zero but subsequently diminish drastically approaching zero. In general, there is a gradual increase in the priorities of both wind and NG, which starts to decrease again after approximately 40 years with a pattern that is opposite to both CSP and PV. This implies that the potential tendency towards both CSP and PV will start after2050, when less attention is paid to wind and NG by these actors. However, this changing pattern exists at different levels between actors. In the scenario of "policy makers", the priority of wind is higher than that of other actors, showing more affinity towards this technology. This scenario also shows a lower priority curve of NG han that of CSP and PV. In the sustainable scenario, the priorities of wind and NG are almost coinciding, whereas the priorities for CSP and PV start bifurcating halfway through the simulation period. This points to an increasing trend of CSP and a decreasing trend of PV but at a lower rate than that of CSP.

The map visualizations of the energy landscapes for three scenarios at year 2015 and 2100 are presented in Figure 5. The maps illustrate the spatial DMs (cells) with the maximum priority technology in one of the four tested actor scenarios, the sustainable scenario, and the game scenario at two different points in time. In the "experts" scenario, CSP starts to have a predominant priority in most of the spatial DMs, the rest being distributed between PV, wind, and NG. This highlights that PV coverage exceeds that of wind. As the model runs, the coverage of CSP and PV decreases whereas wind and NG coverage increases. In the sustainable scenario, the landscape starts with a balanced mix including all technology types except coal. This

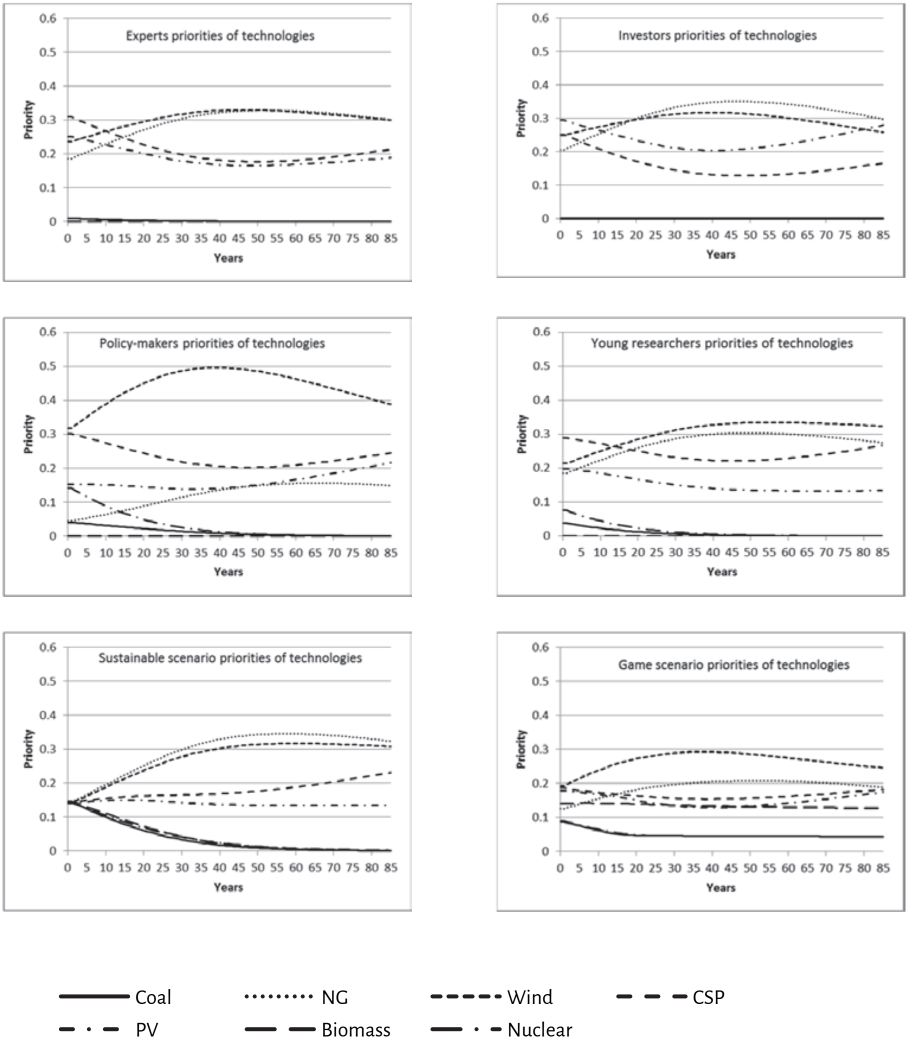
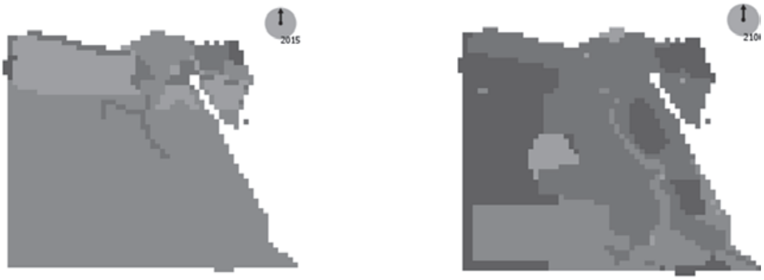
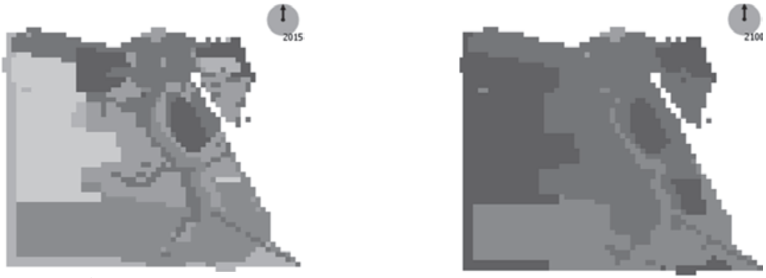


Figure 4: The average priorities of the technologies per actor type changing with time.



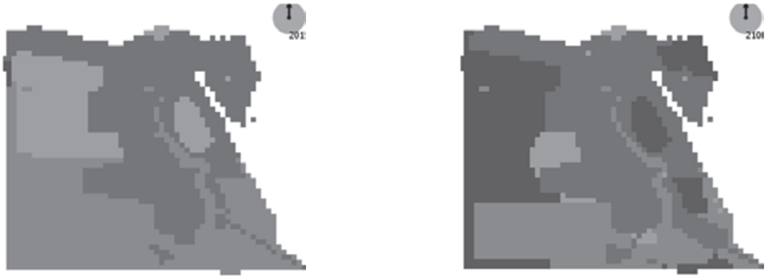
a: experts 2015

b: experts 2100



c: sustainable scenario 2015

d: sustainable scenario 2100



e: game scenario 2015

f: game scenario 2100

■ Coal	■ Wind	▢ PV	▢ Nuclear
■ NG	▢ CSP	▢ Biomass	

Figure 5: Energy landscape transition displaying the maximum priority technology in each scenario in 2015 and 2100.

is because the priorities are affected only by the spatial factors without including the technology assessment through the MCDA during the model setup. However, this distribution changes drastically after the model runs. There is an abrupt drop of biomass, PV, and nuclear coverage leaving the landscape with major coverage of NG, wind, and CSP. In the game scenario, the landscape starts with major coverage of wind and CSP at equal proportions and the remainder being covered by PV. As the model runs, NG coverage replaces that of CSP and PV in some cells.

In the game scenario, each actor sets up an initial preference of the sustainability dimensions and plays the game with the target of achieving the maximum value of the maximum priority technology in each spatial cell relative to the other actors. In order to control the compliance of each actor's strategy with the results in the game scenario, there are several possibilities. The first is to compare the average priorities of the technologies of each actor with those in the game scenario. The second is to compare the landscape coverage of each technology by each actor with that in the game scenario. In each step, each actor can observe how much deviation exists from his actual plan. These checks are useful to ensure conformity with the main target of the game that is concerned with selecting an energy technology, in which the winning actor could select the same technology as another actor who "loses" the game because of a lower priority of that technology. According to this logic, conflicts between the actors can be avoided. For the future, other game scenarios are possible based on collective decision-making representing a majority or joint benefit decision rules.

Future projected energy-mix

The following part presents the predicted electricity-mix scenarios based on the preferences made by the actors and the dynamic assessment of the technologies. Based on the average priorities of the technologies that are presented in Figure 4, I calculate the future projected energy-mix. In 2015, I use the actual energy-mix in Egypt of 2014 based on the energy generated not on the installed capacity, which are shown in Table 3. I use the predicted future electricity consumption that is shown in Figure 6 and calculate the amount of the predicted electricity demand during each period. The priority-mix of the technologies for each actor is multiplied by the amount of the predicted electricity demand, yielding a new distribution of energy sources. For instance, if 30 TWh (Terawatt hours) of electricity are needed to be supplied between 2015 and 2020, the priorities will be distributed among the different sources for this amount and then it will be added to the previously supplied amounts of each source. I assume that the old systems remain included in the energy-mix and are not substituted or decommissioned.

	hydropower	NG	oil	wind	solar
TWh	13.4	119.3	34	1.3	0.02
% TWh	7.9	70.9	20.3	0.8	0.01

Table 3: Electricity mix of Egypt in 2014. Source: EEHC 2014.

The values of the energy-mix in percentage are shown in Figure 7. In 2020, coal ranges between being completely absent in the energy-mix as preferred by investors to about 2 % in the sustainable scenario, which corresponds to 0.8 GW. Approximately 0.5 GW would be accepted by all actors according to the game scenario. In 2100, coal would be accepted if it did not exceed 4 % of the energy-mix with an installed capacity in the range of 5 GW. For NG, which currently constitutes about 70 % of the energy-mix, the share is expected to decline to about 60 % with an installed capacity of about 23 GW in 2020. There is no big difference in the prediction levels of NG between actors in 2020. However, in 2100, the gap increases between actors regarding this technology, which ranges between shares of 25 % and 40 % in the energy-mix, corresponding to a predicted installed capacity ranging between from 36 to 58 GW.

The share of wind energy is predicted to average approximately 5 % with a range of 3.5 – 7 % and an installed capacity of about 5 GW in 2020. In 2100, there is also a big difference between actors' predictions. The share of wind energy ranges between 20 – 35 %, which corresponds to an installed capacity range of 70 – 113 GW. For CSP, the share initially ranges between 2.7 – 5 % with an installed capacity ranging between 5.5 – 10.5 GW. In 2100, the share of CSP is expected to rise to a range of 12 –

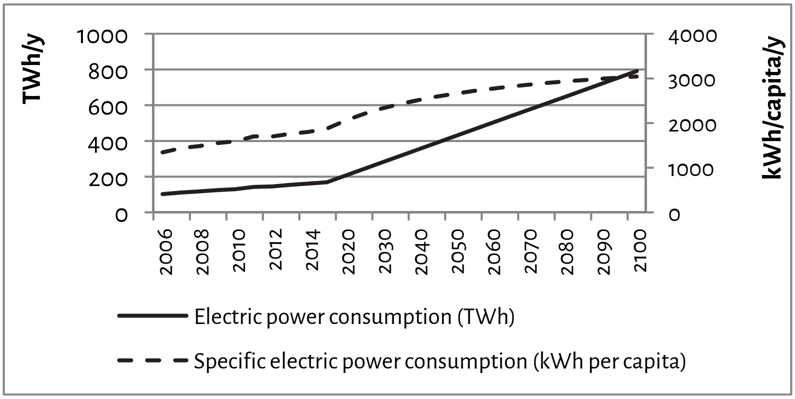
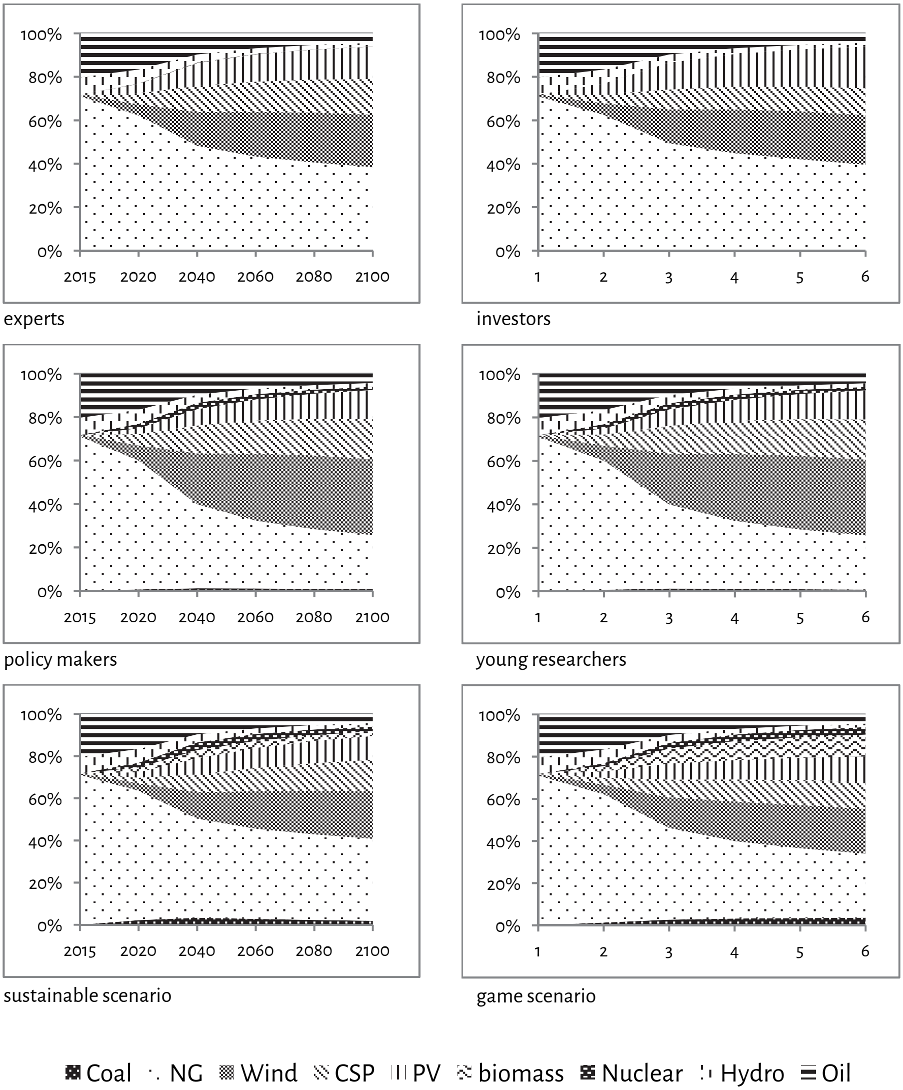


Figure 6: Electricity consumption in Egypt (past, current, and future trend). Source: The World Bank 2014a, b.



experts

investors

policy makers

young researchers

sustainable scenario

game scenario

Figure 7: Predicted energy-mix for Egypt in percent according to actors' priorities.

20 % with an average installed capacity of about 120 GW. The PV share is expected to have the same range like that of CSP in 2020 and 2100, which is in accordance with the preferences of different actors. Moreover, the installed capacity will be in the range of 3 – 6 GW in 2020 and about 50 – 85 GW in 2100, which differs from that of CSP due to the differences in the full load hours. According to the sustainable scenario, it is desirable to include a share of 2.2 % of biomass in 2020 and 2100 as a diversification of technology security. The same applies to nuclear technology, which initially ranges from 0 – 2.2 % in 2020 with an average installed capacity of 0.4 GW. Although the range of shares is preferred to remain unchanged, however, the installed capacity will be increased to an average of 2 GW in 2100.

GHG assessment results

An important output of the model is the comparative assessment of the contribution to climate change and global warming from the different energy-mix scenarios as obtained from the analysis of the decisions made by actors in the simulations. Figure 8 illustrates this comparison in two graphs, where the left graph represents the GHG relative emissions based on the average priority-mix of the technologies while the right graph shows the GHG emissions in million tons of CO2 equivalents (Mio tons CO2 eq.) from the energy-mix, estimated by each actor over the whole simulation period. The proposed energy-mix scenario by policy makers emits fewer GHGs compared to the other scenarios while the sustainable scenario depicts the highest level of GHG emissions due to the inclusion of biomass and a higher share of coal. However, the emissions of the sustainable scenario approach those of the other three actors. I can conclude from these graphs that the average GHG emissions would double by 2100, which is likely to negatively contribute to climate change.

Summary and conclusion

According to the results obtained from the simulations presented in this paper, I conclude that, the decision making process in the energy sector to secure future electricity supply for the coming generations is a complex process. It involves a multidimensional analysis of all possible potential technologies by means of evaluation of indicators whose values change over space and time. Moreover, the actors involved

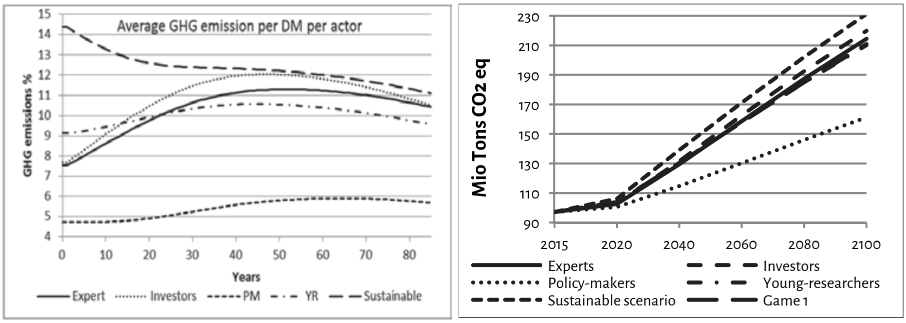


Figure 8: Comparison of the GHG emissions of the priority-mix and the energy-mix of the technologies.

in the decision making process have different preferences for these indicators and their decisions could be affected by the decisions of other actors. Although the sustainable scenario constitutes a normative decision approach with an unbiased affinity towards any of the sustainability dimensions – making it a target for all countries in their energy planning – in practice, there are many actors who decide differently and interact with each other. Therefore, I cannot confirm that the energy-mix obtained from any of the single actors including the sustainable scenario is "the" best. Instead, a balanced energy-mix resulting from the interaction of the actors in the game scenario could represent a realistic and better approach of predicting an acceptable, sustainable, and secure future energy-mix in Egypt. The results of the game scenario indicate how important it is for the Egyptian government to show more concern for renewable energy projects and the transition of the energy landscape from fossil fuel-fired energy systems to renewable ones. Energy diversification, through the inclusion of other resources like coal or nuclear in a limited amount, adds more security by gaining knowledge and experience from their operation and reduces the potential of conflicts.

It is recommended to extend the model by including a higher number of assessment indicators, spatial factors, and other actors. Moreover, the spatial factors should be analyzed at a higher resolution and should exclude the locations that cannot be used for the installation of power plants at all. As more variables, in terms of indicators, spatial factors and actors, and a higher resolution are included in the model, the accuracy of the results is likely to improve considerably. Therefore, this model could be used as a building block for future projects through changing the alternatives, the assessment indicators, the external spatial factors, the country of study, and the actors.

References

Abu Taha, R. and T. Daim, 2013: Multi-Criteria Applications in Renewable Energy Analysis, a Literature Review. In: T. Daim, T. Oliver, and J. Kim., eds., Research and Technology Management in the Electricity Industry. London: Springer, 17–30.

Billari, F. C., T. Fent, A. Prskawetz, and J. Scheffran, eds., 2006: Agent-Based Computational Modelling, Contributions to Economics. Heidelberg: Physica.

Demirtas, O., 2013: Evaluating the Best Renewable Energy Technology for Sustainable Energy Planning. International Journal of Energy Economics and Policy, 3, 23–33.

Doukas, H., A. Papadopoulou, N. Savvakis, T. Tsoutsos, and J. Psarras, 2012: Assessing energy sustainability of rural communities using Principal Component Analysis. Renewable and Sustainable Energy Review, 16, 1949–1957.

EEHC, 2014: Egyptian Electricity Holding Company annual report. Cairo: Ministry of electricity and renewable energy.

Evans, A., V. Strezov, and T. J. Evans, 2009: Assessment of sustainability indicators for renewable energy technologies. Renewable and Sustainable Energy Review, 13, 1082–1088.

Gilbert, G. N., 2008: Agent-based models, Quantitative applications in the social sciences. Los Angeles: Sage.

Góralczyk, M., 2003: Life-cycle assessment in the renewable energy sector. Applied Energy, 75, 205–211.

Islam, M. T., S. A. Shahir, T. M. I. Uddin, and A. Z. A. Saifullah, 2014: Current energy scenario and future prospect of renewable energy in Bangladesh. Renewable and Sustainable Energy Review, 39, 1074–1088.

Liu, G., 2014: Development of a general sustainability indicator for renewable energy systems: A review. Renewable and Sustainainable Energy Review, 31, 611–621.

Ness, B., E. Urbel-Piirsalu, S. Anderberg, and L. Olsson, 2007: Categorising tools for sustainability assessment. Ecological Economics, 60, 498–508.

Pehnt, M., 2006: Dynamic life cycle assessment (LCA) of renewable energy technologies. Renewable Energy, 31, 55–71.

Pohekar, S. D. and M. Ramachandran, 2004: Application of multi-criteria decision making to sustainable energy planning—A review. Renewable and Sustainable Energy Review, 8, 365–381.

Scheffran, J., 2010: Criteria for a Sustainable Bioenergy Infrastructure and Lifecycle. In: P. N. Mascia, J. Scheffran, and J. M. Widholm, eds., Plant Biotechnology for Sustainable Production of Energy and Co-Products. Heidelberg: Springer, 409–447.

Scheffran, J. and B. Hannon, 2007: From complex conflicts to stable cooperation: Cases in environment and security. Complexity, 13, 78–91.

SE4All, 2011: Sustainable Energy for All http://www.se4all.org/our-vision, last accessed 28 January 2019.

Shaaban, M., 2017: The Roadmap to Energy Security in Egypt. University of Hamburg, Hamburg, Germany.

Shaaban, M. and J. Scheffran, 2017: Selection of sustainable development indicators for the assessment of electricity production in Egypt. Sustainaible Energy Technologies and Assessments, 22, 65–73.

Shaaban, M., J. Scheffran, J. Böhner, and M. S. Elsobki, 2018: Energy Landscape Transition Analysis and Planning in Egypt (ELTAP-Egy). https://doi.org/10.25937/zre0-r244, last accessed 28 January 2019.

Shaaban, M., J. Scheffran, J. Böhner, and M. S. Elsobki, 2019: A Dynamic Sustainability Analysis of Energy Landscapes in Egypt: A Spatial Agent-Based Model Combined with Multi-Criteria Decision Analysis. Journal of Artificial Societies and Social Simulations, 22(1), 4.

Singh, R. K., H. R. Murty, S. K. Gupta, and A. K. Dikshit, 2009: An overview of sustainability assessment methodologies. Ecological Indicators, 9, 189–212.

Terrapon-Pfaff, J., C. Dienst, J. König, and W, Ortiz, 2014: A cross-sectional review: Impacts and sustainability of small-scale renewable energy projects in developing countries. Renewable and Sustainable Energy Review 40, 1–10.

The World Bank, 2014a: Total population. http://data.worldbank.org/indicator/SP.POP.TOTL, last accessed 19 Jauary 2019.

The World Bank, 2014b: Electric power consumption . Electr. Power Consum. URL http://data.worldbank.org/indicator/EG.USE.ELEC.KH.PC, last accessed 19 January 2019.

Troldborg, M., S. Heslop, and R. L. Hough, 2014: Assessing the sustainability of renewable energy technologies using multi-criteria analysis: Suitability of approach for national-scale assessments and associated uncertainties. Renewable and Sustainable Energy Review, 39, 1173–1184.

United Nations, 2016: United Nations sustainable development agenda. U. N. Sustain. Dev. URL http://www.un.org/sustainabledevelopment/development-agenda/, last accessed 19 January 2019.

US EIA (Energy Information Administration), 2015: Egypt energy analysis, https://www.eia.gov/beta/international/analysis.cfm?iso=EGY, last accessed 19 January 2019.

Varun, Bhat, I. K., and R. Prakash, 2009: LCA of renewable energy for electricity generation systems—A review. Renewable and Sustainable Energy Review 13, 1067–1073.

Vera, I. amd L. Langlois, 2007: Energy indicators for sustainable development. Energy, 32, 875–882.

Wang, J.-J., Y.-Y, Jing, C.-F. Zhang, and J.-H. Zhao, 2009: Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renewable and Sustainable Energy Review, 13, 2263–2278.

Winzer, C., 2012: Conceptualizing energy security. Energy Policy, 46, 36–48.