Contributions of Information Systems Research to Decision Support for Wind Market Players

Von der Wirtschaftswissenschaftlichen Fakultät der
Gottfried Wilhelm Leibniz Universität Hannover
Zur Erlangung des akademischen Grades

Doktor der Wirtschaftswissenschaften
– Dr. rer. pol. –

genehmigte Dissertation

von

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geboren am 26.05.1991 in Alfeld/Leine

2022

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Tag der Promotion:	14. Juli 2021

This thesis is dedicated to Laura,
who has always inspired and supported me,
and to my family and friends,
who have always kept my back
and motivated me in a variety of ways.

I. Abstract

The mitigation of climate change through the transition toward sustainable and efficient energy systems based on renewable energy technologies is one of the greatest challenges of the 21st century pursued by an ever-growing number of individuals, organizations, and societies in large. The extensive financial support of many nations for renewable energies has led to a rapid global spread of these technologies in the last two decades. Nowadays, as renewable energy technologies are maturing, governments tend to implement more market-based support mechanisms in order to scale back financial support, which poses new challenges for all market players. Consequently, in a consolidating market environment, only those players can establish themselves in the market, who have the right information at the right time in order to make the best possible decisions on newly emerging issues. In this context, this thesis demonstrates the high potential of information systems (IS) research on decision support systems (DSS) in making solution-oriented and impactful contributions to affected renewable energy stakeholders by improving the decision-making process through aggregated information. Six consecutive thematic topics are presented and discussed based on several research articles, each addressing a specific challenge of different renewable energy stakeholders by means of quantitative design science research (DSR) on DSS. The thematic spectrum ranges from micro-level challenges of individual renewable energy operators to macro-level challenges of policy-makers. A strong focus is placed on renewable energy finance and policy topics in the field of the wind energy sector. Findings indicate that the role of appropriate and customized DSS is becoming increasingly important for all market players, due to the constantly growing diversity of information and amount of data available in the rapidly digitalizing renewable energy sector. They further point to the strength and necessity of IS research with regard to its integrative function between other research areas and how this property could be used in order to respond to the need for more practical support for decision-makers concerned with environmental and sustainability issues.

Keywords: Renewable Energy, Wind Energy, Information Systems Research, Decision Support, Simulation, Optimization, Design Science

Abstrakt

Die Abschwächung des Klimawandels durch den Übergang zu nachhaltigen Energiesystemen auf Grundlage Erneuerbarer Energien (EE) ist eine der größten Herausforderungen des 21. Jahrhunderts. Die umfangreiche Förderung vieler Nationen für EE hat in den vergangenen zwei Jahrzehnten weltweit zu einer großen Verbreitung dieser Technologien geführt. Da EE seither immer wettbewerbsfähiger werden, neigen politische Entscheidungsträger vieler Nationen heutzutage dazu, zunehmend marktbasierte Fördermechanismen einzuführen, um die finanzielle Förderung dauerhaft zu reduzieren, wodurch neue Herausforderungen für Marktteilnehmer entstehen. In einem sich konsolidierenden Marktumfeld können sich nur diejenigen Akteure langfristig am Markt etablieren, die über die richtigen Informationen zur richtigen Zeit am richtigen Ort verfügen. In diesem Zusammenhang zeigt die vorliegende kumulative Dissertation das hohe Potenzial der IS Forschung im Bereich von Entscheidungsunterstützungssystemen (EUS) lösungsorientierte und wirkungsvolle Beiträge gegenüber EE- Marktteilnehmern zu leisten, indem sie deren Entscheidungsprozesse durch aggregierte Informationen verbessert. Sechs aufeinander folgende thematische Abschnitte werden auf Grundlage von Forschungsartikeln vorgestellt und diskutiert und befassen sich jeweils mit der Lösung einer spezifischen Herausforderung eines oder mehrerer Marktteilnehmer mittels quantitativer DSR Methoden. Das thematische Spektrum reicht von mikroskaligen Herausforderungen einzelner EE-Betreiber bis hin zu makroskaligen Herausforderungen politischer Entscheidungsträger. Ein besonderer Schwerpunkt liegt auf dem Windenergiemarkt. Die Ergebnisse deuten darauf hin, dass die Rolle von EUS für alle Marktteilnehmer aufgrund der ständig wachsenden Diversität an Informationen und Datenmengen im sich schnell digitalisierenden EE-Sektor immer wichtiger wird. Sie weisen ferner auf die Stärke und Notwendigkeit der IS Forschung im Hinblick auf ihre integrative Funktion zwischen anderen Forschungsbereichen hin und zeigen auf, wie diese Eigenschaft eingesetzt werden kann, um dem Bedarf an praxisorientierter Unterstützung für Entscheidungsträger zu begegnen.

Schlagworte: Erneuerbare Energien, Windenergie, Wirtschaftsinformatikforschung, Entscheidungsunterstützung, Simulation, Optimierung, Design Science

II. Management Summary

Mitigating climate change through energy transition to renewable energy technologies is one of the greatest challenges of the 21st century. In this regard, wind and solar energy plants in particular are an important pillar of a sustainable energy mix in most regions. Consequently, many governments have promoted the rise of wind and solar markets through extensive financial support mechanisms with low market integration in the past to allow these technologies to compete with conventional power generation. This has led to rapid increases in efficiency and cost reductions in these technologies due to strong market growth and high competition between manufacturers.

Today, wind and solar energy account for a significant proportion of global electricity generation and the corresponding markets have become important drivers of job and value creation in many regions. As markets mature, governments around the world tend to use more market-based support mechanisms to determine financial support through market mechanisms and reduce subsidy costs. The resulting reduction in profit margins and increase in sensitivity to risk and uncertainty lead to extensive market consolidations. In the long term, only those players can establish themselves in the market who have the right answers to the newly emerging challenges in a changing market environment. Hence, it is highly essential for all market players to have the right information at the right time in order to make the best possible decisions regarding these challenges.

In this context, information systems (IS) research on decision support systems (DSS) has a high potential to make solution-oriented and effective contributions to affected market players. DSS contribute to improved decision making through the use of approaches, models and tools that enable the collection of decision-relevant information from data of different types, sizes and sources. Consequently, as the diversity of information and the amount of data available in the rapidly digitalizing energy sector grows significantly, the role of appropriate and customized DSS is becoming increasingly important.

In order to support affected market players in finding the best possible solutions to current and future issues in the field of renewable energies, this thesis presents

and discusses quantitative decision support for various stakeholders on the basis of several research articles with a special focus on the wind market. The thesis is divided into six sections, each dealing with a specific issue and the respective stakeholders. Figure 1 illustrates the thematic structure with corresponding conference and journal publications.

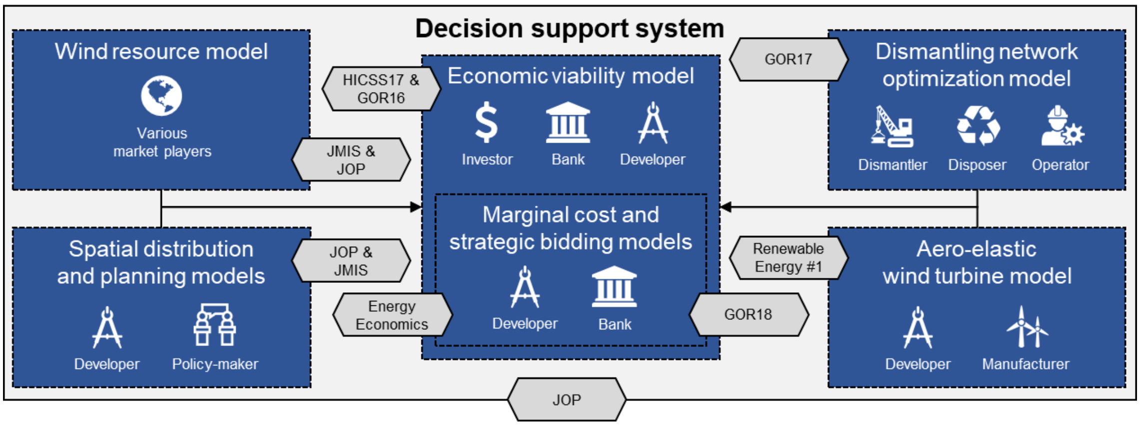

Figure 1. DSS, models, addressed market players and corresponding research articles.

In the following, a short summary of the addressed issues, proposed solutions and related publications is given:

Valuation of Wind Farms under Risk and Uncertainty:

For project developers as well as equity and debt investors the global trend toward market-based support mechanisms means a compression of margins, a greater exposure to risk and less room for errors when investing in wind and solar farms. As a result, current studies forecast substantial additions of renewable energy capacity in the next decades to be at risk due to extensive funding gaps and lower investment activity. The latter is, inter alia, due to difficult and inaccurate risk-return analyses caused by an insufficient understanding of the influence of major risk factors and their correlations. In order to increase the investment appetite in a consolidating market environment, decision support is provided for the identification of investment opportunities that feature specified return requirements and risk-bearing capacity. The corresponding DSS utilizes a probabilistic economic viability model, which combines a discounted cash-flow (DCF) calculation with a Monte Carlo simulation (MCS). Risk factors and their correlations are simulated with the MCS and under consideration of the integration of Iman-Conover (IC) algorithms into the simulation. As shown in Figure 2, the perspective of debt investors is represented through a debt sizing/sculpting module focusing on debt service coverage requirements, while a valuation module represents the perspective of equity investors and enables the analysis of risk-return key performance indicators (KPI).

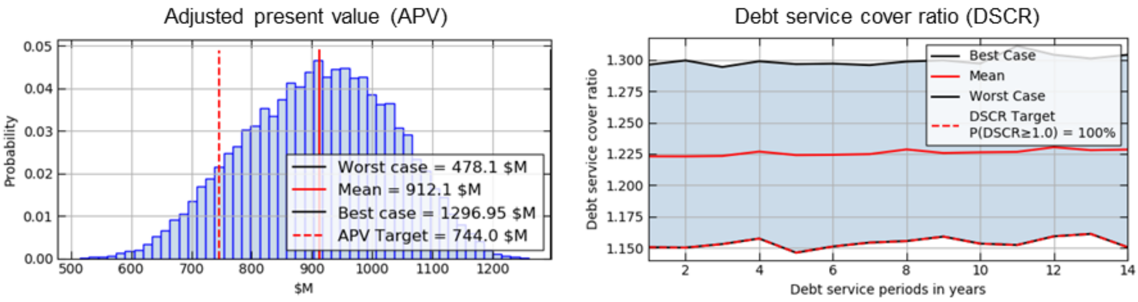

Figure 2. Exemplary risk-return KPIs of the economic viability model.

The applicability of the DSS and the economic viability model is initially evaluated in a case-study of the Mexican wind energy market using data on five currently operating wind farms. In addition, the economic viability model is further evaluated in all subsequent sections, since all presented solutions to the issues considered in this thesis extended this approach with various aspects.

Competitive Bidding in Renewable Energy Auctions

In the context of the shift toward market-based support mechanisms, a large number of countries have opted for the introduction of auctions for renewable energy projects in recent years. Auctions introduce competition among project developers for permissions, financial support, procurement rights and/or remuneration contracts through competitive bidding processes. In current state-of-the-art auctions project developers compete by specifying their demanded sales price (e.g., in ct/kWh) as well as a capacity (e.g., in MW) to be installed and only the most cost-competitive projects with the lowest offered sales prices are granted until the auction volume (e.g., in MW) is reached. Consequently, the new challenge in developing renewable energy projects under auction-based support mechanisms is the precise quantification of competitive and sustainable bidding strategies. In order to enable project developers to be in a competitive position in upcoming auctions, decision support is provided for the optimization of bidding strategies under consideration of the investment requirements of both equity and debt investors and given assumptions about future auction results. For this purpose, the economic viability model from Section 2 is extended by a marginal cost model, which is implemented a strategic bidding optimization (see Figure 3).

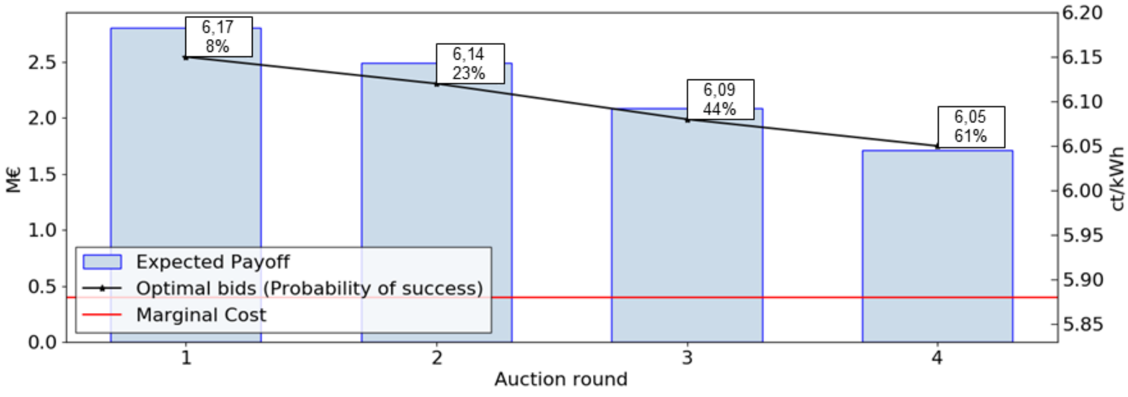

Figure 3. Optimal bidding strategy and expected payoff.

The applicability of the extension is evaluated in a case-study of a project developer participating in the newly introduced auctions for onshore wind farms in Germany. In addition, the marginal cost model is further evaluated in Section 4 and 5, since it is also the basis for the corresponding case-studies.

Politico-Economic Simulation of Renewable Energy Auctions to Design Incentives for a Spatially-Diversified Deployment:

From the perspective of policy-makers, renewable energy auctions enable managing a cost-efficient expansion of deployment through competitive bidding processes and predefined auction volumes determining future capacity additions. The competitive pricing prevents overcompensation of project developers and investors and is likely to result in comparatively low remuneration levels and substantial reductions of financial support over time, as only the most cost-efficient projects are granted. However, as the cost-efficiency of renewable energy projects is highly dependent on the in-situ resources (e.g., wind or solar), an unintentional effect of auctions is the imminent accumulation of renewable energy capacity at most resource-rich locations within an auction area. Due to highly correlated resource availabilities at these locations, the spatial concentration of capacity increases the volatility of electricity supply, which impairs the system integration of intermittent renewable energies and the corresponding costs. In order to enable policy-makers to manage the arising trade-off between cost-efficient renewable electricity supply and reliable and cost-efficient electricity distribution, decision support is provided for the optimal design of auction features incentivizing an appropriate spatially-diversified deployment. For this purpose, the economic viability model from Section 2 and the marginal cost model from Section 3 are extended by a wind resource simulation and an economic agent simulating the investment decisions of equity and debt investors. By applying the approach to a variety of potential wind energy sites in an auction region, appropriate location-based incentives (see Figure 4) can be derived that foster better system integration through diversified spatial deployment of capacity.

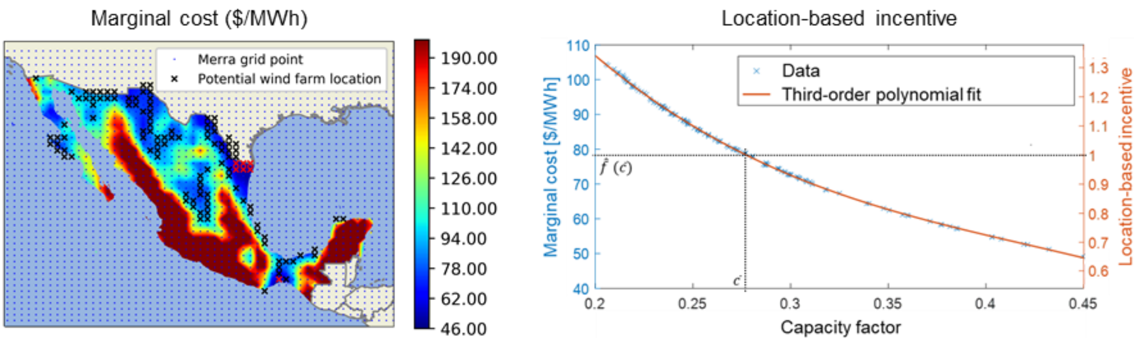

Figure 4. Marginal cost of and location-based incentive for Mexican wind farms.

The applicability of the politico-economic approach is evaluated in a case-study of the recently introduced auction-based support mechanism in Mexico.

Interdisciplinary Techno-Economic Optimization of the Structural Design of Offshore Wind Turbines:

The primary objective in the field of wind energy research is generally to reduce the corresponding technology costs from the perspective of the wind turbine manufacture. This also applies to the area of research on optimal designs for offshore wind turbine substructures. The corresponding engineering models typically minimize the mass of structural designs as a cost indicator. However, a reduction in mass also results in a reduction in reliability and reduces the expected lifetime, which negatively effects the risk-return-ratio due to lost revenues at the end of the life cycle. In order to enable wind turbine manufactures to develop cost-efficient structural designs for offshore wind turbines, decision support is provided that is based on an analysis of the trade-off between variable lifetime and component costs of a substructure design. For this purpose, the economic viability model from Section 2 and the marginal cost model from Section 3 are coupled with an aero-elastic wind turbine model in an interdisciplinary probabilistic modelling approach combining both economic and engineering aspects. The applicability of the techno-economic approach is evaluated in a case-study of an offshore wind farm located in the German North Sea by comparing several more or less durable substructure designs (see Figure 5).

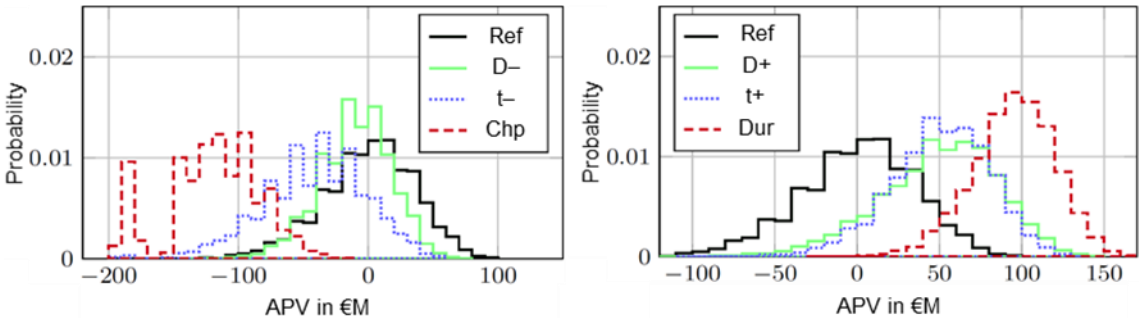

Figure 5. APV of offshore wind farm given different substructure designs.

Results show that a change in paradigm for optimal designs is needed, since the more durable substructure designs feature more appropriate risk-return ratios than the less cost-intensive designs over the entire operational lifetime.

Interdisciplinary Optimization for the Design of Cost-Efficient Dismantling and Disposal Networks for Wind Turbines:

The issue of the operational lifetime is currently also becoming increasingly important in another context, which is the dismantling and disposal of end-of-life wind turbines. In the upcoming years, more and more wind turbines will reach the end of their technical and/or economic lifetime. Consequently, in comparison to past dismantling volumes, the numbers of wind turbines to be decommissioned will increase massively in many countries worldwide. The current state-of-the-art of dismantling wind turbines is to conduct the whole process entirely on-site. However, this is highly time-consuming and implies risks and challenges of ecological, economic, and logistical kind. An option to supersede this undistributed dismantling is to establish a network allowing for a partial dismantling of specific wind turbine components on-site and a later transportation of the partly dismantled components to specialized dismantling sites for further handling. Although the dismantling is more ecological and cost-efficient in the specialized factories, additional costs arise for their initialization as well as additional transports in the network. In order to enable dismantling companies to design efficient dismantling and disposal networks for large numbers of end-of-life wind turbines, decision support is provided that is based on an optimization of the trade-off between dismantling and transportation costs. For this purpose, an optimization model is presented that solves the corresponding location and allocation problems by selecting best locations for the dismantling factories and allocating the dismantling tasks cost-optimally to the possible dismantling sites. The applicability of the optimization model is evaluated in a case-study of a selected region in Northern Germany in which more than 60 wind turbines are to be decommissioned annually over the next five years. Results show that a distributed dismantling and disposal in an optimally designed network has significant cost reduction potentials for the entire end-of-life processing of wind turbines (see Figure 6).

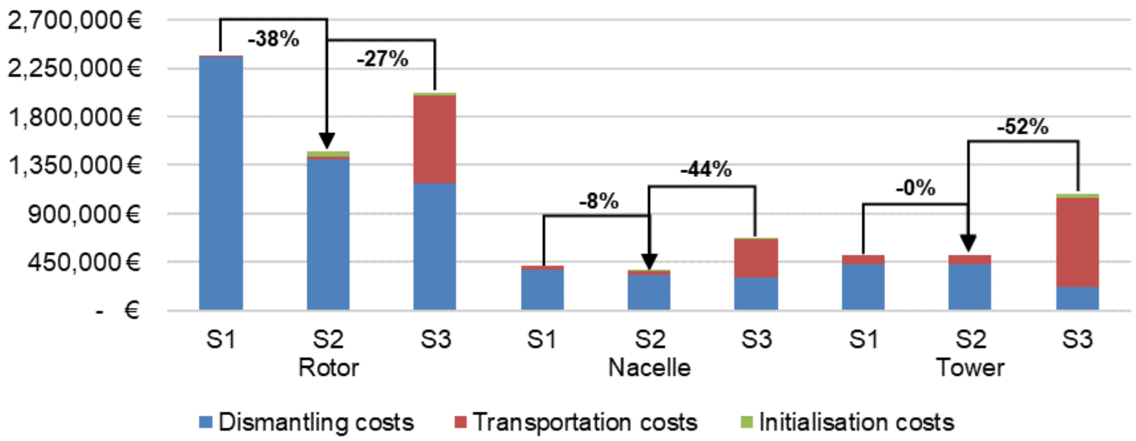

Figure 6. Cost reduction potential of a distributed wind turbine dismantling (Scenario - S2).

Geographic Information System (GIS) Based Analyses to Design Optimal End-of-Funding Strategies for Ageing Wind Turbines:

As mentioned above, the end-of-life of many wind turbines is approaching worldwide. Particularly in Germany a large number of wind turbines will reach the end of their feed-in tariff funding period in the upcoming years. Around 13,000 wind turbines (≈ 16.4 GW) will be affected until the end of 2025. Consequently, operators are increasingly concerned with selecting and designing optimal end-of-funding strategies for their individual turbines (i.e., lifetime extension, repowering or permanent shutdown). Since the operators can only implement these strategies with the help of a wide range of higher-level stakeholders (e.g., project developers, investors, policy makers, wind turbine manufacturers, dismantlers or waste management companies), various other market players at the macro-level are also concerned with end-of-life/funding. In order to design optimal strategies, both spatial and economic aspects must be considered and all possible strategies must be simultaneously examined and permanently compared. However, the current research tends to consider all aspects and strategies separately. In order to enable operators and other higher-level stakeholders to find optimal solutions for end-of-funding strategies, decision support is provided by means of a GIS that simulates and compares all possible end-of-funding strategies for an individual wind turbine or wind farm and selects the best strategy by solving an optimal stopping problem based on the risk-return-requirements of the corresponding operator. For this purpose, the economic viability model from Section 2 and the wind resource simulation from Section 4 are supplemented by a differential investment analysis and coupled with a spatial planning model.

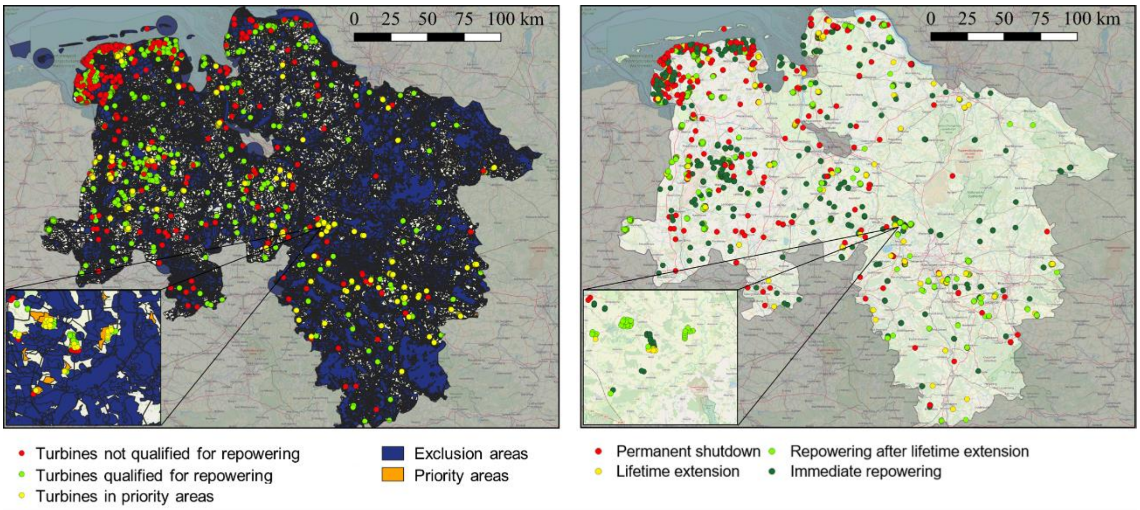

Figure 7. Optimal end-of-funding strategies for the wind fleet of Lower-Saxony.

The underlying modelling approach enables analyses in different spatial scaling, reaching from detailed analyses on single turbine or wind farm level up to macro-level analyses of entire wind fleets. The applicability of the GIS-based approach is evaluated in a case-study of the 1,645 wind turbines located in Lower-Saxony reaching the end of their feed-in-tariff funding by 2021 (see Figure 7). Results show high repowering and lifetime extension potentials in the German wind fleet, which must be exploited to the full extent due to the decreasing availability of new green field areas in Germany, in order to enable the wind industry to continue playing a pioneering role in the energy transition.

In this thesis, current challenges of the changing renewable energy market are investigated and tackled with IS research. The resulting findings of the corresponding publications mainly address two objectives. On the one hand, they point out the strength and necessity of IS research in terms of its integrating function between other research areas (here: renewable energy finance and policy, wind resource assessment, spatial planning, structural dynamics, and logistics). On the other hand, they respond to the need for more practical assistance for decision makers in this context, as outlined by Dedrick (2010), by providing DSS specifically addressing practical problems of various renewable energy market players (here: project developers, investors, policy-makers, wind turbine manufacturers, dismantlers, disposers, and operators).

For the purpose of designing the DSS in light of the two main principles of IS research – rigor and relevance – well-established design science research (DSR) approaches oriented toward Peffers et al. (2008) and Hevner et al. (2004, 2007) were employed for the research presented in this thesis. This involved the identification of domain-specific problems, the specification of well-defined research objectives and corresponding questions as well as the design, development, demonstration, evaluation and communication of technological artifacts in a loop of process iterations, as proposed by Hevner (2004). The conducted research additionally addresses the relevance principle by focusing on the contribution of DSS solutions to real-world issues and challenges. Following the DSR knowledge framework of Gregor and Hevner (2013) the resulting technological artifacts can be classified as nascent design theories, since they establish certain generalized design principles, which can be useful for the development of other artifacts that address related issues and challenges.

In summary, this thesis shows that quantitative decision support based on rapidly growing volumes of data directly contributes to the needs of market players in an increasingly digitalized (renewable) energy market by improving the decision-making process through aggregated information. Consequently, as information is a prerequisite for making appropriate decisions on sustainability actions (Malhotra et al., 2013; Gholami et al., 2016; Seidel et al., 2017), IS research on DSS has a tremendous potential to make solution-oriented and impactful contributions to the mitigation of global warming and issues surrounding the transition toward renewable energies.

III. Table of Contents

IV. List of Figures

V. List of Tables

VI. List of Abbreviations

AIS	Association for Information Systems
API	Application Programming Interface
APV	Adjusted present value
CAPEX	Capital expenditures
CAPM	Capital asset pricing model
CDM	Clean development mechanism
CENACE	Centro Nacional de Control de Energía[1]
CFADS	Cash flow available for debt service
CPU	Central processing unit
DCF	Discounted cash-flow
DECEX	Decommissioning expenditures
Disc.	Discount
DSCR	Debt service cover ratio
DSR	Design science research
DSS	Decision support system
EBIT	Earnings before interest and taxes
EEG	Erneuerbare-Energien-Gesetz[2]
Eq.	Equation
FCF	Free cash-flow
GAMS	General Algebraic Modeling System
GI-FB WI	Fachbereich Wirtschaftsinformatik der Gesellschaft für Informatik[3]
GIS	Geographic information system
GRP	Glass-reinforced plastic
GUI	Graphical user interface
HICSS	Hawai'i International Conference on System Sciences
IC	Iman-Conover
IEA	International Energy Agency

[1] English: National Energy Control Center
[2] English: Renewable Energy Sources Act
[3] English: Department of Information Systems of the German Informatics Society

IRENA	International Renewable Energy Agency
IRR	Internal rate of return
IS	Information system
IT	Information technology
IWI	Institut für Wirtschaftsinformatik[4]
JMIS	Journal of Management Information Systems
JONSWAP	Joint North Sea Wave Project
JOP	Journal of Physics
JQ	Jourqual
KPI	Key performance indicator
LUH	Leibniz Universität Hannover
LOESS	Locally estimated scatterplot smoothing
MATLAB	MATrix LABoratory
MCS	Monte Carlo simulation
MERRA	Modern-Era Retrospective analysis for Research and Applications
MXN	Mexican New Peso
NASA	National Aeronautics and Space Administration
NREL	National Renewable Energy Laboratory
OC3	Offshore Code Comparison Collaboration
OPEX	Operation expenditures
PDF	Probability density function
PERT	Program evaluation and review technique
PPA	Power purchase agreement
Prem.	Premium
OR	Operations Research
Rails	Ruby on Rails
RAM	Random-Access Memory
REN21	Renewable Energy Policy Network for the 21st Century
RQ	Research question
SQL	Structured Query Language

[4] English: Institute for Information Systems Research

VHB	Verband der Hochschullehrer für Betriebswirtschaft e.V.[5]
VWF	Virtual Wind Farm
WACC	Weighted average cost of capital
WKWI	Wissenschaftliche Kommission Wirtschaftsinformatik[6]
5Y-IF	5-year impact factor

[5] English: Association of University Teachers for Business Administration e.V.
[6] English: Scientific Commission for Information Systems

VII. Preliminary Remark: Overall View of Publications

A chronological overview of the publications that serve as the basis for this thesis is presented in this section. The publications, involved authors, dates of publication and the journal or conference proceedings in which they were published are shown in Table 1. In addition, the corresponding appendices as well as sections of this thesis are outlined, in which the publications are discussed in more detail. In total, the publication overview lists ten publications, of which eight had already been published at the time of submission of this thesis.

In order to provide an overview on the rating of the respective journals and conference proceedings, the VHB JOURQUAL version 3 rating (VHB/JQ3) (Hennig-Thurau et al., 2015; Hennig-Thurau und Sattler, 2015b) and the *Wirtschaftsinformatik-Orientierungslisten*[7] (WKWI) rating (Heinzl et al., 2008) are provided. The VHB/JQ3 is the official rating of journals and conference proceedings of the *Verband der Hochschullehrer für Betriebswirtschaft e.V.* (VHB) and reflects a classification conducted by the VHB members (Hennig-Thurau and Sattler, 2015a). The WKWI rating is the official rating provided by the *Wissenschaftliche Kommission Wirtschaftsinformatik im Verband der Hochschullehrer für Betriebswirtschaft* (WKWI) as well as the *Fachbereich Wirtschaftsinformatik der Gesellschaft für Informatik* (GI-FB) and represents a classification of journals and conference proceedings belonging to the IS research domain from business informatics perspective (Heinzl et al., 2008).

[7] English: Business Informatics Guidelines

Table 1. Overview of publications.

#	Publication Date	Title	Authors	Conference/Journal	VHB/JQ3	WKWI	Section	Appendix
9	07/2020	Competitive and Risk-Adequate Auction Bids for Onshore Wind Projects in Germany	Stetter, C. Piel, J.-H. Hamann, J.F. Breitner, M.H.	Energy Economics, In Press, Journal Pre-proof	B	-	3	9
8	08/2019	Enhancing Strategic Bidding Optimization for Renewable Energy Auctions: A Risk-Adequate Marginal Cost Model	Stetter, C. Piel, J.-H. Koukal, A. Breitner, M.H.	Operations Research Proceedings 2018, Dresden, Germany, pp. 217-223.	D	-	3	8
7	06/2019	Influence of Structural Design Variations on Economic Viability of Offshore Wind Turbines: An Interdisciplinary Analysis	Hübler, C. Piel, J.-H. Stetter, C. Gebhardt, C.G. Breitner, M.H. Rolfes, R.	Renewable Energy, 145, pp. 1348-1360.	-	-	5	7
6	04/2019	Lifetime Extension, Repowering or Decommissioning? Decision Support for Operators of Ageing Wind Turbines	Piel, J.-H. Stetter, C. Heumann, M. Westbomke, M. Breitner, M.H.	Journal of Physics: Conference Series (JOP), 1222 (2019), 012033.	-	-	7	6
5	05/2018	An Optimization Model to Develop Efficient Dismantling Networks for Wind Turbines	Westbomke, M. Piel, J.-H. Breitner, M.H. Nyhuis, P. Stonis, M.	Operations Research Proceedings 2017, Berlin, Germany, pp. 239-244.	D	-	6	5
4	05/2018	Decoupled Net Present Value – An Alternative to the Long-Term Asset Value in the Evaluation of Ship Investments?	Schrader, P. Piel, J.-H. Breitner, M.H.	Operations Research Proceedings 2017, Berlin, Germany, pp. 271-276.	D	-	-	4
3	12/2017	Promoting the System Integration of Renewable Energies: Toward a Decision Support System for Incentivizing Spatially-Diversified Deployment	Piel, J.-H. Hamann, J.F. Koukal, A. Breitner, M.H.	Journal of Management Information Systems (JMIS), 34(4), pp. 994-1022.	A	A	4	3
2	07/2017	Applying a Novel Investment Evaluation Method with Focus on Risk – A Wind Energy Case Study	Piel, J.-H. Humpert, F.J. Breitner, M.H.	Operations Research Proceedings 2016, Hamburg, Germany, pp. 193-199.	D	-	-	2
1	01/2017	Financial Decision Support System for Wind Energy – Analysis of Mexican Projects and a Support Scheme Concept	Koukal, A. Piel, J.-H.	Proceedings of the 50th Hawai'i International Conference on System Sciences (HICSS), Big Island, Hawaii, USA, pp. 972-981.	C	B	2	1

1. Introduction

1.1. Research Motivation, Problems and Questions

Climate change mitigation through the transition to energy systems with a high share of renewable energy technologies is one of the most critical challenges of the twenty-first century and pursued by an ever-growing number of individuals, organizations, and societies in large (Watson et al., 2010; Gholami et al., 2016). In many regions, in particular wind and solar energy plants are an important pillar on the path to a sustainable and low-carbon energy mix. In recent decades, many governments have fostered the rise of wind and solar markets by means of extensive financial support mechanisms with low market integration as these technologies were unable to compete with conventional electricity generation (Abolhosseini and Heshmati, 2014). The resulting market growth and highly competitive situation for wind and solar manufacturers have led to rapid efficiency improvements and cost reductions in these technologies (McKenna et al., 2015). As a result, renewable energies were already accounting for over 25% of the global power output in 2018, of which wind and solar energy comprise the largest share (IEA, 2018). Consequently, many national renewable energy markets have become a significant driver for job-, value- and wealth-creation. Only in 2017, more than 500,000 new jobs were created leading to a total number of 10.3 million people employed in the renewable energy sector worldwide (IRENA, 2018).

Nowadays, many national renewable energy markets are at a point where they are increasingly maturing and the competition between diverse stakeholders is intensifying (Henzelmann et al., 2016). Simultaneously, as the contributions of renewable energies to the national energy mixes increase, governments are scaling back their financial support in order to avoid overcompensation of market players and reach substantial subsidy cost reductions (Huntington et al., 2017). Worldwide, the remuneration of renewable energy projects is made increasingly market-based through auctions and variable feed-in tariffs for example (REN21, 2016). For most market players this leads to significantly decreasing profit margins, which highly increases the sensitivity to risks and uncertainties and thus decreases acceptable valuation errors. The results of these developments are extensive consolidations in global renewable energy markets leading to many market players being driven out of the market.

Consequently, in the long term, only those players can establish themselves in the market who have the right answers to the newly arising challenges in a changing market environment. For making the best possible decisions access to aggregated and processed information, which is based on accurate, reliable and consistent data, is of essential importance. Since the diversity of information and the available amount of data are rapidly growing in the increasingly digitalized energy sector, the importance of appropriate decision support is constantly intensifying.

Table 2. Investigated research questions and addressed market players.

Topic	Stakeholder	Research Questions
Valuation of Wind Farms under Risk and Uncertainty	Equity and debt investors	RQ: *"How can IS research support renewable energy investors in investment decision-making under risk and uncertainty in order to stimulate future investments and facilitate further capacity expansion?"*
Competitive Bidding in Renewable Energy Auctions	Project developers	RQ: *"How can the strategic bidding in renewable energy auctions be improved through a risk-constrained marginal cost optimization approach?"*
Politico-Economic Simulation of Renewable Energy Auctions to Design Incentives for a Spatially-Diversified Deployment	Policy-makers	RQ: *"How to quantify investment incentives for improving the spatial distribution of wind energy deployment under renewable energy auctions?"*
Interdisciplinary Techno-Economic Optimization of the Structural Design of Offshore wind Turbines	Wind turbine manufacturers	RQ: *"How can the structural design of an offshore wind turbine be optimized with regard to the risk-return ratio over the entire operational lifecycle?"*
Interdisciplinary Optimization for the Design of Cost-Efficient Dismantling and Disposal Networks for Wind Turbines	Dismantling and disposal companies	RQ: *"How can the cost-efficiency of the dismantling and disposal processes for wind turbines be optimized by an optimal dismantling network design?"*
GIS-Based Analyses to Design Optimal End-of-Funding Strategies for Ageing Wind Turbines	Operators and higher-level stakeholders	RQ: *"How can optimal end-of-funding strategies for ageing wind turbines be designed on micro- and macro-level?"*

In this regard, IS research on DSS has a high potential to provide solution-oriented and impactful contributions to renewable energy market players (Malhotra et al., 2013; Gholami et al., 2016; Seidel et al., 2017). DSS are IS that contribute to an enhanced decision making through the use of approaches, models, and tools enabling to gather decision-relevant information from quantitative and/or qualitative data. In order to support renewable energy market players in finding the best possible solutions to current and future issues, this thesis presents and discusses quantitative financial decision support for different stakeholders based on corresponding research articles. A special focus is placed on the wind energy sector. The thesis provides an overview of research contributions addressing the identified issues and is divided into six thematic sections of which each addresses a specific issue and the corresponding stakeholder. Table 2 shows the stakeholders and research questions (RQ) addressed in the respective sections.

1.2. Research Methodologies

IS research seeks to gain insights into the deployment of information technology (IT) for managerial and administrative activities (Zmud, 1997) under consideration of two research paradigms: behavioral and design sciences (March and Smith, 1995). The behavioral paradigm attempts to elaborate, validate or legitimize theories that explain or predict human and organizational behavior by describing the effects of technology on individuals, groups and organizations. In contrast, the design science paradigm is oriented toward problem solving and aims to create new and innovative technological artifacts in order to expand the boundaries of human problem solving and organizational capabilities (Hevner et al., 2004). Even though both research paradigms have a very different focus, they complement each other in many ways (Ayanso et al., 2011).

Since the publications presented and discussed in this thesis have a strong practical focus, the underlying research followed a rigorous design science process in combination with quantitative methods. The DSR approach according to Peffers et al. (2008) was employed and enhanced by key recommendations of Hevner et al. (2004, 2007) and March and Smith (1995). Figure 8 shows an example of the applied approach.

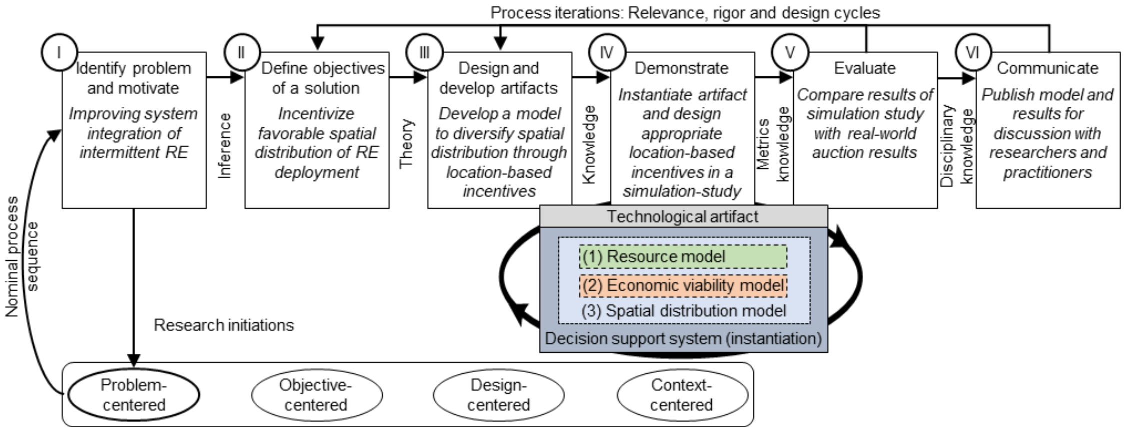

Figure 8. Example of applied DSR approach (here: research project underlying Section 4).

The DSR approach involves a process of analytical techniques that help to contribute effectively to IS research by addressing relevance and increasing rigor of the research process and results (March and Storey, 1995). Innovative technological artifacts (Hevner, 2007) are to be created to support in solving observed problems, making research contributions, evaluating designs and communicating the results to appropriate audiences (Peffers et al., 2007). Following Peffers et al. (2007), the DSR approach is divided into the six process steps shown in Figure 8, while Hevner (2007) recommends the adoption of process cycles to implement loop iterations in research. These loop iterations involve relevance, rigor as well as design cycles (Hevner, 2007). The initiation of DSR can either be problem-, objective-, design- or context-centered (Peffers et al. 2007).

With regard to the publications presented and discussed in this thesis the underlying research was in all cases triggered through the identification of real-world problems. The specific problems investigated are explained in the introductions to the individual sections and led to the specific RQs shown in Table 2. In order to address the identified problems and corresponding RQs, several consecutive technological artifacts were designed. In order to provide proofs-of-concept, these technological artifacts were demonstrated in several case-studies. In line with the sixth guideline "Design as Search Process" mentioned by Hevner (2007), the subsequent evaluation and communication of the proofs-of-concept triggered iterative revisions of the technological artifacts through benchmarking and feedback.

Regarding the types of technological artifacts March and Smith (1995) differentiate between constructs, models, methods, and instantiations. Since DSS were designed and extended based on developed mathematical models throughout the entire research process underlying this thesis, the resulting technological artifacts can be classified as models and instantiations. When positioning these models and instantiations within the DSR knowledge framework of Gregor and Hevner (2013), they can be described as nascent design theories. In the end, these nascent design theories can be seen as the higher-level contributions of this thesis to IS research, since they comprise generalized design principles relevant for the development of artifacts that address similar problems.

1.3. Structure of the Thesis

In Section 0 the thesis begins with an overview of the underlying research publications followed by an introduction in Section 1 and the six thematic parts. Each of these parts presents the research results from the underlying research projects and publications. The thesis ends with a discussion of contributions and limitations, a conclusion and an outlook in Section 8.

Section 2 and 3 deal with current challenges from the perspective of project developers and investors (both equity and debt), which are the evaluation of wind farms under risk and uncertainty with regard to profitability and financial viability (see Section 2) as well as the optimization of strategic bidding in auction mechanisms recently introduced for wind and solar farms in many countries worldwide (see Section 3). Section 4 discusses renewable energy auctions from a policy perspective and examines solutions for the undesirable effect of spatial concentration of solar and wind energy capacity caused through these mechanisms. In Section 5 the perspective of wind energy manufacturers is taken in order to provide decision support for the optimal design of wind turbine substructures regarding the trade-off between lifetime extension and cost by means of an interdisciplinary techno-economic approach. Section 6 deals with the increasingly important end-of-life/funding issue of wind turbines from the perspective of dismantlers and disposers and provides decision support for the cost-optimal design of dismantling and disposal networks for ageing wind turbines. Section 7 finally unites the perspectives of the various market players by rolling out decision support for the individual wind farm operator regarding the end-of-life/funding issue to entire wind fleets in order to further enable higher-level stakeholders to derive lifetime extension, repowering and decommissioning potentials at macro level.

2. Valuation of Wind Farms under Risk and Uncertainty

This section refers to the article "Financial Decision Support System for Wind Energy - Analysis of Mexican Projects and a Support Scheme Concept" (see Appendix 1). The author of this thesis wrote the article in cooperation with André Koukal (Institut für Wirtschaftsinformatik (IWI), Leibniz Universität Hannover (LUH)) and presented the article at the 50th Annual Hawai'i International Conference on System Sciences (HICSS) 2017 in Waikoloa Village, Big Island, Hawaii, USA (January 04, 2017). The acceptance for the article presentation at the conference and publication in the conference proceedings was preceded by a double-blind peer review process with one revision round. HICSS is a conference of the Association for Information Systems (AIS) and is widely considered to be one of the most prestigious conferences for IS and IT research worldwide. The article was presented in the mini-track "Addressing Grand Challenges with Information Technology" of the track "Decision Analytics, Mobile Services, and Service Science", nominated for the "Best Conference Paper Award" and published in the Proceedings of the 50th Annual HICSS, which were classified in category "B" by WKWI and GI-FB WI and received the ranking "C" in the VHB/JQ3. HICSS is the top IS conference in terms of citations as recorded by Google Scholar.

On the basis of this article, Prof. J. S. Giboney (University of Albany), Prof. R. O. Briggs (San Diego State University) and Prof. J. F. Nunamaker Jr. (University of Arizona) invited the author of this thesis and André Koukal to submit a significantly expanded article to the Journal of Management Information Systems (JMIS) for a HICSS Special Issue (see Section 4 and Appendix 3) in February 2017. In addition, the cash-flow and risk models as well as the implementation of the MCS and IC algorithm published in the HICSS article served as the basis for the articles presented in Sections 3, 4, and 5.

2.1. Introduction

Worldwide, the financial support for renewable energy projects is made increasingly market-based through e.g., auctions in combination with variable feed-in tariffs (REN21, 2016). At the same time, the global renewable energy market is in consolidation and many market players are driven out of the market. For investors this means a compression of margins, a greater exposure to risks and less room for error when investing in renewable energy projects.

As a result, current studies forecast the substantial addition of renewable energy capacity in the next decades to be at risk due to extensive funding gaps and lower investment activity. In the New Energy Outlook 2017, Bloomberg New Energy Finance (2017) estimated cumulative investments of 7.31 trillion to be needed in order to reach the current global expansion targets until 2040. However, due to the recent market developments, many investors are restrained in respect to investments at current time, although they require a sustainable and future-oriented allocation of their scarce time and money resources more than ever before. Many market players face budgetary constraints and are unwilling to make investments highly fraught with risk. Although the possible returns of renewable energy investments can be attractive, investors are avoiding investing due to difficult and inaccurate value-at-risk (VAR) analyses that are caused by an insufficient understanding of major risk factors (Montes et al., 2011). Only if economic viability and debt coverage are still adequate when taking risk and uncertainty into account, will renewable energy investments become attractive for a wide range of investors (Rubel et al., 2013). The current insufficient access to capital rather prevents the expansion of renewable energy deployment and will lead to even greater funding gaps in the future. Consequently, comprehensive methodological support that enables investors to make investment decisions based on risk adjusted cost-benefit analyses is needed. In this regard, as stated by Malhotra et al. (2013) and Gholami et al. (2016), IS research can aid by conducting more design-, impact- and solution-oriented research focusing on developing, evaluating and providing such methodological support within the framework of DSS.

Consequently, a DSS is presented, which is based on a cash flow model and a risk model that considers important risk factors and corresponding correlations. With the DSS decision makers can perform VAR analyses of relevant key figures, such as the adjusted present value (APV) or the debt service cover ratio (DSCR), via MCS. Based on the VAR analyses, investors can evaluate renewable energy investments against the background of their individual return expectations, risk aversion and risk-bearing capacity in order to finally improve their resource allocation. When conducting the research on the DSS, finding appropriate answers to the following RQ has always been the focus of all investigations:

RQ: “*How can IS research support renewable energy investors in investment decision-making under risk and uncertainty in order to stimulate future investments and facilitate further capacity expansion?*”

2.2. Theoretical Foundation and Literature Review

In recent decades, research on renewable energy technologies has mainly been focusing on technical aspects. The development and investigation of technology innovations with respect to potential cost reductions were at the center of interest. One recent change in renewable energy research goes beyond the pure cost consideration and deals with the technologies’ general economic viability (Koukal and Breitner, 2013). However, research articles that go one step further and focus on the economic viability under consideration of risk and uncertainty from an investor perspective are still rare, yet they are urgently needed to stimulate the future willingness to invest. Since over the past years new literature on this topic has emerged, the literature review conducted by Koukal and Piel (2017) has been updated by the author of this thesis.

The literature research indicates that the evaluation of renewable energy projects in practice is commonly performed with conventional DCF methods based on deterministic models, and under consideration of a constant cost of capital (Christensen et al. 2014; Wu and Sun, 2015). These methods also appear most frequently in scientific literature (Santos et al., 2014). Representative examples are the articles from De Oliveira and Fernandes (2011), Peña et al. (2014), Colmenar-Santos et al. (2015), and Rodrigues et al. (2016). Nonetheless, the use of deterministic DCF methods in the context of renewable energy investments and project financing in general is criticized (Chang, 2013; Santos et al., 2014).

Firstly, the vast majority of models applied to renewable energy investments does not consider time-varying capital and risks structures and discounts cash-flows at a static cost of capital, even though the required return on capital varies over time due to changes in capital and risk (Christensen et al., 2014). This shortcoming can be addressed by applying the APV instead of the most frequently implemented weighted average cost of capital (WACC) approach. This is due to the ability of the APV approach to account for the dynamics in capital and risk structures by valuing the tax shield resulting from interest payments separately (Christensen et al., 2014). In contrast to the WACC approach, which requires the periodical debt-to-equity ratio as the weighting in the cost of capital calculation, this allows the discount factors used in the APV approach to be independent of the debt-to-equity ratio. However, if consistently applied with varying discount factors, the WACC approach would lead to the same project value (Piel et al., 2017). Today, the APV approach is so far only applied in few financial models in the context of renewable energy project valuation (Koukal and Piel, 2017; Jenkins and Miguel Guevara, 2014; Harsh and Hamilton, 2010).

Secondly, the perspective of lenders is not or only partially covered by most studies (Tao and Finenko, 2016). Although they typically follow the WACC valuation approach and thus consider the cost of capital (Wright et al., 2013), including both equity and debt, the underlying financial models most frequently do not account for important debt coverage KPIs demonstrating the financial soundness of a renewable energy project. Some rare examples of scientific literature on the valuation of renewable energy projects thus recommend additionally analyzing debt service coverage KPIs (Koukal and Piel, 2017; Pacudan, 2016; McInerney and Bunn, 2017) in order to account for the investment requirements of banks.

Thirdly, the most significant critique concerns the insufficient reflection of specific risks factors as most financial models consider risk and uncertainty only through a risk adjustment in the discount rate (Chang et al., 2013). To facilitate a more appropriate consideration, Gatzert and Kosub (2016) provide a comprehensive literature review on specific risk factors and risk management techniques for renewable energy projects. Balks and Breloh (2014) add a comprehensive risk analysis to their simulation and analyze the influence of risk factors by applying scenario and sensitivity analyses based on a deterministic DCF model. Similar approaches are applied by Prässler and Schaechtele (2012), Weaver (2012), and Zountouridou et al. (2015). Such deterministic scenario and sensitivity analyses enable investigating relative and absolute impacts of risk factors as well as predicting the range of financial key figures. However, their applicability in determining investment decisions is limited, due to insufficient aggregation of individual risk factors into total investment risk (Falconett and Nagasaka, 2010). Research addresses these limitations with probabilistic approaches employing MCS (Montes et al., 2011; Gillenwater, 2013; Khindanova, 2013; Caralis et al., 2016) and real option analyses (Lee, 2011; Boomsma et al., 2012), while the prevalence of these approaches in practice is limited (Christensen et al., 2014). The latter can be explained by the fact that the application of MCS and the interpretation of its results also entail additional complexity in addition to the additional information.

MCS permit accounting for model inputs subject to uncertainty and variability via stochastic parameters (Ioannou et al., 2017). In the realm of renewable energy projects, e.g., resource availabilities, capital expenditures (CAPEX), operational expenditures, and project life cycle phases (Piel et al., 2017; Koukal and Piel, 2017; Arnold and Yildiz, 2015) have already been modelled via MCS. Relying on random sampling based on probability density functions (PDFs) assigned to stochastic parameters (Caralis et al., 2014), MCS compute a large number of numerical solutions for the model outputs. Hence, when applied to DCF calculations, MCS yield PDF estimations for KPI (Koukal and Piel, 2017) eventually representing the quantified and aggregated influence of risks and uncertainties. These PDF permit obtaining confidence estimates for each KPI (Ioannou et al., 2017), such that investors can complement their investment requirements by confidence levels implicitly specifying their acceptable level of total investment risk.

Although only rare research examples applying APV-based DCF calculations for analyses of shareholders' profitability KPI, specific models for debt coverage KPI, and MCS for investment risk KPI were identified, combining the various elements has not yet been in focus of previous research. For this reason, the goal of this study is to develop and evaluate a comprehensive financial model for the valuation of renewable energy projects, which combines a state-of-the-art DCF calculation for the estimation of APV and DSCR with an MCS and a debt sizing model in order to optimize the borrowing of debt capital and thereby the risk-return profile from shareholders perspective due to the optimal use of the leverage effect.

2.3. Methodology

The financial model is tailored to the specific characteristics of renewable energy projects financed via non-recourse financing in special purpose vehicles, as this funding model is most represented in the renewable energy sector. Special purpose vehicles are separate and independent companies established exclusively for a single project, financed by several investors and typically characterized by a high debt-share (Lüdeke-Freund and Loock, 2011). Because lenders focus on cash flow-related lending when deciding to invest in special purpose vehicles (Lüdeke-Freund and Loock, 2011; Daube et al., 2008), the financial model is based on DCF calculations to estimate a renewable energy project's future cash-flows and assess the cash-flow streams in relation to the overall investment risk in order to determine the project's financial soundness and profitability.

2.3.1. Risk Quantification and Risk Correlations

In order to determine the investment risk, the cash-flow calculation considers risk factors as stochastic parameters using MCS. The modelling of the specific risk factors is oriented toward the results of a comprehensive literature review on risks and risk management techniques for renewable energy investments by Gatzert and Kosub (2016) in combination with a risk quantification framework for renewable energy investments developed by Michelez et al. (2011). For the incorporation of the modelled risk factors, the MCS is applied to the financial model according to the following process: (1) specification of a PDF type for every stochastic parameter; (2) specification of distribution parameters for every PDF; (3) specification of correlations matrices; (4) specification of the number of iterations or the minimum level of simulation accuracy; (5) generation of random numbers by drawing from the PDF in every iteration; (6) modification of drawn random numbers according to the predefined correlations; (7) computation of the DCF calculation based on the correlated random numbers; and (8) estimation of PDF for every KPI from the simulated data. This process aggregates the manifold effects of the stochastic parameters in the resulting PDF of the KPI, which finally describe the relation between the total investment risk and the returns as well as the debt service capacity respectively.

In order to allow for the consideration of correlations between the stochastic parameters within the financial model, the IC method was implemented into the MCS. The rational of this method goes back to Iman and Conover (1982), who investigated that rank order correlations can be induced between randomly distributed variables irrespective of their distributions and without changing their shape. Figure 6 provides an example of the method’s process.

Input matrix from Monte Carlo simulation

$$\begin{bmatrix} 391 & 368 & 372 & 354 & 364 & 371 & 389 & 371 & 347 & 373 & 373 & 394 & 389 & 382 & 356 & 390 & 363 & 370 & 403 & 360 & 384 & 361 & 399 & 394 & 362 \\ 107 & 100 & 104 & 112 & 104 & 103 & 106 & 100 & 110 & 116 & 105 & 109 & 99 & 104 & 105 & 114 & 101 & 109 & 103 & 107 & 101 & 113 & 106 & 98 & 109 \\ 578 & 555 & 583 & 566 & 575 & 565 & 574 & 586 & 560 & 576 & 580 & 552 & 568 & 561 & 567 & 589 & 578 & 564 & 571 & 556 & 585 & 570 & 569 & 587 & 567 \end{bmatrix}$$

Prescribed correlation matrix

$$\begin{bmatrix} 1 & 0.5 & 0.5 \\ 0.5 & 1 & 0.5 \\ 0.5 & 0.5 & 1 \end{bmatrix}$$

Iman-Conover method

Output correlation matrix

$$\begin{bmatrix} 1 & 0.46 & 0.56 \\ 0.46 & 1 & 0.47 \\ 0.56 & 0.47 & 1 \end{bmatrix}$$

Output matrix

$$\begin{bmatrix} 391 & 368 & 372 & 354 & 364 & 371 & 389 & 371 & 347 & 373 & 373 & 394 & 389 & 382 & 356 & 390 & 363 & 370 & 403 & 360 & 384 & 361 & 399 & 394 & 362 \\ 103 & 99 & 113 & 104 & 104 & 110 & 107 & 109 & 98 & 109 & 100 & 107 & 104 & 103 & 101 & 101 & 109 & 106 & 114 & 105 & 105 & 106 & 112 & 116 & 100 \\ 566 & 555 & 556 & 576 & 567 & 578 & 587 & 578 & 564 & 575 & 569 & 580 & 571 & 567 & 565 & 574 & 560 & 589 & 586 & 552 & 570 & 568 & 585 & 583 & 561 \end{bmatrix}$$

Figure 9. Process of Iman-Conover method.

The input matrix consists of three row vectors (probability density functions) generated in an MCS with 25 iterations. As random experiments, by definition, lead to independent distributed random numbers, the row vectors of the input matrix must be uncorrelated when assuming a sufficiently large number of iterations. Consequently, the vectors’ elements need to be re-sorted to produce the correlations shown in the prescribed correlation matrix, which is realized by means of the algorithm developed by Iman and Conover (1982). The output matrix presents the results of the resorting process. The first column vector still equals the corresponding vector of the input matrix, while the elements of the other column vectors are re-sorted according to the prescribed correlations and the first column vector (Mildenhall, 2006). As shown in the output correlation matrix, the prescribed correlations are approximately reached. The approximation accuracy increases with the number of iterations.

In order to evaluate the relation between risk and return, decision makers can apply VAR analyses to the KPI PDF. VAR analyses are typically used by organizations and regulators of the financial sector. They utilize the VAR as a risk measure for financial positions in order to estimate the amount of assets required to cover potential losses. In this regard, the VAR specifies the maximum monetary loss that is not exceeded within a fixed period of time and an explicit confidence level (Koukal and Breitner, 2013). Consequently, in combination with MCS, the VAR can also be used to consider risk and risk aversion in project finance and expresses the investment risk in one ratio (Gottschlich et al., 2014). For example, when applied to the internal rate of return (IRR), the VAR expresses the minimum annualized effective compounded return on total capital that is not undershot by a certain probability, also referred to as confidence level. Hence, in this context, VAR analyses also evaluate the probability that the IRR undershoots the cost of capital, which finally represents the total investment risk.

The VAR can analogously be applied to other KPI PDF characterizing the profitability of renewable energy projects, while debt coverage KPI PDF need to be analyzed by means of the cash-flow-at-risk (CFAR). The CFAR differs from the VAR only with regard to the reference value, which is the cash-flow. When applied to the DSCR, the CFAR expresses the minimum excess of the cash-flow available for debt service (CFADS) over interest and principal payments for a given confidence level and thus measures the relation between risk and debt service capacity. Both VAR and CFAR were applied in different research articles summarized in this thesis in order to enable considering the risk-bearing capacity within the investment requirements of renewable energy stakeholders.

2.3.2. Cash-Flow Model

Table 4 shows the mathematical formulation of the cash-flow model, which results in periodical PDF of the unlevered free cash-flow (FCF). The notation of the cash-flow model is shown in Table 3. The cash-flow model is utilized to calculate a renewable energy project's unlevered FCF over the entire project life cycle. The unlevered FCF is the after-tax cash flow available to all investors but must initially be used to cover the contractual debt service.

Table 3. Cash-flow model: sets and parameters.

Set	Description	Set	Description
$t = (1, \dots, T)$	Years	$v = (1, \dots, V)$	Wind speeds
Parameter	**Description**	**Parameter**	**Description**
T_i^P	End of pre-construction period	ΔT_i^P	Length of pre-construction period
T_i^C	End of construction period	ΔT_i^C	Length of construction period
T_i^O	End of operation period	ΔT_i^O	Length of operation period
T_i^D	End of decommissioning period	ΔT_i^D	Length of decommissioning period
T_i^{DEP}	End of depreciation period	ΔT_i^{DEP}	Length of depreciation period
$FCF_{i,t}$	Unlevered free cash flow	$EBIT_{i,t}$	Earnings before interest & taxes
$TAX_{i,t}$	Tax	$DEP_{i,t}$	Depreciation
$A_{i,t}$	Accruals for decommissioning	$DECEX_{i,t}$	Decommissioning expenditures
$TV_{i,t}$	Terminal value	$R_{i,t}$	Revenues
$OPEX_{i,t}$	Operation expenditures	τ	Corporate tax rate
$CAPEX_{i,t}$	Capital expenditures	$Y_{i,t}$	Electricity yield
$p_{i,t}$	Sales price per unit of electricity	$k_{i,t}$	Weibull shape parameter
$a_{i,t}$	Weibull scale parameter	W_v	Cumulative power curve
$NOH_{i,t}$	Net operating hours	$\delta_{i,t}$	Wind farm efficiency

The cash-flow model is divided into four modules and each module includes one or multiple equations (Eq.). Module (1) describes the project life cycle, which consists of several sequential periods. According to Eq. (1.1), the total length of the project life cycle is equal to the sum of the lengths of all periods. The length Δ of each period is treated as a stochastic parameter. Each stochastic parameter is denoted with the index $i = (1, \dots, I)$ with I as the total number of Monte Carlo iterations. Therefore, the total length of the project life cycle is stochastic as well as all equations which depend on the length of a period. This is particularly important for modelling time-dependent cost parameters in the CAPEX, OPEX and DECEX. These cost parameters are scaled with the ratio of the realized period length and the average period length over all Monte Carlo iterations. CAPEX, OPEX and DECEX consist of various subordinate cost parameters that can be defined as required by specifying the reference value (e.g., installed capacity in MW or electricity output in MWh) and the relevant time period.

Table 4. Cash-flow model: equations.

Equation		
$T_i = \Delta T_i^P + \Delta T_i^C + \Delta T_i^O + \Delta T_i^D$	$\forall\, i \in I$	(1.1)
$FCF_{i,t} = EBIT_{i,t} - TAX_{i,t} + DEP_{i,t} + A_{i,t} - DECEX_{i,t} + TV_{i,t}$	$\forall\, T_i^C < t \leq T_i;\ i \in I$	(2.1)
$EBIT_{i,t} = R_{i,t} - OPEX_{i,t} - DEP_{i,t} - A_{i,t}$	$\forall\, T_i^C < t \leq T_i;\ i \in I$	(2.2)
$TAX_{i,t} = \max(0, EBIT_{i,t} * \tau)$	$\forall\, T_i^C < t \leq T_i;\ i \in I$	(3.1)
$DEP_{i,t} = \frac{\sum_{t=1}^{T_i^C} CAPEX_{i,t}}{\Delta T^{DEP}}$	$\forall\, T_i^C < t \leq T_i^{DEP};\ i \in I$	(3.2)
$A_{i,t} = \frac{\sum_{t=T_i^O+1}^{T_i} DECEX_{i,t} * \frac{1}{\Delta T_i^O}}{(1+r^A)^{(\Delta T_i^O - t - T_i^C)}}$	$\forall\, T_i^C < t \leq T_i^O;\ i \in I$	(3.3)
$R_{i,t} = Y_{i,t} * p_{i,t}$	$\forall\, T_i^C < t \leq T_i^O;\ i \in I$	(4.1)
$Y_{i,t} = \int_{v=0}^{V} \left(\frac{k_{i,t}}{a_{i,t}} * \left(\frac{v}{a_{i,t}} \right)^{k_{i,t}-1} * e^{\left(\frac{v}{a_{i,t}}\right)^{k_{i,t}-1}} * W_v \right) dv * NOH_{i,t}$	$\forall\, T_i^C < t \leq T_i^O;\ i \in I$	(4.2)
$NOH_{i,t} = 8760 * \delta_{i,t}$	$\forall\, T_i^C < t \leq T_i^O;\ i \in I$	(4.3)

Module (2) describes the unlevered FCF calculation, in which the unlevered FCF is derived in Eq. (2.1) directly based on the earnings before interest and taxes (EBIT) calculated in Eq. (2.2). Module (3) describes the tax calculation in Eq. (3.1). Eq. (3.2) models the linear depreciation of the renewable energy project and Eq. (3.3) implements accrual expenditures related to dismantling obligations, which will occur at the end of the life cycle. Module (4) describes the revenue calculation in Eq. (4.1). As the model is specifically tailored to the evaluation of wind farms, the electricity yields are determined based on Weibull distributions of the average hourly wind speed in Eq. (4.2). Electricity losses from wake effects, technical failures and other loss factors are modelled by Eq. (4.3).

2.3.3. Debt Structuring

The unlevered FCF resulting from the cash-flow model are the cash-flows before interest payments on raised debt capital are considered within the tax calculation. The unlevered FCF are thus approximately equal to the CFADS. Consequently, a project's debt carrying capacity can be determined based on the unlevered FCF, such that the optimal capital structure is reached. Optimizing the capital structure by raising additional debt capital utilizes the leverage effect of debt financing, which increases the equity IRR if the cost of debt is lower than the IRR and thus improves the profitability of the investment (Lang, 1996). For this purpose, debt sculpting is applied within the financial model, which structures the debt repayment schedule such that debt service, including interest and principal payments, exactly corresponds to the CFADS (McInerney and Bunn, 2017).

The debt sculpting ensures that a specific DSCR target is maintained at the confidence level $1{-}\propto$ during all debt service periods. The DSCR measures the coverage of interest and amortization by the CFADS and is determined as follows:

$$DSCR_{i,t} = \frac{FCF_{i,t}}{P_t + I_t} \qquad \forall\, T^{PG} < t \leq T^{DS};\ i \in I \tag{5.1}$$

where P_t is the principal payment, I_t is the interest payment, T^{PG} is the number of grace periods and T^{DS} represents the final debt service period. Based on the DSCR, a project is considered financially sound from the lenders' perspective if a minimum ratio of one is reached in each debt service period. Consequently, the maximum debt service capacity DSC_t is calculated based on a predefined minimum DSCR target β as follows:

$$DSC_t = \frac{F^{-1}_{FCF,t}(\alpha)}{\beta} \qquad \forall\, T^{PG} < t \leq T^{DS} \tag{5.2}$$

Both $\propto$ and β capture the investment criteria of lenders, as they are generally willing to issue debt if a DSCR target of $\beta = 1.2$ is maintained at the confidence level $1{-}\propto = 0.75$ during all debt service periods (McInerney and Bunn, 2017). Assuming the debt to be raised in the form of zero-coupon bonds, the maximum amount of debt capital D can be determined as the sum of the periodic debt servicing capacity discounted to the date of issuance:

$$D = \sum_{t=1}^{T^{DS}} \frac{DSC_t}{(1 + r^d)^t} \tag{5.3}$$

where r^d is the cost of debt. As the discounting is also applied for the grace periods the negative effect of accrued interests on the maximum amount of debt is considered indirectly. On the basis of the maximum debt service capacity, the principal payments can be calculated as follows:

$$P_t = \frac{DSC_t}{(1 + r^d)^t} \qquad \forall\, T^{PG} < t \leq T^{DS} \tag{5.4}$$

Afterwards, the interest payments are estimated as the difference between the maximum debt service capacity and the principal payments:

$$I_t = DSC_t - P_t \qquad \forall\, T^{PG} < t \leq T^{DS} \tag{5.5}$$

As debt sculpting is applied, the sum of principal and interest payments must finally correspond to the debt service capacity in each debt service period.

2.3.4. Valuation

The aim of using DCF calculations in this financial model is to derive present value estimates from which the profitability of a renewable energy project can be inferred. As reasoned in Section 2.2 and following Myers (1974), the APV approach is applied in the financial model for valuation purposes as follows:

$$APV_i = \sum_{t=0}^{T_i} \frac{FCF_{i,t}}{(1 + r^u)^t} + \frac{\tau * I_t}{(1 + r^d)^t} \qquad \forall\, i \in I \tag{6.1}$$

where the first fraction describes the discounting of the unlevered FCF by the unlevered cost of equity r^u and the second fraction describes the discounting of the tax shield by the cost of debt. The tax-shield represents the tax advantages arising from debt financing, as the tax deductibility of interest payments increases the APV. It is crucial that FCFs are not leveraged under this method, i.e., the taxes themselves are calculated on EBIT. Consequently, the unlevered FCF are discounted by the unlevered cost of equity which are calculated according to the capital asset pricing model (CAPM) as follows:

$$r^u = r^f + (r^m - r^f) * \beta^u \tag{6.2}$$

where r^f is the risk-free rate, r^m is the market return, and β^u is the unlevered beta factor. By considering the latter, which accounts for the systematic risk, the corresponding risk premium is calculated representing the expected return on the risky asset. The implementation of such a risk-adjusted discount rate in the valuation is aimed at considering a theoretical IRR that could be expected from a risk-equivalent investment opportunity (Fama and French, 2004). The real IRR is derived by setting the APV function to zero and solving for IRR (Alchian 1955):

$$IRR_i := \sum_{t=0}^{T_i} \frac{FCF_{i,t}}{(1+IRR_i)^t} + \frac{\tau * I_t}{(1+r^d)^t} = 0 \qquad \forall\, i \in I \qquad (6.4)$$

The IRR indicates the annualized effective compounded return on total capital (De Oliveira and Fernandes, 2011). However, as the IRR is based on the unlevered FCF before deduction of debt services, the expected cash-flows being distributed to shareholder are not represented, which is why project developers and equity investors are more interested in the equity IRR. The annualized effective compounded return on equity capital is calculated based on the IRR as follows (Fernandez, 2006):

$$IRR_i^e = r_f + \beta_i^l * \left(\frac{IRR_i - r^f}{\beta^u + r^f} - r^f\right) \qquad \forall\, i \in I \qquad (6.5)$$

Consequently, computing the equity IRR requires the calculation of the levered beta factor β_i^l, which, in turn, depends on the effective debt to equity ratio. The latter is calculated as the division of the effective debt and the value of equity E that differs from the equity provided. When calculating the effective debt, the value of debt D is reduced by the discounted tax shield. The equity and debt values are the sum of the corresponding discounted future shares. Based on the effective debt to equity ratio, the levered beta factor is calculated as follows:

$$\beta_i^l = \beta^u * \left(1 + \left((1+\tau) * \frac{D - \sum_{t=0}^{T_i} \frac{\tau * I_t}{(1+r^d)^t}}{E}\right)\right) \qquad \forall\, i \in I \qquad (6.6)$$

By using the levered beta factor, the equity IRR is adjusted by the leverage, determined by means of debt sculpting, such that it can be compared with the levered cost of equity. Thus, the equity IRR yields the required return on equity that earns the levered cost of equity. It follows that decision makers should not undertake an investment opportunity if the equity IRR is lower than the cost of equity.

2.3.5. Implementation

In order to permit the application of the presented methodology to renewable energy projects and investments, the financial model and MCS were implemented by the author of this thesis into a DSS in collaboration with Julian Hamman and Chris Stetter (IWI, LUH). The DSS integrates the financial model and MCS into a single system and provides a graphical user interface (GUI) for data entry, configuration, and visualization of simulation results. The system front-end is realized as a web-application created with the web-framework Ruby on Rails (Rails). The system back-end, including the financial model and MCS, is implemented in Python. This split system architecture allows for differentiation between implemented algorithms and simulation data. Figure 10 outlines the system architecture and data flow of the DSS. Users interact with the front-end.

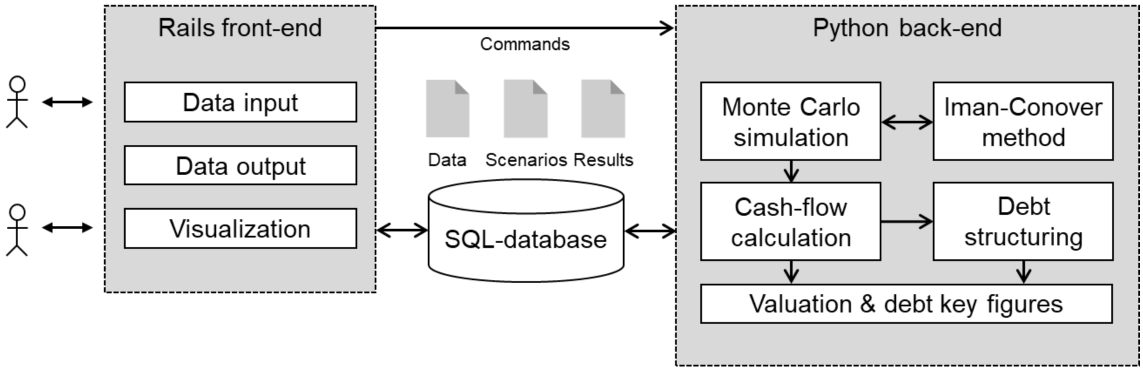

Figure 10. Economic viability model: DSS architecture.

The front-end reads data from and writes data to the database, sends commands to the Python back-end, and presents simulation results to the users. It provides a web-based GUI, which can be accessed through common web-browsers. The Rails framework supports multi-user systems with authorization and authentication measures, database management, and database administration. The SQL-database facilitates the interaction between the Rails front-end and Python back-end. Users provide their respective datasets and configure different simulations through multiple scenarios, which specify parameter and PDF settings. Simulation results for scenarios can be compared to support evaluation of possible decisions. The Python back-end receives commands from the Rails-front-end. When a simulation starts, it loads a dataset and corresponding scenario from the SQL-database. PDF settings are forwarded to the MCS, while deterministic parameters are directly forwarded to the mathematical model. Based on PDF settings, MCS generate realizations for risky parameters, which are then passed to the mathematical model. The mathematical model is computed for each iteration and afterwards results are aggregated and written to the SQL-database.

2.4. Applicability Check: Evaluation of Mexican Onshore wind Farms

2.4.1. Data

To demonstrate applicability and highlight capabilities the DSS is applied to Onshore wind farms located in five different federal states of Mexico. As multiple Mexican wind farms were granted with financial support from the clean development mechanism (CDM) and are thus forced to publish real data and results of economic project calculations, Mexico was chosen as the area of investigation. Table 5 presents the locations and corresponding settings of the in-situ wind speed PDF (Jaramillo and Borja, 2004; Jaramillo et al., 2004). Table 6 and Table 7 present the project characteristics of the reference wind farm, which is assumed to be build and operated at each of the locations.

The project characteristics were derived from the CDM project database. Further, the renewable energy cost database provided by the International Renewable Energy Agency (IRENA) was used and the results of the first Mexican auction were considered for the purpose of comparison and evaluation.

Due to insufficient data on risk factors of Mexican onshore wind farms, the parameters of the PDF were estimated using the project evaluation and review technique (PERT), which is a three-point estimation technique (Malcolm et al., 1959). The PERT estimation requires specification of the mode, minimum, and maximum values, which can be approximated using literature and expert interviews.

Expected values were used as estimators for the modes and minimum and maximum values were derived through percentage deviations from these expected values. The deviations incorporate uncertainty from lack of data as well as inherent volatility of corresponding risk factors. Their determination is based on data from sensitivity analyses provided by the CDM project database.

Table 5. Wind resource data of Mexican wind farms.

	La Venta Oaxaca	La Laguna BCS	San Quintin BCN	Telchac Puerto Yucatan	Matamoros Tamaulipas
Average wind speed [m/s]	12.54	8.65	7.43	7.25	6.67
Weibull scale parameter	1.90	2.39	2.58	2.74	1.88
Weibull shape parameter	13.57	9.19	7.80	7.58	6.93

Table 6. Financial data of a reference wind farm in Mexico: deterministic parameters.

	Value
Turbine	41x Gamesa G114-2.5MW
Project start	01.01.2017
Operation [years]	20
Corporate tax rate [%]	30
Cost of debt [%/year]	8.22%
Unlevered cost of equity [%/year]	9.18%
Debt service period [years]	14
Debt payout	01.01.2017
Repayment period	01.01.2020
Straight line depreciation [years]	16
Provision expenses [%]	5.5

Table 7. Financial data of a reference wind farm in Mexico: PDFs.

	BetaPERT - Mode	Disc./prem.
Pre-construction [years]	1	-25%/+25%
Construction [years]	1.5	-25%/+50%
Decommissioning [years]	0.5	-25%/+50%
CAPEX (pre-construction) [MXNM]	387	-10%/+10%
CAPEX (construction) [MXNM]	3,487	-5%/+15%
OPEX [MXNM/year]	101.9	-10%/+10%
DECEX [MXNM]	390	-25%/+75%
Terminal value [MXNM]	80	-25%/+25%
Farm efficiency [%]	88.5%	-10%/+10%

2.4.2. Discussion of results

As shown in Table 5, the region in La Venta, Oaxaca outperforms the other selected regions in terms of the in-situ wind resources. Consequently, this region enables a highly competitive operation of wind turbines, which is why most operating Mexican wind farms are located in this region. In 2017, the second project phase of the *Piedra Larga* wind farm, which is located in La Venta, was completed and 69 wind turbines were put into operation. This project recently received a power purchase agreement (PPA) at a price of 1,120 MXN/MWh for a period of 20 years in order to permit a financially viable and profitable operation. To investigate whether this electricity price is also sufficient for a financially viable and profitable operation of wind turbines in other regions of Mexico, all five selected wind farms were evaluated taking this electricity price into account.

For this purpose, the DSS was applied to the project characteristics of each of the five wind farms. The MCS was performed with 20,000 iterations on an Intel® Core™ i7-4710MQ CPU with 2.5 GHz, 20 GB RAM and Microsoft Windows 7 64-bit as the operating system and took 25 seconds. Figure 11 shows the results for the wind farm located in La Venta given an equity share of 35%.

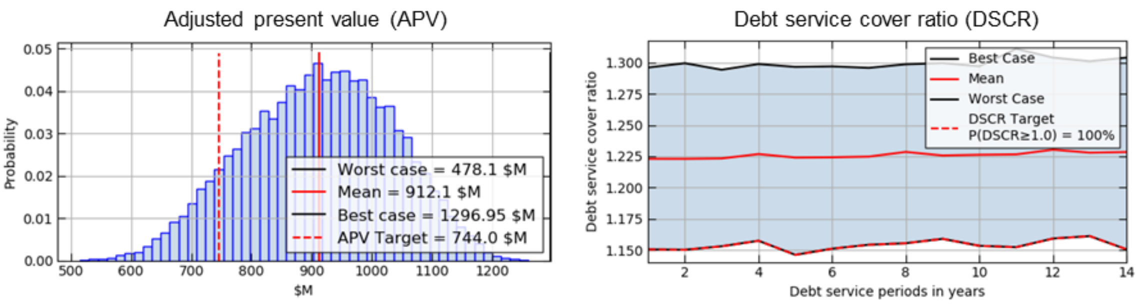

Figure 11. APV (left) and DSCR (right) of wind farm in La Venta, Oaxaca, Mexico.

Both, the probability distribution of the APV and the periodic probability distributions of the DSCR meet the typical investment conditions of wind farm investors. At the 10th percentile the APV is positive and the minimum DSCR is higher than one. Accordingly, the risk of an unprofitable wind farm operation is less than or equal to 10% (i.e., 90% confidence). This confidence level is typically chosen by both banks and equity investors of wind farms in order to ensure a sufficient investment certainty. The identical procedure was also applied to all other wind farms. Table 8 shows the evaluation results for three different equity shares. The results allow different conclusions to be drawn about the projects' profitability and financial viability: (1) only the wind farm located in La Venta, offers positive returns for investors and sufficient coverage of debt service regardless of the given equity share; (2) the wind farm located in La Laguna, Baja California Sur shows

Table 8. Mean APV and minimum DSCR of wind farms in Mexico.

	70/30 debt/equity		65/35 debt/equity		60/40 debt/equity	
	APV [MXNM]	Min DSCR	APV [MXNM]	Min DSCR	APV [MXNM]	Min DSCR
La Venta, Oaxaca	814.7	1.07	744.0	1.15	665.4	1.25
La Laguna, BCS	10.4	0.86	-31.2	0.92	-77.8	1.00
San Quintin, BCN	-794.2	0.65	-832.0	0.70	-687.9	0.76
Telchac Puerto, Yucatan	-931.9	0.61	-964.3	0.66	-1013.9	0.71
Matamoros, Tamaulipas	-1390.3	0.45	-1436.9	0.49	-1466.8	0.53

that a profitable project does not necessarily have to be financially viable at the same time (positive APV, but minimum DSCR less than 1 at 30% equity) and vice versa (negative APV, but minimum DSCR of 1 at 40% equity); (3) In all other regions except La Venta, the revenue from the sale of electricity produced at a price of 1,120 MXN/MWh is too low to simultaneously meet the investment requirements of investors and lenders. It follows from (2) that the successful construction and operation of a wind farm always depends on a smart management of the debt-to-equity ratio of the project in order to appropriately balance the interests of equity and debt investors. This finding is considered in Section 3. In addition, it follows from (3) that a significant increase in wind energy deployment in Mexico requires PPA with higher electricity prices in order to support the expansion of wind energy in other Mexican regions. This finding provided the basis for the research shown in Section 4.

3. Competitive Bidding in Renewable Energy Auctions

This section refers to the article "Competitive and risk-adequate auction bids for onshore wind projects in Germany" (see Appendix 9). The author of this thesis wrote the article in cooperation with Chris Stetter, Julian F. H. Hamann and Michael H. Breitner (IWI, LUH). The article was initially submitted to Energy Economics on 23.08.2019. Based on the reviews sent by the editor-in-chief Richard Tol on 19.12.2019, the article was significantly revised and resubmitted on 28.05.2020 and accepted for publication on 01.07.2020. Energy Economics is a peer-reviewed journal published by Elsevier and is considered the premier field journal for energy economics and energy finance. It has received the ranking "B" in the VHB/JQ3 and had an impact factor of 3.910 in 2017 and a 5-Year impact factor of 4.963.

A first research article with the title "Enhancing Strategic Bidding Optimization for Renewable Energy Auctions: A Risk-Adequate Marginal Cost Model" (see Appendix 8) has been presented on 12.09.2018 at the International Conference on Operations Research in Brussels hosted by the German Operations Research Society. The article has been published in the peer-reviewed Operations Research Proceedings 2018 on 30.08.2019, which received the ranking "D" in the VHB/JQ3. The article presented in this section is a significantly expanded version of the article published in Operations Research Proceedings 2018.

3.1. Introduction

The number of countries adopting renewable energy auctions has grown constantly in recent years (REN21, 2016). These auctions introduce competition among project developers for permissions, financial support, procurement rights and/or remuneration contracts and permit managing a cost-efficient expansion of renewable energy deployment through competitive bidding processes and predefined auction volumes determining future capacity additions. In particular, auctions for the determination of feed-in tariff or premium levels are increasingly in the focus of current policy-making in various countries.

A recent example is the newly introduced auction-based support mechanism for solar and wind farms in Germany, which entered into force with the latest amendment of the Renewable Energy Sources Act (EEG) in 2017. Like most recently implemented renewable energy auctions, it is designed as a tendering process in which project developers compete by specifying their demanded sales price (in ct/kWh) as well as a capacity (in MW) to be installed and only the most cost-competitive projects with the lowest offered sales prices are granted until the auction volume (in MW) is reached. From policy-perspective, this competitive pricing prevents overcompensation of project developers and investors and is likely to result in comparatively low remuneration levels and substantial reductions of financial support over time. From project developers' perspective, it however significantly decreases profit margins, which highly increases the sensitivity to risks and uncertainties and thus decreases acceptable valuation errors.

Consequently, under auction-based support mechanisms with such tendering processes, the new challenge in developing renewable energy projects is the precise quantification of competitive and sustainable bidding strategies. If bids are set too high, projects are non-competitive and not granted with remuneration contracts, while otherwise, if bids are set too low, granted projects are either not implemented or unprofitable investments. However, existing literature puts little focus on the development and evaluation of methodological support enabling project developers to derive optimal bidding strategies for renewable energies. Anatolitis and Welisch (2017) and Voss and Madlener (2017) were the only research articles to be identified that focus on deriving bid price quantification methods in the context of renewable energy technologies. This could be justified by the fact that the mathematical formulation of an optimal bidding strategy is always highly depended on the country-specific auction design (REN21, 2016).

Nonetheless, regardless of the auction design, in optimal bidding strategies project developers commonly obscure the true cost of a project. In order to maximize the expected profit from auction participation, they add premiums on top of the marginal cost of their projects within the bidding process. Therefore, the strategic bidding optimization must always be based on a reliable quantification of the marginal cost, which is the minimum sales price per unit of electricity required to construct and operate a project profitable and financially viable at an acceptable level of risk. When quantifying the marginal cost, current strategic bidding optimization is typically based on conventional DCF models without incorporating project specific risks and uncertainties, resulting in biased and imprecise bidding strategies.

For this reason, this study focusses on improving existing strategic bidding optimization models by developing and evaluating an upstream optimization model enabling renewable energy project developers to quantify risk-adequate marginal cost. Consequently, the RQ under investigation is as follows:

RQ: "*How can the strategic bidding in renewable energy auctions be improved through a risk-constrained marginal cost optimization approach?*"

3.2. Theoretical Foundation

Auction theory is an intensively researched area of economics and a large variety of different auction designs has been studied in real-world environments already. However, specific research on strategic bidding in renewable energy auctions is still at the beginning and only little literature deals with this topic.

A conducted literature review shows that the majority of current renewable energy auctions is designed similar to a proposal by Rio and Linares (2014), although each national auction-mechanism has its own specific design features (IRENA, 2017). The efficient auction design proposed by Rio and Linares (2014) is very similar to the German implementation. They suggest that project developers should compete by submitting a bid including a price per unit of produced electricity as well as an amount of electricity to be produced or capacity to be installed. Once bids are submitted, they are listed in ascending order starting with the lowest bid price and are awarded until the tender volume - typically determined through capacity caps - is reached. Afterwards, awarded bidders receive remuneration contracts for a certain period of time or amount of electricity (Rio and Linares, 2014), while the level of remuneration depends on the applied pricing rule (Anatolitis and Welisch, 2017).

In the regard of pricing rules, current policy-making favors the pay-as-bid pricing over uniform pricing and other alternatives (Rio and Linares, 2014). This is due to the ability of pay-as-bid pricing to permit adjusting the level of remuneration to the marginal costs of different bidders because awarded bidders receive remuneration at the level of their individual bid prices (Kreiss et al., 2017). In contrast, under uniform pricing all awarded bidders receive the same level of remuneration equal to the market-clearing price. The latter indicates the level of the highest awarded bid and thus maximizes the attainable profit of each bidder (Voss and Madlener, 2017). Under discriminatory pricing rules, such as pay-as-bid pricing, project developers at least bid their marginal cost, typically supplemented by a certain margin on top. The optimal margin maximizes the expected profit and depends on several determinants, such as the competitive situation, the chance of being awarded and the number of auction rounds (Anatolitis and Welisch, 2017). Auction theory refers to this strategic bidding behavior as bid shading (Menezes and Monteiro, 2005). Therefore, real-world project developers initially seek to most accurately estimate their marginal cost before employing strategic bidding optimization models (Anatolitis and Welisch, 2017). Given uniform pricing, bidding the marginal cost is a weakly dominant strategy (Milgrom, 2004).

Kitzing and Wendring (2016) refer to the marginal cost as the non-strategic bid price. They define the marginal cost to be the level of remuneration that sets a renewable energy project's expected present value equal to zero. Hence, when being submitted in an auction, this bid price maximizes the chance of winning independent of the competitive situation, while still permitting an attractive investment in case of being awarded. Consequently, quantifying a non-strategic bid price does not include profound game theoretic modeling to enable strategic bidding (Kitzing and Wendring, 2016), but requires advanced financial models for the valuation of renewable energy projects. In this study, the definition from Kitzing and Wendring (2016) is adapted and extended and the marginal cost are considered to be the minimum level of remuneration required to permit a risk-adequate, profitable and financially viable construction and operation of a renewable energy project. In order to satisfy this definition, the marginal cost should meet several requirements. Firstly, such a model has to permit translating the complex cost and financing structures as well as electricity generation and revenue streams of renewable energy projects into a cash-flow calculation. Secondly, it must be capable of incorporating the quantitative influences of the manifold risks and uncertainties of these projects into the estimation of cash-flows and KPI. Thirdly, it has to enable simulating an economic agent that depicts the investment decisions of real-world corporations and finds the minimum level of remuneration necessary to meet the investment requirements. As the implementation of renewable energy projects highly depends on balancing the interests of shareholders and lenders (McInerney and Bunn, 2017), this economic agent must be capable of considering the perspectives of both groups of decision-makers by shedding light on profitability and bankability KPI as well as their trade-offs.

3.3. Methodology

The methodology used in this section to calculate the non-strategic bid price for a renewable energy project in tenders similar to the German implementation extends the methodology presented in Section 3. Figure 12 shows the extended system architecture of the DSS.

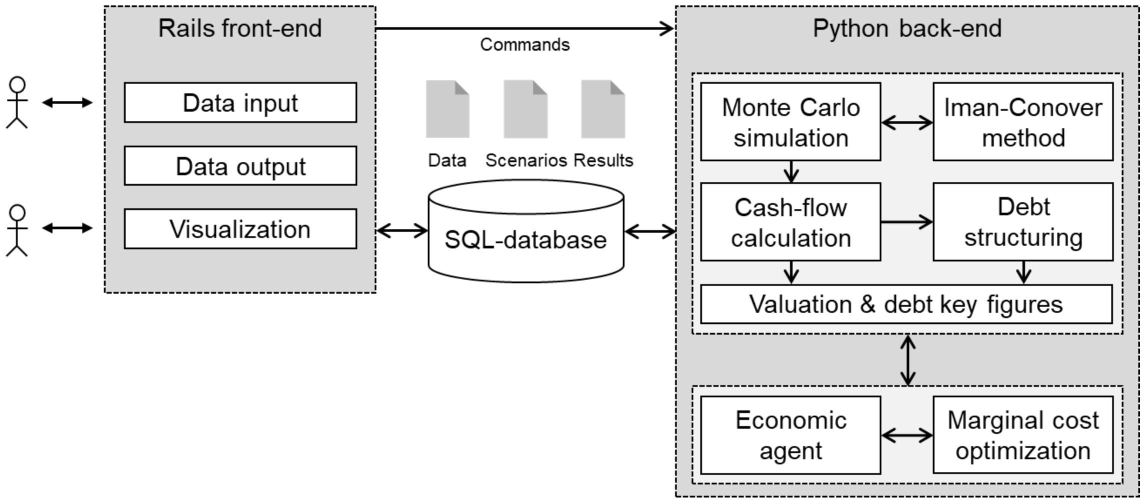

Figure 12. Amendment of DSS architecture by marginal cost model.

In order to enable simulating the mentioned economic agent, the financial model is reformulated as an optimization approach. It yields the required minimum sales price per unit of generated electricity - the marginal cost (in ct/kWh) - for which the analyzed project would exactly meet the investment criteria of real-world corporations. For this purpose, the optimization approach controls for a risk-adequate, profitable and financially viable project realization by automatically applying CFAR and VAR analyses to different KPI PDF in the constraints.

In order to maintain the investment behavior of real-world corporations in the field of renewable energy projects, the optimization approach determines the profitability of the analyzed project by means of the APV, while the financial soundness is controlled for by means of the DSCR. Thus, the perspectives of both equity and debt investors are considered. The optimization problem is formulated in mathematical terms as follows:

$$\boldsymbol{Minimize}\ p\ subject\ to \tag{7.1}$$

$$E(APV) \geq 0 \tag{7.2}$$

$$F_{DSCR,t}^{-1}(\alpha) \geq \beta \qquad \forall\, T^{PG} < t \leq T^{DS} \tag{7.3}$$

where $E(f_{APV})$ is the expected value of the PDF of the APV and $F_{DSCR,t}^{-1}(\alpha)$ is the inverse cumulative distribution function of the DSCR at percentage point α. The first constraint captures the investment criteria of equity investors that the expected APV must be non-negative, which is equivalent to an expected IRR being greater than or equal to the cost of capital (Werner and Scholtens, 2017). Similarly, the second constraint represents the investment criteria of lenders, which ensures the project's ability to cover the contractual debt service at a minimum level β with a probability of $1 - \alpha$ in each debt service period. Based on a first estimate for the marginal cost $p_{initial} \in \mathbb{R}^{+}\{0\}$, the optimization model is solved using the derivative of the expected APV with respect to the electricity price p:

$$\frac{dE(APV)}{dp} = (1-\tau)\sum_{t=1}^{\max(T)} \frac{E(Y_t)}{(1+r^u)^t} + \tau * (1-\tau)\sum_{T^{PG}+1}^{T^{DS}} \frac{\frac{F_{Y,t}^{-1}(\propto)}{\beta}}{(1+r^d)} * (1-(1+r^d)^t) \tag{7.4}$$

where $E(f_{Y,t})$ is the expected value of the electricity yield PDF and $F_{Y,t}^{-1}(\alpha)$ is the αth percentile of the cumulative distribution function of the periodical electricity yields. The first addend refers to the discounting of the unlevered FCF in the APV approach, while the second addend refers to the discounting of the tax-shields and is based on the second constraint. Both summands together represent the first constraint. In a final step, the minimum electricity price that exactly meets the investment criteria of both equity and debt investors is derived as follows:

$$p^* = p_{initial} - \frac{E(APV)}{\frac{dE(APV)}{dp}} \tag{7.5}$$

The resulting marginal costs indicate the cost competitiveness of a project within the framework of auctions. If submitted in a renewable energy auction similar to the German implementation, the bidder would maximize the project-specific competitiveness, while remaining economically sustainable with regard to a probable project realization at an acceptable level of risk.

As the marginal cost are only the starting point of strategic bidding, the author of this thesis in collaboration with Chris Stetter (IWI, LUH) integrated the financial model (Section 2) and the derived optimization approach into a strategic bidding model for the German implementation of renewable energy auctions developed by Voss and Madlener (2017). Following Anatolitis and Welisch (2017), the two dominant strategies are as follows:

$$E\big(\pi(b)\big) = \sum\nolimits_{n=t}^{T} \delta^{n-t} * (b_n - c) * \rho_n * \prod_{x=1}^{n-t} 1 - \rho_n \tag{7.5}$$

$$b = c \tag{7.6}$$

where π is the profit, δ the discount factor and ρ_n the probability of the bid being successful in auction round n. The first equation represents the dominant bidding strategy in a repeated pay-as-bid auction and maximizes the expected profit by putting an optimal premium on top of the marginal cost in order to derive the optimal bid vector b over multiple consecutive auction rounds. The second equation represents the weakly dominant strategy if uniform pricing applies, which is to bid exactly the marginal cost in each auction round. Consequently, both bidding strategies feature the same starting point, which is the marginal cost.

3.4. Applicability Check: Strategic Bidding for a German Wind Farm

3.4.1. Data

In order to enable a proof-of-concept of the methodology, the software prototype was applied to a case study of a German project developer realizing an onshore wind farm project within the framework of the German auction mechanism. Accordingly, the project developer searches for the optimal bid structure for his project over the next four auction rounds. For this purpose, the marginal cost for the project were first calculated in order to determine the lower bid threshold. The marginal cost calculation was then embedded in a strategic bidding optimization in order to find the bidding strategy that maximizes the expected payoff over the four auction rounds, taking the pay-as-bid pricing rule into account. Table 9, Table 10 and Table 11 show the project characteristics of the wind farm, which were mainly derived from Wallasch et al. (2017).

Table 9. Financial data of a reference wind farm in Germany: deterministic parameters.

	Value
Turbine	5x Vestas V150-4.2 MW
Project start	01.01.2019
Construction [years]	2
Operation [years]	20
Corporate tax rate [%]	30
Cost of debt [%/year]	3%
Unlevered cost of equity [%/year]	3.18%
Debt service period [years]	14
Debt payout	01.01.2019
Repayment period	01.01.2022
Straight line depreciation [years]	16
Farm efficiency [%]	90%
Net operating hours [h/year]	8,560
Average wind speed [m/s]	6.45

Table 10. Financial data of a reference wind farm in Germany: BetaPERT PDFs.

	BetaPERT - Mode	Disc./prem.
CAPEX [€M]	31.77	-10%/+10%
OPEX (Year 1-10) [€M/MWh]	21.71	-10%/+10%
OPEX (Year 11-20) [€M/MWh]	23.60	-10%/+10%

Table 11. Financial data of a reference wind farm in Germany: Normal PDFs.

	Normal - Mean	Standard deviation
Weibull scale parameter	2	4.85% of mean
Weibull shape parameter	7.28	3.70% of mean

The wind resources refer to the conditions defined for the EEG reference site, while the standard deviations were determined using real-world wind data from NASA's Modern-Era Retrospective analysis for Research and Applications (MERRA-2) dataset for a grid point with similar average wind resources in Northern Germany. For the marginal cost calculation, an expected unlevered equity IRR of 3.18% was assumed from the perspective of the equity providers. In addition, the lenders were assumed to demand a DSCR exceeding a value of 1.4 with a probability of at least 50% throughout all debt service periods. The subsequent strategic bidding optimization required assumptions about the distribution of bids in the next four auction rounds to be played. The market clearing price was modelled as a beta function. The mean of this function is equal to the average market clearing price of the four auction rounds of 2018 as well as the first of 2019 of 60.7 €/MWh and the maximum value was set to 62 €/MWh as prescribed in the EEG. This was done by setting the beta function parameters α and β to 44.1 and 15.6 respectively as well as the lower bound to 57.1 €/MWh and the upper bound to 62 €/MWh. For the forthcoming rounds the market clearing price distribution was adjusted by means of a learning curve that describes the technological cost development:

$$P_t(X_t) = P_0 * \left(\frac{X_t}{X_0}\right)^{-b} \tag{7.7}$$

where P_t is the lower bound of the beta function, X_t is the cumulative installed onshore wind energy capacity, P_0 was set to 57.1 €/MWh and X_0 was set to 53.2 GW, which is the onshore wind energy capacity installed in Germany in March 2019. The learning coefficient b was derived as follows:

$$b = \frac{\log\left((-LR + 1)^{-1}\right)}{\log(2)} \tag{7.8}$$

where the learning rate LR was set to 9.8% as derived empirically from historical data by Williams et. al (2016). Since the EEG defines 2.8 GW of onshore wind capacity to be tendered annually, it was assumed that the cumulative installed onshore wind energy capacity grows at this rate. Consequently, the optimal bidding strategy considers that the technology cost and thus the market clearing price drop as capacity increases.

3.4.2. Discussion of Results

In order to demonstrate the applicability of the derived model as well as the importance of a precise marginal cost calculation in the realm of strategic bidding, two scenarios were compared: the first scenario considered c to be set to 59.8 €/MWh, while the second scenario considered the real marginal cost of 58.8 €/MWh as the starting point for the calculation of the optimal bidding strategy. Table 12 shows the optimal bidding strategy as well as the probability of being awarded under consideration of the assumed distributions of the market clearing price in the consecutive auction rounds for both scenarios. Figure 13 illustrates the optimal bidding strategy for the marginal cost.

Table 12. Optimal bidding strategy given the calculated marginal cost.

		Auction rounds				Expected payoff [€M]
		1	2	3	4	
Marginal cost 59.8 €/MWh	Bid [€/MWh]	61.8	61.7	61.3	60.8	1.18
	Probability [%]	4%	9%	25%	45%	
Marginal cost 58.8 €/MWh	Bid [€/MWh]	61.7	61.4	60.9	60.5	1.65
	Probability [%]	8%	23%	44%	61%	

Both scenarios feature a declining trend of optimal bids. This is coherent with the results of a simulation study by Welisch and Kreiss (2019), which was carried out using game theory and agent-based modelling. It follows that the optimal strategy, resulting from the characteristics of the auction design, is to place high bids with the possibility of lowering the bid price in order to maximize the probability of winning the next round of the auction. This in turn maximizes the expected profit and shows a high probability of obtaining funding in the final auction round.

Taking into account the increased sales price of 59.8 €/MWh for bid price optimization, the expected profit for participating in four auction rounds is 1.18 €M, while marginal costs give an expected profit of 1.65 €M. Although the revenue-determining bidding prices are lower for marginal costs, the magnitude of a higher probability of obtaining founding outweighs this. The results clearly show the importance of an adequate quantification of marginal costs and the mathematical integration of a suitable present value model into strategic bidding optimization. The latter assumes that for the given marginal costs the present value is zero. If a present value model is chosen that does not adequately take into account the characteristics of project financing, the marginal costs are either over- or underestimated. In both cases, the strategic bidding model would result in a high-risk strategy. The strategy presented in Table 12 for a sales price of 59.8 €/MWh, for which the APV is positive, has lower probabilities of success. Even if a sales price below true marginal cost would lead to higher probabilities of success, it is more likely that the project is unprofitable. It is possible that the offer price granted is below the true marginal costs for which the APV is negative.

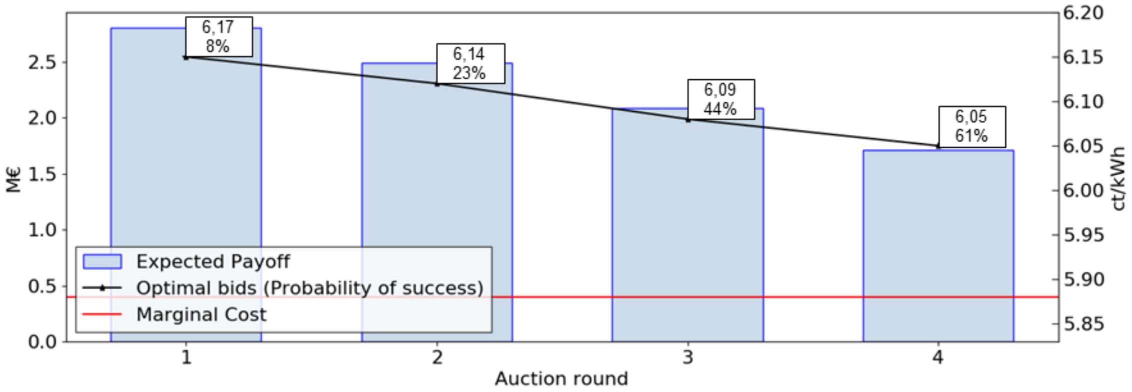

Figure 13. Optimal bidding strategy and expected payoff.

4. Politico-Economic Simulation of Renewable Energy Auctions to Design Incentives for a Spatially-Diversified Deployment

This section refers to the article "Promoting the System Integration of Renewable Energies: Toward a Decision Support System for Incentivizing Spatially-Diversified Deployment" (see Appendix 3). The author of this thesis wrote the article in cooperation with Julian F. H. Hamann, André Koukal and Michael H. Breitner (IWI, LUH). The article was submitted to a HICSS special issue of the JMIS on 15.04.2017 in response to an invitation of Prof. J. S. Giboney (University of Albany), Prof. R. O. Briggs (San Diego State University) and Prof. J. F. Nunamaker Jr. (University of Arizona) to submit an expanded version of the article described in Section 2. After a first double-blind peer review process, the article has been accepted pending revisions. On 08.08.2017 the authors resubmitted a substantially revised version and finally received an acceptance for publication on 15.09.2017 after a second double-blind peer review process. After several further revisions with minor changes, the article was published on 02.01.2018 in the JMIS special issue: Creating Social Value with Information.

JMIS is a peer-reviewed journal in the areas of IS and IT. It is published by Taylor & Francis and is ranked as one of the three top-tier IS journals. JMIS was classified in category "A" by WKWI and GI-FB WI and received the ranking "A" in the VHB/JQ3. Furthermore, JMIS is placed by Financial Times on the list of the Top 50 journals for business schools and is part of the “basket of eight”, which is a list of top management IS journals selected by the AIS, which are focused on behavioral, business-oriented IS research.

4.1. Introduction

The deployment of renewable energies was highly dependent on financial support mechanisms with low integration into market mechanisms in the past in order to enable cost competitiveness operation compared to conventional electricity supply types (Abolhosseini and Heshmati, 2014). These mechanisms highly improved the expansion of renewable energies in many countries, but also led to significant subsidy costs (Huntington et al., 2017). In recent years many different governments have shifted to auctions for subsidies in order to increase the market integration of renewable energies by establishing a price discovery element into the determination of financial support levels (Rio and Linares, 2014). In auctions only most cost-efficient renewable energy projects are granted with support contracts, resulting in significantly decreasing subsidy costs (Huntington et al., 2017; Rio and Linares, 2014).

However, an unintentional effect of auctions is the resulting accumulation of renewable energy capacity at most resource-rich locations within the auction area, as these locations enable most cost-efficient deployment (Abdmouleh et al, 2015; Rio and Linares, 2014). Due to highly correlated resource availabilities at these locations, the spatial concentration of capacity increases the volatility of electricity supply, which impairs the system integration of intermittent renewable energies (van Kuik et al., 2016; Roques et al., 2010). In addition, these resource-rich locations often mismatch with areas with high electricity demands. Hence, the spatial concentration paired with the intermittency of renewable energies leads to high ancillary service and electricity distribution costs as well as technical issues impairing grid stability and reliability of electricity supply (Reichenberg et al., 2017; Rombauts et al., 2011; Roques et al., 2010). Consequently, a trade-off between cost-efficient renewable electricity supply at most resource-rich locations and reliable and cost-efficient electricity distribution can be identified. An option to manage this trade-off is an increase of the spatial diversification of capacity deployment, as intermittency of renewable energies can be geographically smoothed over large regions, which mitigates the stated issues. When planning renewable energy support mechanisms, this trade-off must be controlled for to optimally increase the system integration of renewable energy by fostering an appropriate spatial distribution of capacity (Reichenberg et al., 2017; Roques et al., 2010).

Consequently, the incentives provided through support mechanisms must be carefully designed, such that the entirety of investment decisions by individual investors results in a reasonable and desired spatial distribution of new renewable energy capacity (Reichenberg et al., 2017; González and Lacal-Arántegui, 2016). New auction mechanisms need to weaken the link between competitiveness of renewable energy projects and location-specific resource availabilities in order to establish sufficient incentives for investors to operate projects outside the most resource-rich locations.

For this purpose, recently introduced renewable energy auctions, as for example in Germany (Lang and Lang, 2015), Mexico (IRENA, 2017), and Spain (Huntington et al., 2017), consider specific design elements coupling investment incentives for renewable energy investors with in-situ resource availabilities in order to manage the investors' decisions with regard to the desired spatial distribution of new RE capacity (Lang and Lang, 2015; Rio and Linares, 2014). The design and quantification of these investment incentives however pose substantial challenges for policy-makers, as incorrect designs can have significant negative impacts on the overall efficiency of the entire electricity system (Huntington et al., 2017; Rio and Linares, 2014). Therefore, this study aims at developing and evaluating a modelling approach that improves designing and quantifying such incentives. Because wind energy already contributes noticeably to global electricity supply (Lu et al., 2009) and as spatial concentration of wind energy capacity under renewable energy auctions is a common issue (van Kuik et al., 2016), this study specifically focuses on enhancing the geographical diversification of wind energy deployment. Consequently, the investigated RQ is as follows:

RQ: "*How to quantify investment incentives for improving the spatial distribution of wind energy deployment under renewable energy auctions?"*

4.2. Theoretical Foundation

In a recent review of renewable energy policies by Abdmouleh et al. (2015), past and current implementations were analyzed to determine best practices and support policy-makers in improving solutions for supporting renewable energy deployment. Their results indicate auctions to be the most favorable policies as the introduction of competitive pricing decreases electricity prices for consumers and subsidy costs for governments. This is also evident in recent policy-making, as the number of countries employing renewable energy auctions has more than doubled since 2010, while support mechanisms based on fixed-feed in tariffs have been increasingly phased-out (REN21, 2016). Another review on renewable energy policy design by González and Lacal-Arántegui (2016) with a focus on wind energy also confirmed the trend toward increasing market exposure of renewable energy by promoting competition among project developers. According to their findings, policy-makers sought the main objectives of tracking technology-cost reductions, preventing overcompensation, and reducing total subsidy costs by realizing most cost-efficient projects when employing auctions.

Nonetheless, as the cost-efficiency of a project strongly dependents on the in-situ resource availability (González and Lacal-Arántegui, 2016), auctions tend to promote spatial concentration of renewable energy projects at most resource-rich locations. This is due to fact that these highly competitive projects outperform projects with lower resource availabilities in the bidding process (González and Lacal-Arántegui, 2016; Abdmouleh et al., 2015; Rio and Linares, 2014). However, spatially-concentrated renewable energy deployment leads to different adverse effects. As dispatching of wind and solar energy plants is strongly limited, these technologies add substantial variability into electricity generation (Monforti et al., 2016). Due to highly correlated resource availabilities, a higher spatial concentration of renewable energy deployment at few resource-rich locations additionally amplifies intermittency of electricity generation from renewable energies. In order to ensure a stable electricity supply, this intermittency must be matched with flexibility from conventional power plants, storage technologies and variable demand (Abdmouleh et al., 2015; Blokhuis et al., 2011). Consequently, large proportions of spatially-concentrated wind and solar energy capacity incurs two types of electricity system costs: load-balancing and back-up power (Reichenberg et al., 2017; Roques et al., 2010). While the latter refer to the provision of flexible and mainly unused capacity, load-balancing costs arise from short-term variability and limited predictability of wind velocity and solar irradiation and refer to the matching of electricity supply and demand (Reichenberg et al., 2017; Rombauts et al., 2011; Roques et al., 2010). Furthermore, large investments in grid infrastructure are needed to ensure load balancing and electricity distribution at times with high renewable energy generation (Blokhuis et al., 2011), while new back-up power plants must be built to maintain supply reliability at times with low renewable energy generation (Roques et al., 2010).

These adverse effects can be reduced significantly by fostering a more appropriate spatial distribution of renewable energy capacity by way of specific design elements in support mechanisms (Reichenberg et al., 2017; Roques et al., 2010). Along these lines, prior research has demonstrated that a decentralized deployment of renewable energies over a large geographical area prevents high correlations among resource availabilities and therefore reduces variability by smoothing resource-dependent electricity generation (Reichenberg et al., 2017; Thomaidis et al., 2016; Santos-Alamillos et al., 2016). This geographical smoothing effect decreases load balancing and back-up power costs, as the effects of renewable energy intermittency partially cancel each other out (Reichenberg et al., 2017). Additionally, as electricity generation from renewable energies is more evenly distributed, electricity distribution costs as well as the necessary grid infrastructure investments decrease (Blokhuis et al., 2011).

However, as more spatially-distributed projects are not necessarily realized at the most resource-rich locations, decentralization can reduce the electricity yield from renewable energies for a given capacity (Roques et al., 2010) (also referred to as the capacity factor) and thus decrease the cost-efficiency of electricity generation. This trade-off between yield and variability of electricity generation was addressed by Reichenberg et al. (2017), Roques et al. (2010) as well as Thomaidis et al. (2016), who proposed the spatial distribution of renewable energy capacity to be treated as a multi-objective optimization problem. With their different approaches they were able to show that an efficient spatial distribution substantially reduces variability while maintaining high electricity yields due to diversification effects and concluded that policy and support mechanism improvements with respect to the resulting spatial distribution of renewable energy deployment can yield significant benefits from a system perspective. Hence, policy-makers are advised to incorporate the trade-off between the efficiencies of electricity distribution and generation into support mechanisms' designs and the spatial planning of renewable energy capacity to improve the efficiency of electricity supply.

In order to improve auction mechanisms with regard to the spatial planning, both Huntington et al. (2017) and Rio and Linares (2014) emphasized the need to design incentive payments, also referred to as location-based incentives. These incentives allow for site-specific bids in order to achieve an appropriate regional coordination of renewable energy deployment. Location-based incentives weaken the link between a project's competitiveness and the in-situ resource availability. They establish investment incentives for project developers to realize projects outside the most resource-rich areas and thus promote a less concentrated spatial distribution of renewable energy deployment. They allow the entirety of investment decisions to be influenced as desired while still preserving market mechanisms. Hence, this approach addresses the trade-off between the efficiencies of electricity generation and distribution by way of expansion planning combined with market-based incentives to maintain supply cost-efficiency.

However, as experience has shown (e.g., in Mexico), the design, quantification, and implementation of location-based incentives is a demanding task for policy-makers as errors potentially have extreme adverse effects on the spatial distribution of capacity and can lead to significant market distortions. Additionally, the feedback cycles of design changes with regard to the spatial distribution are rather lengthy due to the development time of new projects and thus implementation errors can remain hidden until awarded projects are realized. Furthermore, Rio and Linares (2014) discouraged periodically changing established support mechanisms due to the amplified uncertainty for investors and instead recommended stable and transparent regulation. Consequently, information on the effect of location-based incentives on the resulting spatial distribution of renewable energy capacity is very valuable to policy-makers as it enables direct feedback and enhances decision-making. This provides the opportunity for IS research to contribute to current issues of energy transition by designing integrated solutions that produce valuable and actionable information for decision-makers.

4.3. Methodology

Three integrated components are needed to set up a model for the quantification of location-based incentives. Firstly, a resource assessment enabling the estimation of available wind resources at arbitrary locations in the area under investigation. Secondly, an economic agent simulating the investment decisions of real-world corporations depending on the chosen incentive design. Thirdly, a superior model that controls the economic agent by means of the incentive design to shape the entirety of investment decisions toward a desired distribution of wind energy capacity deployment. By simulating the interaction between the economic agent and the support mechanism, the optimal design of the location-based incentives can be extracted. To exploit this problem structure, three interdependent models were developed and integrated in a joint system architecture: (1) a resource model, (2) an economic viability model, (3) a spatial distribution model. Figure 14 illustrates the system architecture instantiated as a DSS prototype.

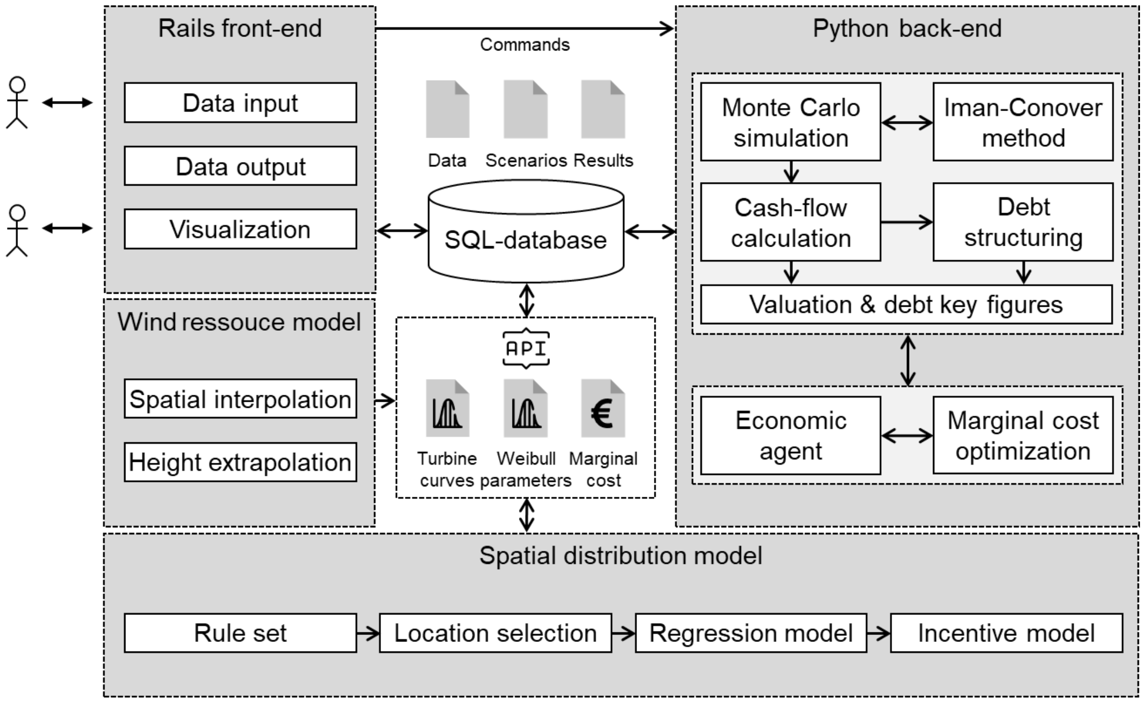

Figure 14. Amendment of DSS architecture by wind and spatial distribution models.

The descriptions of the different models and their inputs, outputs and interactions are referred to the following sections. In order to set up the DSS prototype, the author of this thesis implemented the models in Python in collaboration with Julian Hamann (IWI, LUH). Furthermore, Julian Hamann set up a PostgreSQL-database with the PostGIS extension to enable storing wind resource datasets for large geographical areas and developed a simple web front-end with Ruby on Rails to use the prototype on a compute server.

4.3.1. Resource model

The resource model provides estimates of available wind resources at arbitrary locations and heights. It is based on the Virtual Wind Farm (VWF) model of Staffell and Green (2014). The VWF model is based on high-resolution wind assessments by utilizing NASA’s MERRA-2 data. MERRA-2 is an open-access reanalysis of global atmospheric observations, which combines simulated and globally observed data into a spatially-complete, gridded meteorological dataset and provides hourly resolved wind data on a 0.5° x 0.625° (latitude x longitude) grid (Rienecker et al., 2011). Figure 15 illustrates the process of the resource model.

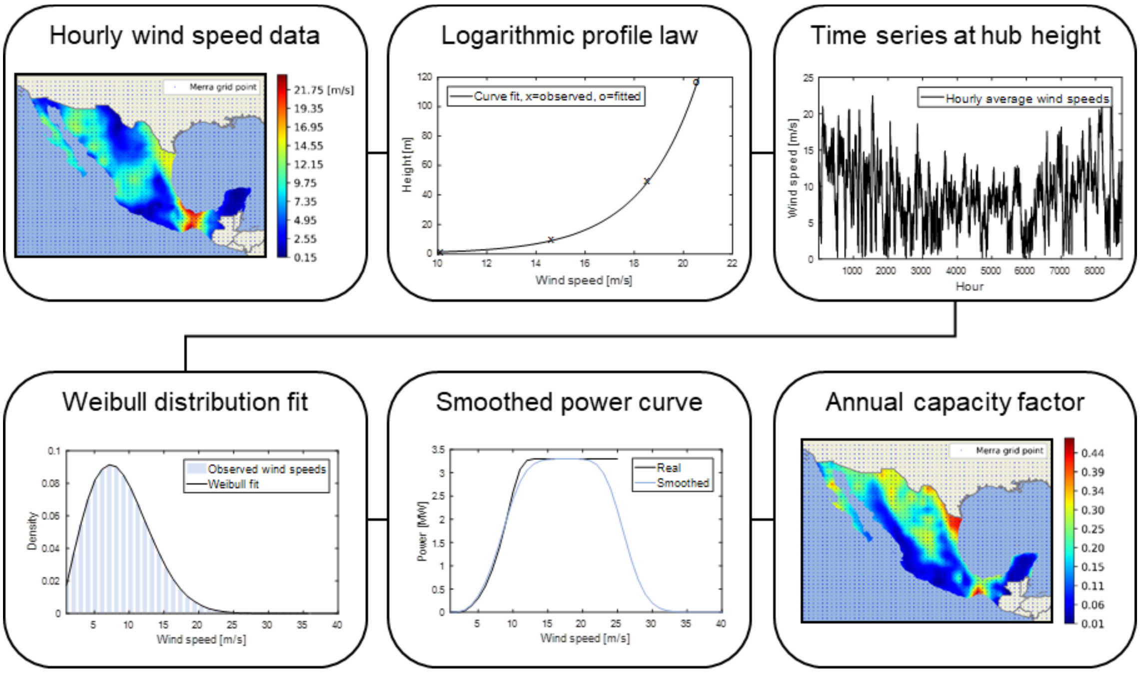

Figure 15. Process structure of the wind resource model.

The resource model is applied according to the following process: (1) capturing of wind speeds at 2m, 10m and 50m above ground at each grid point; (2) interpolation of wind speeds to the geographic coordinates of the investigated turbines using LOESS regression; (3) extrapolation of wind speeds to the hub-height of the investigated turbines using the logarithmic profile law; (4) extraction of annual wind speed PDF for the location and height of the investigated turbines by applying Weibull distribution fits to the hourly wind speeds; (5) conversion of wind speed PDF to power generation PDF by applying the investigated turbines' power curves to the wind speed PDF by means of MCS. In keeping with Staffell and Pfenninger (2016), the turbine power curves were smoothed by applying a Gaussian filter in order to take the distribution of wind speeds over a geographically-dispersed wind farm into account.

In order to use the resource model, a (potential) wind farm must be specified with regard to location and turbine characteristics. The position of the wind farm is given as a pair of longitude and latitude coordinates and the turbines are characterized by their power curves and heights. Afterwards, the resource model is applied to the parameterized wind farm and yields the annual power output PDF as well as the average annual capacity factor.

4.3.2. Economic viability model

The economic viability model used in this study is a combination of the financial model presented in Section 2 and the optimization approach presented in Section 3, which is why it is not described in detail in this Section. It uses the annual power output PDF provided by the resource model to simulate the future cash-flow streams of the respective wind farm. For this purpose, a variety of investment data is fed into the economic viability model, as for example CAPEX, OPEX, and decommissioning expenditures (DECEX) in the form of PDF. In addition, various deterministic parameters are provided, such as the financial structure and project life cycle. As described in Section 3, the economic viability model is used to calculate the marginal cost (in ct/kWh) based on the resulting KPI PDF as well as the corresponding equity and debt investors' investment criteria. In a competitive auction, the determined marginal cost corresponds to the optimal non-strategic bid price. By applying location-based investment incentives, the optimal non-strategic bid price can be adjusted, such that the competitiveness of the wind farm in the auction is changed. Consequently, the marginal cost represents the basis on which the optimal location-based investment incentives are derived.

4.3.3. Spatial distribution model

Combining the resource and economic viability models enables simulating the competitiveness of wind farms at arbitrary locations. Based on the combined models, the spatial distribution model simulates the entirety of investment decisions in conjunction with the influence of policy-making on these decisions. Afterwards, the resulting information is used to quantify the optimal location-based investment incentives in order to shape new wind energy deployment to the desired spatial distribution in future auctions.

To permit specific assumptions regarding the bidding behavior of investors, the spatial distribution model assumes a pay-as-bid auction-mechanism oriented toward the proposal of Rio and Linares (2014) in this study. With regard to their proposal, they recommended using location-based incentives to promote appropriate regional coordination of deployment by adjusting bid prices to the availability of resources. To quantify these adjustments, the spatial distribution model is applied according to the following process: (1) defining a number of potential wind farm locations and corresponding projects; (2) applying the resource and economic viability models to each location and project; (3) setting and calculating a resource availability measure for each location; and (4) regressing the resulting marginal cost against the resource availability measure for all projects in order to parametrize the location-based investment incentives.

4.4. Applicability Check: Location-Based Investment Incentives for the Mexican Renewable Energy Auctions

4.4.1. Data

In order to demonstrate and evaluate the modeling approach, a simulation study is conducted for the wind energy market in Mexico. As shown in Figure 16, Mexico has high but heterogeneous wind resources (Carrasco-Díaz et al., 2015), especially at the Isthmus of Tehuantepec in the southeastern state of Oaxaca (Jaramillo and Borja, 2004). Consequently, Mexico's currently installed wind energy capacity is strongly concentrated in this region (Pierrot, 2017). However, Figure 16 also indicates that there are also other Mexican regions with high wind resources that could be used to a greater extent for wind turbine operation. In addition, as shown in Figure 16, most of these regions show only minor positive or even negative correlations with the wind resources in Oaxaca. Therefore, there is a great potential of significantly reducing the variability of electricity generation by diversifying the spatial distribution of wind energy deployment, while still maintaining a constant high average electricity yield.

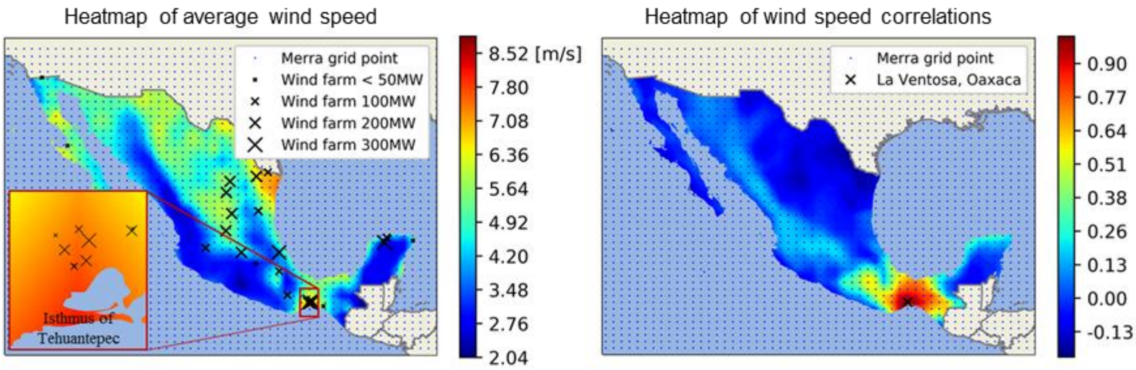

Figure 16. Average wind speeds and wind speed correlations in Mexico.

This potential was also anticipated by Mexican policy, which implemented location-based incentives in the current auction-mechanism for renewable energies. However, the design of these incentives proved difficult, as demonstrated by the implementation of extensive design changes in the Mexican case following highly undesirable results in Mexico's first round of auctions in 2016 (IRENA, 2017).

For the simulation study, the resource model was supplied with wind resource data from NASA’s MERRA-2 database and technical characteristics of the Vestas V112-3.3 wind turbine, which serves as the reference wind turbine due to its widespread use in Mexico. In addition, the economic viability model was supplied by investment data for the reference wind farm, which is derived from the CDM project database, including twenty Mexican wind farms, and the renewable energy cost database provided by IRENA.

4.4.2. Discussion of Results

Based on the results of the resource model and the Mexican grid infrastructure (CENACE, 2016), a set of potential wind farm locations was preselected and supplied to the economic viability and spatial distribution models. In order to avoid high grid connection costs, the preselection excluded locations with more than 50 km distance to the next grid connection point. Furthermore, all locations with a capacity factor lower than 22% were excluded from the preselected dataset. This minimum capacity factor was chosen to ensure that the average capacity factor of all remaining locations of 28.66% is approximately equal to the average capacity factor of Mexico's current wind fleet.

The results of the economic viability model including the simulated marginal cost for each of the remaining 115 potential wind farm areas are shown in Figure 17. As the marginal cost decreases exponentially with increasing capacity factor, it is inappropriate to subsidize sites with too low capacity factors. Consequently, based on this finding, a minimum capacity factor or maximum remuneration should be a design element of location-based investment incentives.

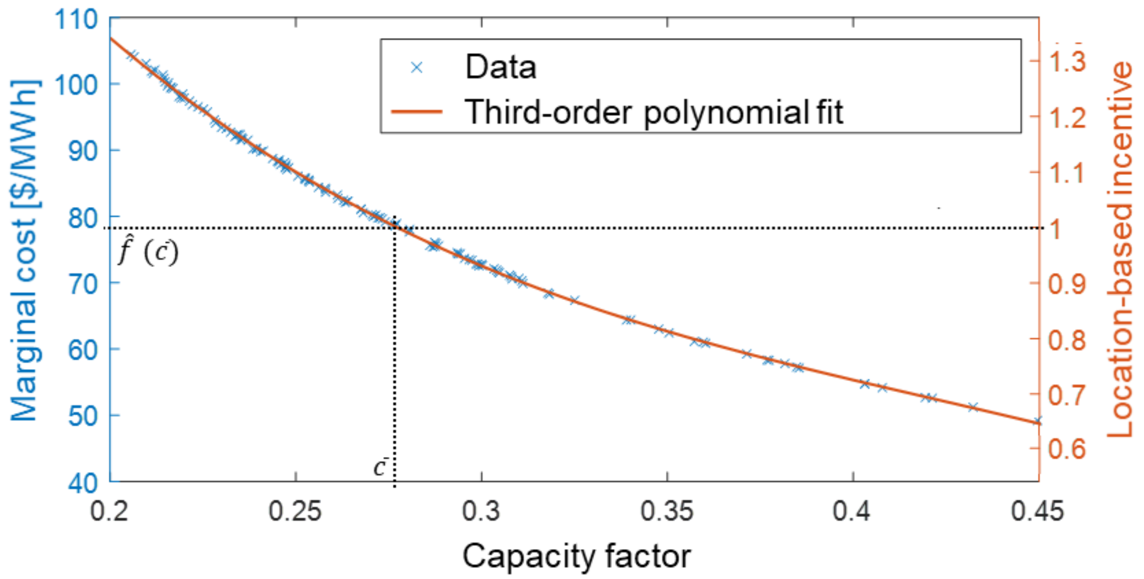

Figure 17. Determined optimal location-based incentives for wind farms in Mexico.

In order to weaken the link between competitiveness and wind resources, the spatial distribution model is applied to the data and parametrizes the link between marginal cost and capacity factor by means of an ordinary least squares regression. The best regression fit $\hat{f}(c)$ was conducted for a third-order polynomial model:

$$\hat{f}(c) = 269.19 - 1249.68 * \mathrm{c} + 2564.06 * \mathrm{c}^2 - 1943.00 * c^3$$

with c as the capacity factor. In order to shape the results of upcoming auction rounds toward the desired spatial distribution of wind energy deployment, the regression fit is used to adjust the bids of auction participants according to the following rationale:

$$b_a = b * \frac{\hat{f}(\bar{c})}{\hat{f}(c)}$$

where b is the original bid, b_a is the adjusted bid and $\bar{c}$ is the capacity factor of the reference wind farm, such that all bids are adjusted relative to the reference location. By applying the regression fit the resource-based competition is reduced as it increases the bids of projects with higher resource availabilities and reduces the bids of projects with lower resource availabilities than the reference wind farm. Differences in resource availabilities no longer affect competition and new wind energy capacity is uniformly distributed among all selected locations. For the selected 115 locations in Mexico, a uniform distribution of capacity would reduce the standard deviation of the hourly capacity factors by 15.92%, while maintaining the average capacity factor of the current Mexican wind fleet.

5. Interdisciplinary Techno-Economic Optimization of the Structural Design of Offshore wind Turbines

This section refers to the article "Influence of Structural Design Effects on Economic Viability of Offshore Wind Turbines: An Interdisciplinary Analysis" (see Appendix 7). The author of this thesis wrote the article in cooperation with Clemens Hübler, Christian G. Gebhardt and Raimund Rolfes (Institut für Statik und Dynamik, LUH) as well as Chris Stetter and Michael H. Breitner (IWI, LUH). The article was submitted to Renewable Energy on 04.05.2018. After a double-blind peer review process with four revision rounds the authors received an acceptance for publication on 20.06.2019. Renewable Energy is a peer-reviewed journal published by Elsevier and covers research on renewable and sustainable energy and the energy transition from various disciplines. It had an impact factor of 4.900 in 2017 and a 5-Year impact factor of 4.981. The article has a strong interdisciplinary nature, since it combines an engineering model provided by the researchers from Institut für Statik und Dynamik, LUH with the financial modelling approach described in Section 2 and Section 3 in order to optimize the structural design of offshore wind turbines from engineering perspective against the background of an economic objective function.

5.1. Introduction and Theoretical Background

Even though offshore wind energy is a progressively developing business sector (Kaldellis and Apostolou, 2017) and a promising power supply type to reach the goals set for renewable energy deployment, its levelized cost of electricity is still high compared to other conventional as well as renewable energy technologies (EIA, 2017). Offshore wind energy is not yet cost-competitive without additional financial support (Mbistrova and Nghiem, 2017), as current electricity market prices do not enable economically viable operation of offshore wind farms. Accordingly, improving cost efficiency of offshore wind farms is the major objective of current research in this business sector. Optimizing the design of substructures and foundations regarding costs and reliability is one favorable strategy to enhance cost efficiency, as these components cause nearly 20% of the overall offshore wind farm CAPEX (Prognos and Fichtner, 2013). In order to reach cost efficiency improvements, a change in paradigm for optimal designs is needed. State-of-the-art optimization approaches merely focus on minimizing the overall costs of structural designs. However, finding cost-efficient designs for substructures and foundations requires analyzing and optimizing the trade-off between variable lifetime and component costs in interdisciplinary approaches. Such interdisciplinary approaches, combining complex engineering and economic models and features of structural designs, are rare.

A comprehensive review of engineering optimization approaches is given by Muskulus and Schafhirt (2014). They demonstrate that most approaches typically minimize the mass of structural designs as a cost indicator (Lee et al., 2014; Kallehave et al., 2015; Häfele and Rolfes, 2016; Oest et al., 2017). Some rare examples apply cost models instead of weight considerations and approximate the overall costs by empirical formulations considering material, production, and installation costs (Maness et al., 2017; Farkas and Jármai, 2013). Nevertheless, these models do not evaluate the effects of lower weights/costs of substructures and foundations on the economic viability of the entire offshore wind farm, as economic features, as for example risk-adjusted discount rates and variable lifetimes, remain unconsidered. However, setting the lifetime of structural designs to deterministic values disables optimizing the trade-off between lifetime and costs. Ziegler et al. (2018) were the first to present an approach allowing for variable lifetimes in engineering models for offshore wind turbines, although they dispense with complex economic features and merely focus on the trade-off between variable lifetimes and weights of structural designs.

As with most engineering models, economic models consider the lifetime of offshore wind turbines as a constant value mostly set to 20 years and treat substructures and foundations as a single CAPEX input (Salo and Syri, 2014; Ederer, 2014; Gernaat et al., 2014). Although some economic analyses conduct sensitivity analyses with respect to the deterministic lifetime, they renounce considering dependencies of the lifetime on other model inputs (Afanasyeva et al., 2016;

Raadal et al., 2014). Rubert et al. (2018) were the first to analyze the effects of lifetime extension measures for onshore wind turbines on the levelized cost of electricity by linking the deterministic lifetime to model inputs, as for example retrofits of different components.

The substantial variability of offshore conditions however requires applying probabilistic approaches, as they lead to very different economic effects resulting from varying structural designs and their stochastic lifetimes. As comprehensive probabilistic economic analyses considering the complex effects of structural designs on the trade-off between lifetime and offshore wind turbine costs were not found, a combination of an aero-elastic offshore wind turbine model with an economic viability model is presented in this study in order to address the research gap. The RQ to be answered with the combined model is as follows:

RQ: "*How can the structural design of an offshore wind turbine be optimized with regard to the risk-return ratio over the entire operational lifecycle?*"

5.2. Methodology

5.2.1. Aero-elastic wind turbine model

Nonlinearities, transient load cases, scattering environmental conditions, strongly coupled subsystems and other specific features lead to a highly complicated dynamic offshore wind turbine behavior. Consequently, standards for design requirements of offshore wind turbines demand aero-hydro-servo-elastic simulations conducted in time domain for designing turbines. In this study, the NREL FASTv8 software code is used to simulate the NREL 5MW reference wind turbine (Jonkman et al., 2009) under consideration of the OC3 phase I monopile as the substructure (Bak, 2013), since it is capable of simulating the different coupled systems in real-time (Jonkman, 2013). Using FASTv8 different design changes of the OC3 monopile are simulated in order to enable simulating their effects on the economic viability of the entire offshore wind turbine. In this regard, the aero-elastic model enables calculating time series of forces and moments acting on all substructure components based on several environmental conditions. As fatigue damages are most critical, the design of steel is focused and time-series are postprocessed, to estimate the fatigue lifetime. The simulations are run in accordance with current standards and previous research: 10 minutes simulation length and between 60 to 720 seconds run-in time (Jonkman and Musial, 2010). In addition to the FASTv8 software code, the software TurbSim (Hübler et al., 2017) is used for the turbulent wind field calculations based on the Kaimal model and irregular waves are computed with the JONSWAP spectrum.

With FASTv8 time series of forces and moments can be simulated for a given set of environmental conditions. However, in order to enable computing well-founded lifetime estimations, a sufficient number of changing load cases need to be considered, such that the entire offshore wind turbine lifetime is depicted by these load cases. In doing so, current research proposes two different approaches: a deterministic, design load case based approach, as demanded by offshore wind turbine design standards, or a probabilistic, equally distributed MCS approach (Jonkman and Kilcher, 2012). The latter enables simulating more iterations for high wind speeds with very low probability mass, such that errors occurring from limited sampling can be reduced. The probabilistic approach is applied using various PDF for wind speeds and directions, wave heights, periods, turbulence intensities, and wind shear exponents derived from measurement data of the FINO3 mast in the North Sea (Jonkman and Musial, 2010).

The entire procedure used to calculate the substructure lifetime is the probabilistic lifetime calculation proposed in Hübler et al. (2018). As stresses are concentrated in the monopile welds, the procedure intends the welds to be exposed to higher fatigue damages than the other parts of the monopile. Consequently, Eurocode 3, part 1-9 is used to calculate hot spot stresses at transversal welds and the size effect of the monopile wall thickness is applied as an additional stress concentration factor (Zwick and Muskulus, 2015). The design driving hot spot shown in Figure 18, for which the lifetime calculation is conducted, is at mudline, as this location is being exposed to the highest bending moments. A detailed mathematical description of the applied procedure is given in Hübler et al. (2018).

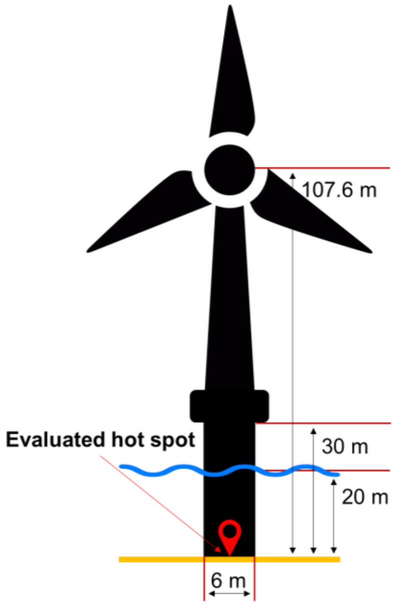

Figure 18. Identification of evaluated hot spot at offshore wind turbines.

In order to ensure calculating substructure design-dependent costs in addition to the lifetime probability distributions, a cost model for offshore wind turbine substructures by Häfele and Rolfes (2016) is applied. The CAPEX include costs for the monopile, transition piece, tower, and several secondary components. The monopile costs, in turn, include costs for raw materials, welding, fixed production, and coating. Following Maness et al. (2017) and de Vries et al. (2011) material costs are set proportional to mass, welding costs to weld volume, and coating costs to surface area. The tower costs are derived from Bjerkseter and Ågotnes (2013), while the transition piece costs are determined by Maness et al. (2017).

5.2.2. Economic viability model

The economic viability model used in this study is a combination of the financial model presented in Section 2 and the optimization approach presented in Section 3. It is used to enable evaluating the cost efficiency of offshore wind turbine substructure designs based on corresponding lifetime and electricity yield PDF as well as cost estimates provided by the aero-elastic wind turbine model. Figure 19 illustrates the combination of both models realized with a programming interface.

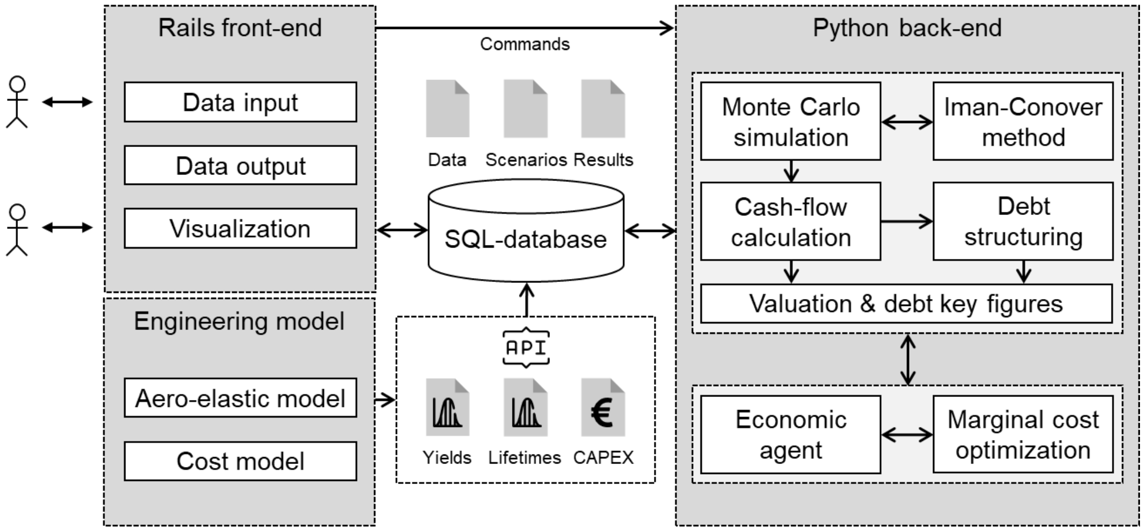

Figure 19. Amendment of DSS architecture by the engineering model.

In order to enable estimating the cost efficiency of different substructure designs, the combined models need to be applied to an entire offshore wind farm given each individual substructure design. For each substructure design the economic viability model yields the marginal cost of the entire wind farm, which is utilized as the competitiveness criterion for comparison of various substructure designs according to the following rationale: the lower the marginal cost of the wind farm, the higher the cost efficiency of the substructure design under investigation.

5.3. Applicability Check: Optimal Monopile Designs for Offshore Turbines of a German Wind Farm

5.3.1. Data

The coupled models were applied to an offshore wind farm located in the German exclusive economic zone of the North Sea as part of a case study in order to determine the economically optimal structural designs. For this purpose, seven different substructure designs were evaluated. Table 13 shows the different designs and their corresponding changes in diameters and wall thicknesses compared to the reference design as well as the corresponding lifetimes and costs. The latter were calculated using the cost model by Häfele and Rolfes (2016).

Table 13. Cost and lifetime data of investigated substructure designs.

	Substructure designs						
	Ref	D+	D-	t+	t-	Dur	Chp
Change in diameter	-	+1%	-1%	-	-	+1%	-1%
Change in wall thickness	-	-	-	+2%	-2%	+2%	-2%
Substructure cost [€M]	2.84	2.87	2.81	2.88	2.80	2.91	2.78
Lifetime: expected value [years]	23.4	26.6	22.7	26.7	21.0	30.2	17.3
Lifetime: coefficient of variation	0.086	0.091	0.066	0.076	0.094	0.068	0.084

In addition to the statistics shown in Table 13, Figure 20 shows the lifetime PDFs of the different substructure designs, which were simulated using the aero-elastic wind turbine model.

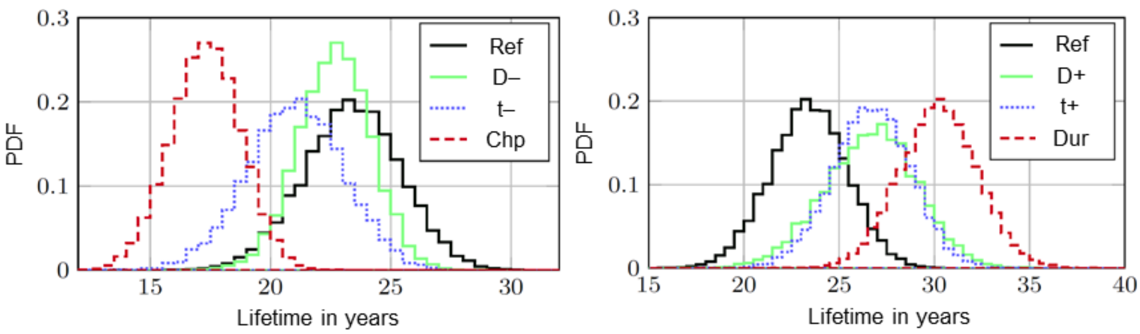

Figure 20. Lifetimes of investigated substructure designs.

The PDFs and statistics for the cheaper designs indicate that decreased diameters and wall thicknesses result in lower cost, on the one hand, but also lead to lower mean lifetimes compared to the reference design, on the other hand. Analogical results are apparent for the durable designs, which feature higher costs, but also higher mean lifetimes than the reference design. This trade-off between cost and lifetime has diametrical effects on the profitability and financial soundness of an offshore wind farm from investors' perspective.

Consequently, the different substructure designs and their corresponding costs and lifetimes were additionally evaluated using the economic viability model in order to find the most cost-efficient design. Table 14 shows the project characteristics of the offshore wind farm under investigation.

Table 14. Financial data of a reference offshore wind farm in Germany.

	Value
Distance to shore [km]	10
Distance to port [km]	20
Water depth [m]	20
Turbine	80x NREL 5 MW
Commissioning date	01.01.2020
Operation [years]	Lifetime PDF
Corporate tax rate [%]	31
Cost of debt [%/year]	3.5
Unlevered cost of equity [%/year]	5.6
Debt service period [years]	16
Wind resource	Wind speed PDF
Farm efficiency [%]	74
CAPEX [€M]	994 + Substructure cost PDF
OPEX [€M/year]	24
DECEX [MXNM]	40.8
Straight line depreciation [years]	16
Provision expenses [%]	5.5

5.3.2. *Discussion of Results*

The economic viability model is applied to the project characteristics given each substructure design separately. Table 15 shows the resulting marginal cost of the offshore wind farm for each substructure design as well as their change compared to the reference design. In addition, Figure 21 shows the APV PDF of the wind farm under consideration of the different substructure designs and given the marginal cost of 8.57 ct/kWh calculated for the reference design.

Table 15. Marginal cost of investigated substructure designs.

	Marginal cost [ct/kWh] (deviation from Ref)			
	unltd	max30	max25	max20
Ref	8.75 (0.00 %)	8.57 (0.00 %)	8.59 (0.23 %)	8.99 (4.84 %)
D+	8.28 (-3.39 %)	8.28 (-3.39 %)	8.44 (-1.57 %)	8.99 (4.91 %)
D-	8.64 (0.76 %)	8.64 (0.76 %)	8.64 (0.79 %)	**8.97 (4.68 %)**
t+	8.27 (-3.50 %)	8.27 (-3.48 %)	8.43 (-1.71 %)	9.00 (4.94 %)
t-	8.85 (3.25 %)	8.85 (3.25 %)	8.85 (3.26 %)	9.03 (5.40 %)
Dur	**8.03 (-6.29 %)**	**8.08 (-5.70 %)**	**8.41 (-1.87 %)**	9.01 (5.08 %)
Chp	9.50 (10.90 %)	9.50 (10.90 %)	9.50 (10.90 %)	9.51 (10.90 %)

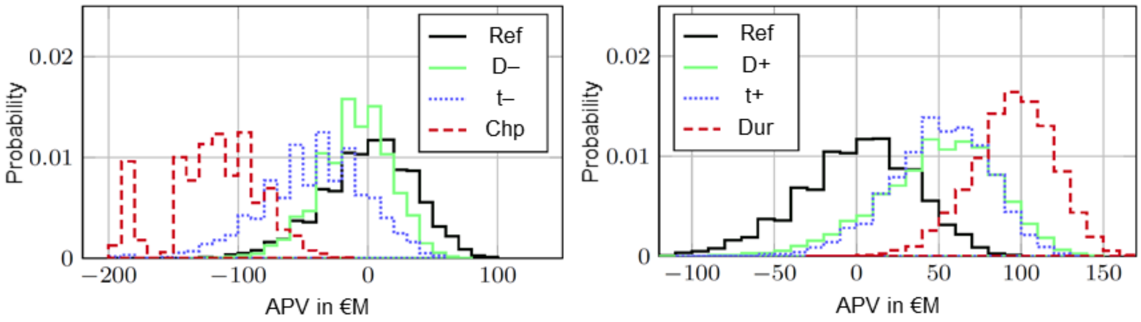

Figure 21. APV of investigated substructure designs.

The corresponding expected APV and unlevered IRR are shown in Table 16. The results of the coupled models indicate that the offshore wind farm has the lowest marginal cost considering the durable substructure, which has the highest cost but the longest expected lifetime. Thus, according to the specified competitiveness criterion, the durable design is the most cost-efficient solution among all substructures. Accordingly, the cheapest substructure has the highest marginal cost. Considering all substructures, the results show that the marginal costs decrease with increasing diameter and wall thickness. Therefore, given the present configuration (i.e., turbine, project characteristics, minor design changes, etc.), the following applies: the more durable a substructure design is, the more competitive it is compared to the reference design and vice versa.

Table 16. Mean APV and mean IRR of investigated substructure designs.

	APV [€M] (IRR)			
	unltd	max30	max25	max20
Ref	0 (5.56 %)	0 (5.56 %)	-3.14 (5.52 %)	8.0 (4.54 %)
D+	49.4 (6.25 %)	48.6 (6.24 %)	21.8 (5.91 %)	8.9 (4.53 %)
D-	-10.1 (5.42 %)	-10.1 (5.42 %)	-10.6 (5.42 %)	**8.9 (4.58 %)**
t+	50.4 (6.27 %)	50.0 (6.27 %)	23.8 (5.95 %)	9.3 (4.53 %)
t-	-41.7 (4.84 %)	-41.7 (4.84 %)	-41.9 (4.84 %)	9.2 (4.39 %)
Dur	**95.1 (6.76 %)**	**85.4 (6.67 %)**	**26.3 (5.98 %)**	9.1 (4.50 %)
Chp	-125 (2.94 %)	-125 (2.94 %)	-125 (2.94 %)	125 (2.94 %)

However, these results are based on the assumption of an unlimited lifetime of all other turbine parts, i.e., the lifetime of the offshore wind farm only depends on the lifetime PDF of the different substructure designs. If a maximum lifetime of 25 or 30 years is introduced, the APV PDF of the more durable designs have a negative skew, since they depend heavily on the lifetime PDF, which is also skewed due to the truncation. Given the limited lifetime, the positive effects of increased lifetime are reduced as the full lifetime potential of the substructures is not fully exploited. This means that the cost efficiency of the more durable design is overestimated for the unlimited case. Nevertheless, the most durable design is still the most cost-efficient. Therefore, it is recommendable to slightly overdesign the monopile. This changes if the maximum lifetime is set to 20 years. Given this lifetime limit, it becomes clear that a significant overdesign leads to lower cost-efficiency. Table 15 shows that in this case a cheaper design is the most cost-effective solution. Nonetheless, it follows that cheap designs with an expected life expectancy of significantly less than 20 years should be avoided and that more durable designs with higher expected lifetimes are promising in most cases.

6. Interdisciplinary Optimization for the Design of Cost-Efficient Dismantling and Disposal Networks for Wind Turbines

This section refers to the article "An Optimization Model to Develop Efficient Dismantling Networks for Wind Turbines" (see Appendix 5). The author of this thesis wrote the article in cooperation with Martin Westbomke, Peter Nyhius, and Malte Stonis (Institut für Integrierte Produktion Hannover gGmbH, LUH) and Michael H. Breitner (IWI, LUH). The article has been presented on 14.09.2017 at the International Conference on Operations Research in Berlin hosted by the German Operations Research Society. The article has been published in the peer-reviewed Operations Research Proceedings 2017 on 26.05.2018, which received the ranking "D" in the VHB/JQ3. The research presented in this section is a significantly expanded version of the article published in Operations Research Proceedings 2017. Like the article presented in Section 5, this article has a strong interdisciplinary nature, as the author of this thesis developed the optimization model published in this article in close cooperation with Martin Westbomke considering economic, engineering, and logistical aspects related to the dismantling and disposal of wind turbines.

The cooperation with the researchers from Institut für Integrierte Produktion Hannover gGmbH began already back in March 2016. The results of the optimization model were published in several specialist journals highly recognized in the German wind energy sector, which has led to a close interaction with practitioners. The latter was further deepened by the scientists setting up a working group in 2016. Since then, the interdisciplinary working group, consisting of operators, project developers, wind turbine manufacturers, consultancies, dismantling contractors, disposal companies as well as research, public and political institutions, has met every six months as part of the so-called "Demontagenetzwerktreffen" (dismantling network meeting). The meetings create opportunities to regularly share and discuss the parties’ current challenges and to develop joint solutions for the dismantling, disposal and recycling of aging wind turbines.

6.1. Introduction

Since 1997, approximately 1,250 wind turbines were installed in Germany in average per year, such that more than 27,000 turbines are in operation in German on- and offshore areas today. These wind turbines are typically designed to be operated for 20 to 25 years (Haapala and Prempreeda, 2014), while the financial support according to the German EEG is guaranteed until 31st December 2020 or for 20 operational years for all wind turbines being commissioned after 31st December 2000. Many of these affected wind turbines are likely to be decommissioned after 20 years of operation. If possible, in terms of distance control to adjacent areas/buildings, some wind turbines will be decommissioned even before the EEG expires in order to be replaced by new and more efficient wind turbines as part of repowering projects (Wallasch et al., 2017). Figure 22 shows an overview of the amount of German onshore wind turbines, which are likely to reach the end of their technical and/or economic lifetime until 2025.

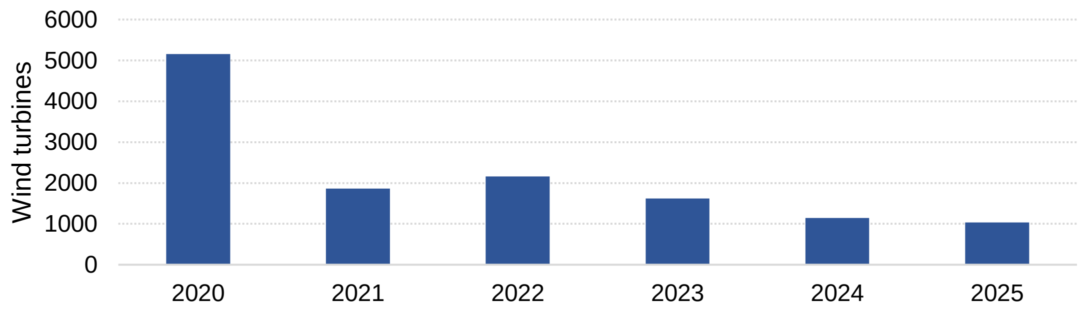

Figure 22. Number of post-EEG wind turbines until 2025.

The forecasted numbers indicate a massive increase of dismantling assignments in upcoming years due to repowering or decommissioning, which will lead to millions of costs for current operators. Furthermore, dismantling and disposal companies must manage lots of dismantling projects as well as the disposal and recycling of thousands of tons of wind turbine components.

Worldwide, aging onshore wind turbines are currently dismantled entirely on-site, which means that the complete dismantling and crushing processes, including the cracking of rotor blades, separation of tower elements, and the cutting of nacelles, are conducted on the “green field”. Such an undistributed dismantling is highly time-consuming (requires approximately two weeks per wind turbine) and implies risks and challenges of ecological (causes pollution through harmful liquids and particles), economic (can cost more than 100,000 € per wind turbine), and logistical (requires manifold dismantling infrastructure) kind. Furthermore, as the comprehensive and expensive dismantling infrastructure needs to be transported to the wind farm site, its operating capacity is insufficiently utilized and the machineries block the space needed to realize potential repowering projects, resulting in costly delays in the construction of new wind turbines.

An option to supersede the undistributed dismantling is to establish a network allowing for a partial dismantling of specific wind turbine components on-site and a later transportation of the partly dismantled components to specialized dismantling sites for further handling. At these specialized dismantling sites, the complex components can be better refined, which enables generating higher revenues from selling the raw materials. Moreover, such a network permits a better utilization and specialization of the dismantling infrastructures' capacity available at the dismantling sites, which significantly reduces the costs for the necessary dismantling steps. However, the distributed dismantling in networks also implies additional costs caused by the additional and complex transportation of largescale components as well as the initialization of the specialized dismantling sites. Hence, dismantling companies designing dismantling networks for wind turbines are faced with the trade-off between dismantling and transportation costs, which is optimally handled by finding the optimal dismantling depth for each wind turbine component as well as the optimal location of the specialized dismantling sites.

In the research field of reverse logistics, such location and allocation problems are extensively investigated (Subramoniam et al., 2010), as for example for end-of-life handling of batteries (Kannan et al., 2010), electrical devices (Qinghua et al., 2010) and vehicles (Cruz-Rivera and Ertel, 2009). However, studies focusing on the dismantling of largescale products, where the dismantling needs to begin on-site, are rare, which limits the extent to which existing solutions can be applied to the dismantling of wind turbines (Behrens et al., 2014). Therefore, this study aims at developing and evaluating a new optimization model for the design of efficient dismantling networks for the end-of-life handling of wind turbines. Consequently, the investigated RQ is as follows:

RQ: “*How can the cost-efficiency of the dismantling and disposal processes for wind turbines be optimized by an optimal dismantling network design?*”

6.2. Theoretical Background and Literature Review

In order to answer the proposed RQ, the optimization model developed and evaluated in this study is utilized to design cost-optimal dismantling networks for wind turbines and to permit comparing the resulting costs of the distributed dismantling with the current state-of-the-art. In the network, the optimal ratio between the more expensive on-site dismantling and the cost-intensive transport of individual turbine parts to specialized dismantling factories is to be achieved. In this regard, the masses of the turbine parts and the transport distances must be taken into account. Hence, the underlying optimization problem is a quadratic allocation problem, as the allocation of the turbine parts is depending on the transport costs and the dismantling costs at the (potential) dismantling or disposal locations always results in at least one quadratic constraint or a quadratic objective function, given the problem is not linearized.

Koopmans and Beckmann (1957) were the first to propose transferring quadratic allocation problems to economic decisions. They found that an economic decision made for one location in a network is not independent of the decisions at all other locations. Applying their findings to the described location planning and allocation problem means that a decision for an initialization of a dismantling site depends not only on the dismantling costs to be paid there, but also on the transport costs that may arise before or after the dismantling process at the corresponding site. Furthermore, the decision depends on the dismantling costs at other locations. Accordingly, there is an antagonistic relationship between transport costs and dismantling costs, if the total network costs are to be minimized: a low (high) dismantling depth at the site with relatively low (high) dismantling costs causes high (low) transport costs.

The only study dealing with the topic of reverse logistic networks for the end-of-life handling of wind turbines is by Cinar and Yildirim (2017). Their developed mixed integer linear programming model enables determining a long-term strategy for the dismantling of wind turbines that minimizes the sum of transportation and operation costs in a dismantling network by determining optimal locations for recycling and remanufacturing sites. Nevertheless, their model is limited to the assumption of fixed component sizes and constant dismantling depths. Given the trade-off between transportation and dismantling costs, the consideration of variable depths is, however, essential for the network optimization.

In order to address this research gap, the optimization model developed in this study considers both the optimal locations of specialized dismantling sites as well as the optimal dismantling depths of each specific wind turbine component. The model allocates each dismantling task of each considered wind turbine to either the wind turbine site or a specialized dismantling site. Figure 23 illustrates the dismantling process according to (Andersen et al., 2016; Januário et al., 2007) starting with the pre-decomposition into the three components rotor, nacelle and tower. The three subsequent disassembly tasks of each component are then carried out one after another. Figure 24 further shows the three possible dismantling strategies, where a wind turbine is dismantled in a multi-stage and distributed process (II) or in an undistributed process completely on-site (I) or completely at the disposal site (III).

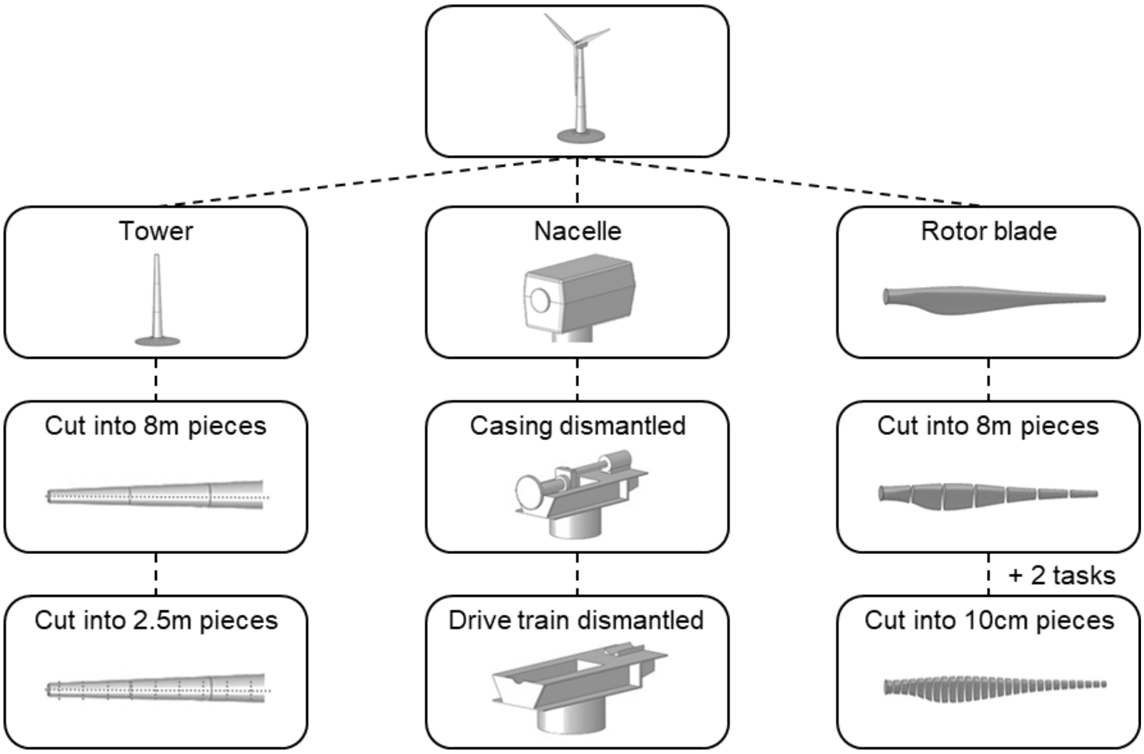

Figure 23. Process steps of dismantling a wind turbine.

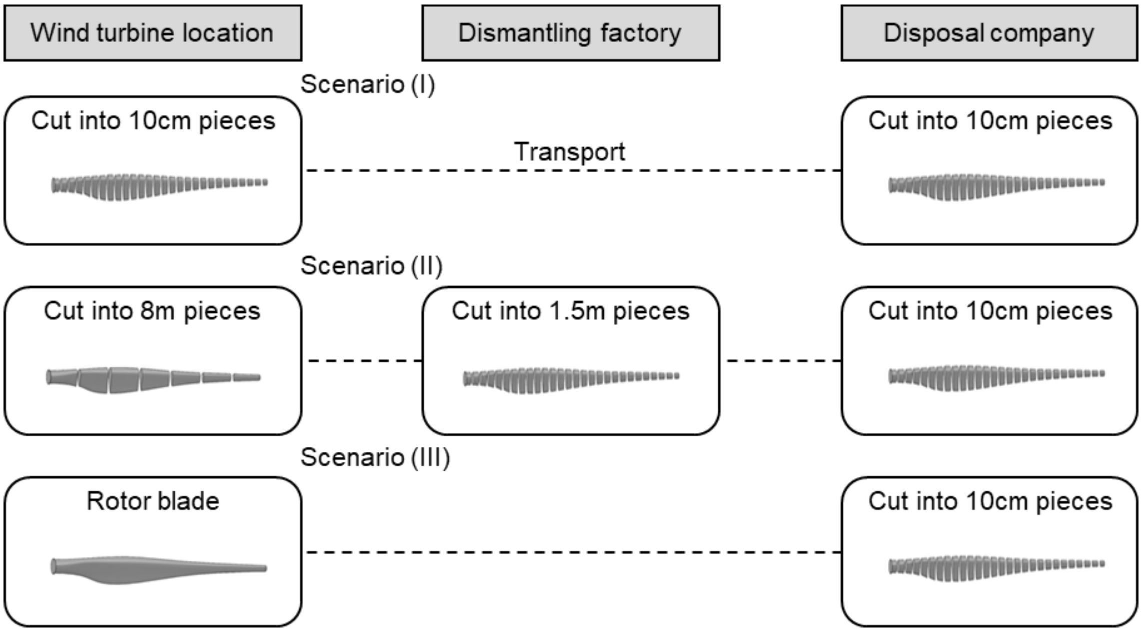

Figure 24. Distributed vs. undistributed dismantling.

6.3. Methodology

The optimization model for the efficient design of a dismantling network for decommissioned wind turbines belongs to the class of Koopmans-Beckmann problems. Accordingly, the Koopmans-Beckmann modeling approach was transferred and adapted to the optimization problem. Table 17 shows the model notation and Table 18 the required model assumptions. The optimization model is described through the equations shown in Table 19.

Table 17. Dismantling network optimization: indices, variables and parameters.

Index	Description
$w = \{1, 2, \dots, W\}$	Wind turbines
$f = \{W+1, W+2, \dots, F\}$	Dismantling factories
$g = \{F+1, F+2, \dots, G\}$	Disposal companies
$k \in W, F, G$	All locations
$l \in F, G$	Dismantling factory and disposal company locations
$m = \{1, 2, \dots, M, M+1\}$	Dismantling tasks

Variable		Description
y_{wkm}	$= \begin{cases} 1, \\ 0, \end{cases}$	if the dismantling task m of wind turbine w takes place at location k else
x_{wklm}	$= \begin{cases} 1, \\ 0, \end{cases}$	if a transport is carried out from location k to location l else
v_k	$= \begin{cases} 1, \\ 0, \end{cases}$	if a dismantling factory is opened at location k else

Parameter	Description
d_{wkm}	Dismantling costs (in €) at location k for dismantling task m of wind turbine w
o_m	Fixed transport and loading costs after dismantling task m
c_{wm}	Transport cost (in €/km) after dismantling task m of wind turbine w
δ_{kl}	Distance (in km) between locations k and l
i_k	Initialization costs (in €) for a dismantling factory at location k

Table 18. Dismantling network optimization: assumptions.

Assumption	Description
A1	The wind turbine locations are fixed and known.
A2	The disposal company locations are fixed and known.
A3	The locations of potential dismantling factories are known and dismantling factories can be opened at these locations as required.
A4	All dismantling tasks must be carried out consecutively in a specified sequence starting with the pre-dismantling.
A5	The pre-dismantling (first task) of each wind turbine into rotor blades, nacelle and tower takes place at the wind turbine location.
A6	The disposal (final task) of each wind turbine takes place in the disposal companies.
A7	The dismantling factories and disposal companies have no capacity limits and can handle all dismantled wind turbines.
A8	A secondary market for the sale of end-of-life wind turbines does not exist. All wind turbines have to be dismantled and disposed.

The optimization model minimizes the total costs for the dismantling of wind turbines within a period in a network of wind turbine, potential dismantling factory and disposal company locations. The objective function (1) is divided into three summands, whereby the first summand (1.1) covers the transport costs, the second summand (1.2) the dismantling costs and the third summand (1.3) the initialization costs. The optimization model takes several constraints into account.

Constraint (2) refers to the model assumption (A3) and stipulates that a dismantling factory is opened as soon as at least one dismantling task $m \in M - 1$ is carried out at the location of the dismantling factory or disposal company respectively. There are no initialization costs for the dismantling task $m = M$, which must be carried out at the site of a disposal company in accordance with the model assumption (A6). Constraint (3) refers to the model assumption (A4) and stipulates that a dismantling task must be followed by either a transport from the wind turbine or dismantling factory location to another dismantling factory or disposal company location or the next dismantling task to be carried out at the current wind turbine or dismantling factory location. The transport condition (4) supports transport condition (3) and provides that a transport between two locations is only recorded if two successive dismantling tasks of a wind turbine are carried out consecutively at these locations.

Table 19. Dismantling network optimization: equations.

Equation		
$min\ Z = \sum_{w=1}^{W}\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{m=1}^{M}(o_m + c_{wm} * \delta_{kl}) * x_{wklm}$		(1.1)
$+ \sum_{w=1}^{W}\sum_{k=1}^{K}\sum_{m=1}^{M} d_{wkm} * y_{wkm}$		(1.2)
$+ \sum_{k=1}^{K} i_k * v_k$		(1.3)
under the constraints		
$\sum_{m=1}^{M-1} y_{wkm} \leq v_k * M$	$\forall\ w \in W, k \in F \cup G$	(2)
$\frac{(y_{wkm} + y_{wlm+1})}{2} \geq x_{wklm}$	$\forall\ w \in W, k \in K, l \in K, m \in M, k \neq l$	(3)
$x_{wklm} - y_{wkm} - y_{wlm+1} \geq -1$	$\forall\ w \in W, k \in K, l \in K, m \in M, k \neq l$	(4)
$y_{wkm} = 1$	$\forall\ w \in W, k \in W, k = w, m = 1$	(5)
$\sum_{k=1}^{K} y_{wkm} = 1$	$\forall\ w \in W, m \in M$	(6)
$\sum_{k=F+1}^{G} y_{wkm} = 1$	$\forall\ w \in W, m = M$	(7)
$y_{wkm} \in \{0,1\}$	$\forall\ w \in W, k \in K, m \in M$	(8)
$x_{wklm} \in \{0,1\}$	$\forall\ w \in W, k \in K, l \in K, m \in M, k \neq l$	(9)
$v_k \in \{0,1\}$	$\forall\ k \in K$	(10)

Constraint (5) refers to the model assumption (A5) and stipulates that the first dismantling task of a wind turbine must always be carried out at the location of the wind turbine. Constraint (6) stipulates that each dismantling and disposal task of each wind turbine must be carried out once. Constraint (7) refers to the model assumption (A6) and stipulates that the last dismantling task of a wind turbine must be carried out in a disposal company and constraints (8), (9), and (10) define the binary variables of the optimization model.

6.4. Applicability Check: Optimal Dismantling Network for Wind Turbines in the Region of Osnabruck

6.4.1. Data

The optimization model is applied in the realm of a proof-of-concept in a case study of the region of Osnabruck. A dismantling network is designed and optimized for all 56 wind turbines that will reach the end of the EEG funding period at the end of 2020. It is assumed that these wind turbines have to be dismantled afterwards. Figure 25 shows the locations of the wind turbines, forty potential dismantling factories and six disposal companies. Only two disposal companies can handle the rotor blades, as they are specialized on glass-reinforced plastic (GRP). The distances between all locations were determined using Google Maps programming interface (API) and stored in a distance matrix.

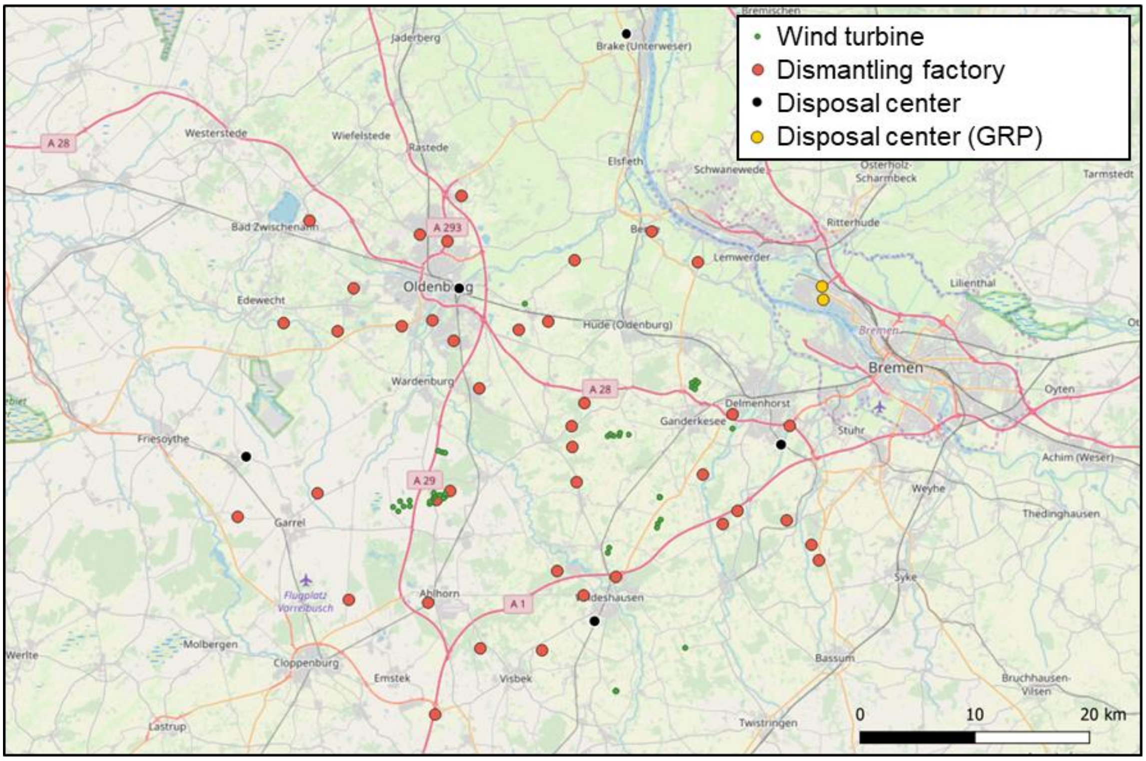

Figure 25. Locations of wind turbines, dismantling factories and disposal centers.

Table 20 provides an overview of the wind turbine types to be dismantled including the total weights of the rotor blades, nacelle, tower, and foundation. In addition, Table 21 contains the transportation and dismantling cost rates for the individual components. If a dismantling task is assigned to a potential dismantling factory or a disposal company, initialization costs of €10,000 are incurred for setting up the dismantling site.

Table 20. Number and weights of investigated wind turbine types.

Turbine type	Amount	Weight (tons)			
		Rotor	Nacelle	Tower	Foundation
AN Bonus 1.3MW/62	5	13	91.6	165.8	334.8
AN Bonus 150/30kW	1	2.5	21.8	80.6	57
Enercon E-18	1	2	21.8	80.6	57
Enercon E-30/3.30	1	5	68.4	106.6	135
Enercon E-40/5.40-500	6	6.4	71.9	106.6	180
Enercon E-66/15.66-1.500	7	14	100.2	188	672
Enercon E-66/18.70-1.800	9	17	100.2	188	404.8
Nordex N27/150	1	2.5	21.8	104.6	57
Nordex N60/1.300	8	13	91.6	122.8	334.8
Vestas V47-660kW	6	6.4	71.9	106.6	180
Vestas V66/1.65MW	6	14	89.8	122.8	410
Vestas V80-2.0MW-2.000	5	20	120.3	287.5	672

Table 21. Dismantling tasks and corresponding costs.

	Task	Transport costs [€] per km and ton	Dismantling costs [€] per ton	
			On-site	Dismantling factory
Rotor	I.1 – Pre-dismantling	5.23	-	-
	I.2 – Cut into 8m pieces	0.25	250	125
	I.3 – Cut into 1.5m pieces	0.1	300	150
	I.4 – Cut into 1m pieces	0.075	350	175
	I.5 – Cut into 10cm pieces	0.05	400	200
Nacelle	II.1 – Pre-dismantling	1.12	-	-
	II.2 – Casing dismantled	0.25	35	30
	II.3 – Drive train dismantled	0.1	65	50
Tower	III.1 – Pre-dismantling	3.92	-	-
	III.2 – Cut into 8m pieces	1	20	10
	III.3 – Cut into 2.5m pieces	0.62	30	15

In addition, for the transport of only preassembled rotor blades, nacelles and towers, fixed transport and loading costs of 9,500€ are considered, as these components are large-capacity and heavy transports. The costs for the pre-dismantling depend on the hub height and the weight of the maximum load to be lifted and amount to € 20,000 for all wind turbines under investigation. The dismantling costs of the foundation at the wind turbine site were set to €60 per ton and the transport costs to the nearest disposal company are set to €0.60 per km and ton. Furthermore, costs and/or revenues are incurred for the disposal of the rotor blades (costs of €200 per ton), nacelle (revenues of €260 per ton) and tower (revenues of €180 per ton).

6.4.2. Discussion of Results

In order to design a cost-optimized dismantling network for the wind turbines under investigation, the optimization model is implemented in the "General Algebraic Modeling System" (GAMS) and applies to the described problem instance. At first, GAMS is used to investigate three different scenarios: (2) distributed dismantling in the dismantling network, (1) undistributed dismantling at the wind turbine site and (3) undistributed dismantling in the disposal company. On an Intel® Core™ i7-4710MQ CPU with 2.5 GHz, 20 GB RAM and Microsoft Windows 10 64-bit as operating system, the applied CPLEX Solver solves the problem instance of scenario (2) in 5 minutes given a relative optimization gap of 5%.

Figure 26 presents the optimal allocation of the dismantling tasks of an exemplarily selected wind turbine in the three scenarios. In addition, the dismantling factories opened in scenario (2) are shown in Figure 26. The results clearly show that the opened dismantling factories are placed centrally in the investigated region. In addition, each direction is covered by a dismantling factory, such that the capacity utilization per dismantling factory is optimized. Figure 27 shows the breakdown of the total costs into the different components. In addition, Table 22 shows the percentage allocation of the dismantling tasks across all wind turbines to the potential dismantling sites for scenario (2).

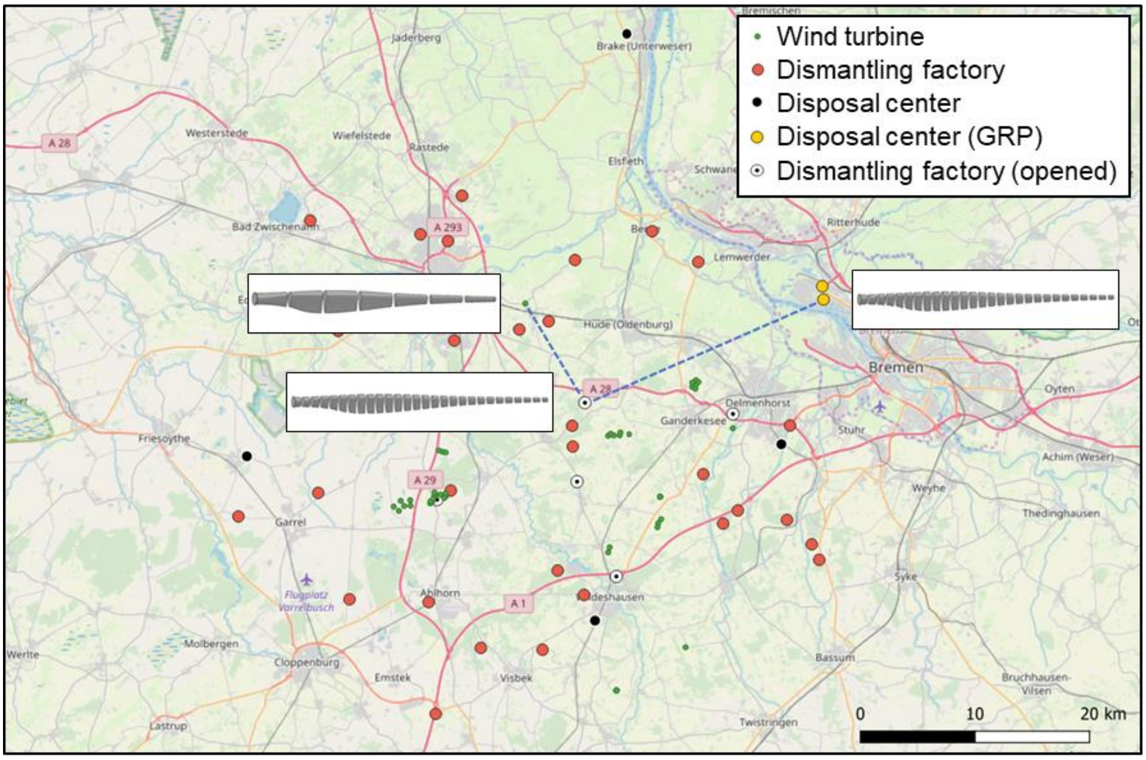

Figure 26. Optimal dismantling network design and exemplary process.

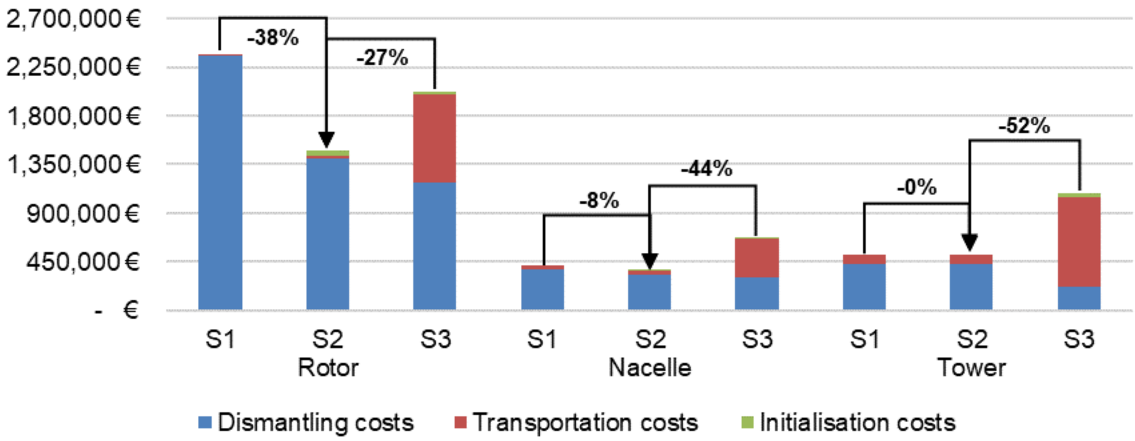

Figure 27. Undistributed vs. distributed dismantling: comparison of costs.

Table 22. Allocation of dismantling tasks: degree of distribution.

Location of dismantling	Ø	Rotor				Nacelle		Tower	
		I.1	I.2	I.3	I.4	II.1	II.2	III.1	III.2
On-site	50%	100%	0%	0%	0%	100%	0%	100%	100%
Dismantling factory	50%	0%	100%	100%	100%	0%	100%	0%	0%
Disposal company	0%	0%	0%	0%	0%	0%	0%	0%	0%

The results clearly indicate that a distributed dismantling and disposal of wind turbines in an optimally designed dismantling network has a high cost reduction potential compared to the current state-of-the-art. This applies in particular for the rotor blades, but also the distributed dismantling and disposal of the nacelle enables a significant cost reduction. For the tower and the foundation, however, undistributed dismantling at the location of a wind turbine remains the most cost-efficient method. This is due to the high influence of the transportation costs regarding these components within a potential dismantling network.

7. GIS-Based Analyses to Design Optimal End-of-Funding Strategies for Ageing Wind Turbines

This section refers to the article "Lifetime Extension, Repowering or Decommissioning? Decision Support for Operators of Ageing Wind Turbines" (see Appendix 6). The author of this thesis wrote the article in cooperation with Chris Stetter, Maximilian Heumann, and Michael H. Breitner (IWI, LUH) as well as Martin Westbomke (Institut für Integrierte Produktion Hannover gGmbH, LUH) and presented the article at the WindEurope 2019 Conference & Exhibition in Bilbao, Spain on 02.04.2019. The acceptance for article presentation at the conference and publication in the Journal of Physics was preceded by a double-blind peer review process, including two revision rounds. The WindEurope 2019 Conference & Exhibition is the world's most important on- & offshore wind conference. The article was presented in the session “Decommissioning Wind Assets: State-of-the-Art Practices” followed by a panel discussion with three other speakers.

7.1. Introduction and Research Background

At the end of 2020, more than 5,000 wind turbines (3.9 GW) located in Germany will reach the end of the feed-in tariff funding period under the Renewable Energy Sources Act (EEG). More than 8,000 turbines (12.5 GW) will follow by the end of 2025. The operators of affected turbines are therefore increasingly concerned with selecting and designing profitable and risk-bearing end-of-funding strategies. If it is technically feasible to extend the lifetime of the old turbines beyond the funding period, one possible option is trading the generated electricity directly or via contracts with trading companies on the European Energy Exchange (EEX). An alternative sales model for a lifetime extension is to conclude PPA with utilities or large industrial partners. Nevertheless, both sales models are likely to result in future prices per unit of electricity being significantly lower than the current feed-in tariff. This raises the question of the extent to which a lifetime extension beyond the EEG funding period is economically viable.

Therefore, besides a lifetime extension, repowering the old turbines with new and more efficient turbines is an interesting option for many operators, as this would lead to another twenty years of feed-in tariff funding given the repowering project is being awarded in the German renewable energy auctions. However, whether a repowering is approvable initially depends on various spatial aspects in the immediate vicinity of the location of the old turbines, which mainly concerns distances to built-up areas and other protected habitats. If both the lifetime extension and repowering are not feasible, only a permanent shutdown of wind turbine operation at the corresponding site remains as an option.

Selecting and designing optimal end-of-funding strategies for a given turbine or an entire wind farm are challenging tasks for different market players, since the economic viability of different options highly depend on various endogenous and exogenous factors. This end-of-funding challenge not only concerns the operator itself, but also incorporates various higher-level market players, which are responsible for implementing the different strategies. For example, this includes project developers and turbine manufactures for a repowering, maintenance service providers and trading companies for a lifetime extension, and logistics companies and recyclers for the dismantling and disposal. Current research tends to investigate the options of lifetime extension (e.g., Rubert et al., 2016; Rubert et al., 2018; Ziegler et al., 2018) and repowering (e.g., Colmenar-Santos et al., 2015; Serri et al., 2018 and Villena-Ruiz et al., 2018) separately. Research that combines both options to decide on the optimal lifetime extension and the corresponding optimal repowering timing (e.g., Madlener and Schuhmacher, 2011; Himpler and Madlener, 2014; Ziegler et al., 2016; Simón-Martín et al., 2019) is rare, although it is urgently needed. In order to support in finding optimal solutions to the arising end-of-funding challenge from the perspective of the various market players, a GIS is presented that allows to systematically evaluate the optimal choice between lifetime extension, repowering and decommissioning for operating wind turbines in Germany in different levels of detail, reaching from detailed analyses on single turbine or wind farm level up to macro-level analyses of entire wind fleets. By means of the GIS the following RQ is investigated:

RQ: "*How can optimal end-of-funding strategies for ageing wind turbines be designed on micro- and macro-level?*"

7.2. Methodology

The GIS processes comprehensive data on topography, wind resources, wind turbines as well as costs and revenues in an integrated system combining a wind resource model with a spatial planning model and an economic viability model. Figure 28 illustrates the combination of the three models.

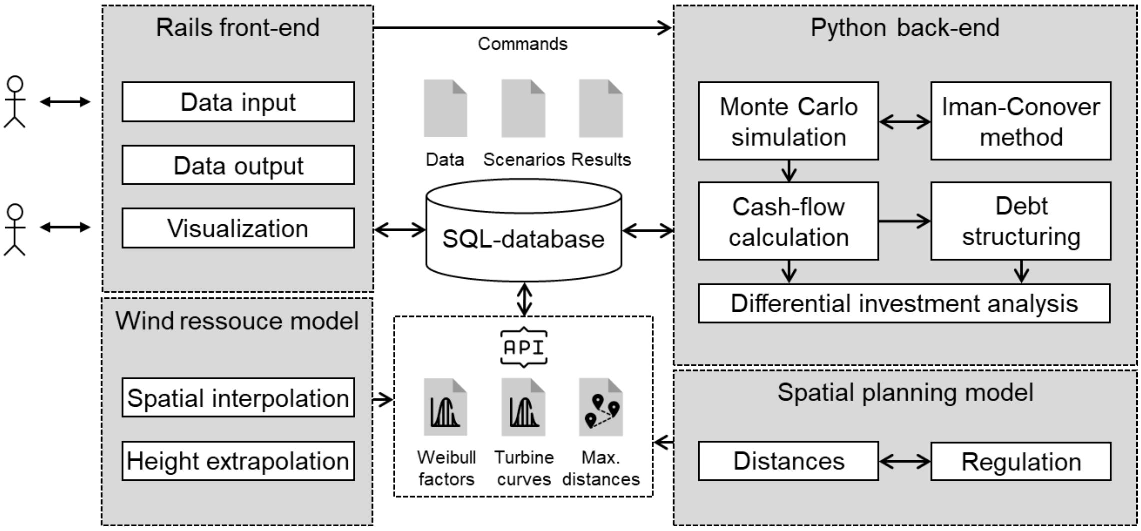

Figure 28. Amendment of DSS architecture by the spatial planning model.

7.2.1. Wind resource model

The wind resource model is an extension of the modelling approach presented in 4.3.1. It combines the VWF model of Staffell and Green (2014) with a spatial statistical downscaling approach following González-Aparicio et al. (2017). This is done by the following process: (1) acquisition of the hourly MERRA-2 wind speeds at 10m and 50m height spatially interpolated to the geographic coordinates of the selected location using LOESS regression according to the VWF model; (2) application of Weibull distribution fits to the wind speed time series; (3) acquisition of the Weibull distributions for the same heights and the closest grid points of the Global Wind Atlas (GWA) featuring micro-scale information using the in-situ roughness data from the European Space Agency's (ESA) Global Land Cover Map; (4) calculation of adjustment factors by means of a comparison between the MERRA-2 and GWA Weibull distributions; and (5) application of the adjustment factors to the MERRA-2 wind speed time series to feature the local wind characteristics as captured by the GWA. Afterwards, the resulting micro-scale wind data is fed into the VWF model for further handling.

7.2.2. Economic viability model

The economic viability model is an extension of the modelling approach presented in Section 2. In order to enable evaluating and comparing the different end-of-funding strategies a differential investment analysis following Madlener and Schuhmacher (2011) is added. A differential investment analysis allows DCF models to be used to compare investment alternatives with different characteristics, such as investment horizons. Consequently, this analysis permits evaluating the economic viability of both repowering and lifetime extension options simultaneously and implements an optimal stopping problem. The latter results in the optimal lifetime extension period and thus represents the optimal repowering timing, which determines the commissioning of the repowering project. The rational of the optimal stopping problem is to maximize the profitability (here: APV) of a hypothetical investment reflecting the difference between the cash-flow streams of the repowering and lifetime extension options. For this purpose, the differential investment analysis constantly compares the costs C and revenues R arising from postponing the start of the repowering project to a later period t and extending the lifetime of the old turbine. The optimal repowering timing is reached once the costs of the hypothetical investment equalize or exceed the revenues:

$$C_t \geq R_t \qquad \forall\, t \in T \tag{6.1}$$

Besides other factors, such as technological advances or the development of electricity spot market prices and feed-in premium levels in future auctions, the costs mainly relate to the additional discounting effect, which reduces the APV of the repowering project, while the revenues mainly include the additional revenues from the lifetime extension of the old turbine. In case both lifetime extension and repowering are not profitable when considered individually, the only option left is the permanent shutdown of the old turbine.

7.2.3. Spatial planning model

The spatial planning model investigates whether the location of an old wind farm is viable for a repowering against the background of spatial aspects, such as distance regulation regarding settlements and other built-up areas as well as relevant protection laws (e.g., nature conversation acts, landscape protection acts and immision protection acts). These regulations result in areas restricted for the operation of wind turbines. Since there are distance regulations which depend on the dimensions of a wind turbine (e.g., a minimum distance from settlements of ten times the turbine height), the calculated exclusion areas are not fixed, but depend on the choice of a repowering turbine.

Accordingly, it is not expedient to calculate the exclusion areas once and then check whether the location of a wind turbine is inside or outside an exclusion area. In order to decide on the spatial viability of repowering, it is rather necessary to calculate the minimum distances of a wind turbine to the individual protected areas and to compare these distances with the distances specified by the regulations considering the characteristics of a repowering turbine.

In the spatial planning model, this process is applied in parallel to a large number of wind turbines. For wind turbines located within an exclusion area, either a smaller repowering turbine must be specified or a lifetime extension remains the only end-of-funding option. In order to enable the described spatial analysis a multitude of available datasets on protected areas as well as the locations of over 27,000 turbines of the German wind fleet were implemented in a PostgreSQL-database and processed as well as visualized with the software QGIS. Figure 29 shows the collected and implemented shapefiles and wind turbine locations for the federal state Lower-Saxony.

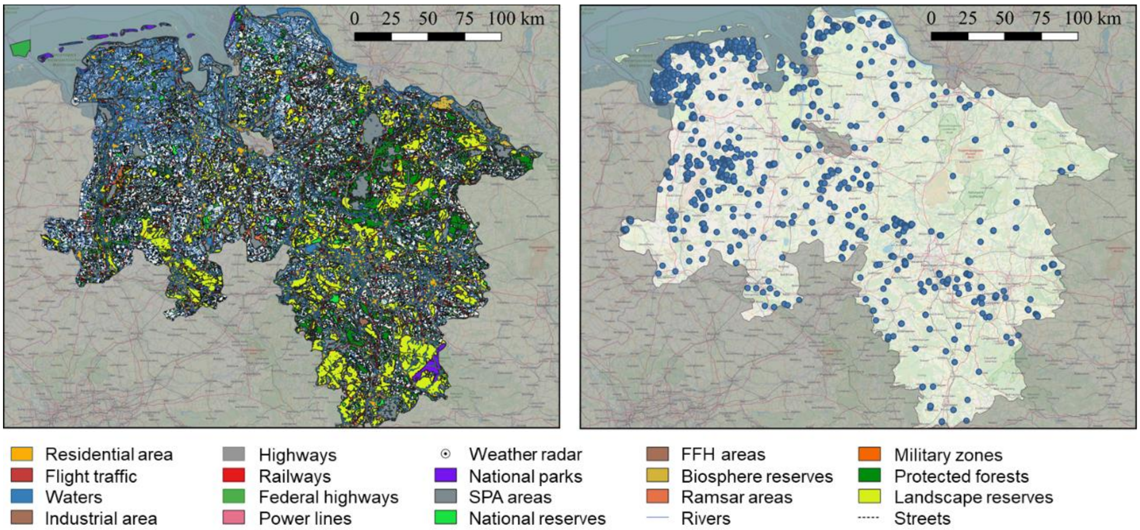

Figure 29. Protection areas (left) and locations of investigated turbines (right).

7.3. Applicability Check: End-of-Funding Strategies for the Wind Fleet of Lower-Saxony

7.3.1. Data

Due to the excellent wind conditions, Lower Saxony is the federal state with the most and oldest wind turbines in Germany. Of the approximately 13,200 wind turbines that will reach the end of the EEG funding period by the end of 2025, more than 26.5% are operated in Lower Saxony. Consequently, 1,645 wind turbines located in this federal state that will reach the end of their feed-in-tariff funding period at the end of 2020 are investigated in this case-study.

Table 23. Distance regulation for wind turbines in Lower Saxony

	Distance regulation	Minimum distances for selected repowering turbines
Residential areas	2 x turbine height	390 meters
Waters	50 meters	50 meters
Weather radar locations	5,000 meters	5,000 meters
Overhead power lines	3 x rotor diameter (RD)	225 meters
Railway	1.5 x (RD + hub-height)	292.5 meters
Highway	40 meters	40 meters
Federal highway	20 meters	20 meters
County roads	20 meters	20 meters
Airports	5,000 meters	5,000 meters

Table 23 shows the model input relevant for the spatial planning analyses, which includes the relevant distance regulations in Lower Saxony as well as the resulting minimum distances based on the characteristics of the reference repowering turbine (150m rotor diameter and 120m hub-height). The inputs for the economic viability model are shown in Table 24. The CAPEX and OPEX for both lifetime extension and repowering depend on the site quality, which reflects the wind resource availability at the specific location of a wind turbine. The latter is calculated using the wind resource model, which feds the turbine-specific electricity yields into the economic viability model. Table 25 shows the additional model inputs.

Table 24. CAPEX and OPEX depending on the site quality.

	Site quality [%]								
	60%	70%	80%	90%	100%	110%	120%	130%	140%
CAPEX [€/kW]	1,355	1,355	1,308	1,308	1,308	1,216	1,216	1,216	1,216
Initial OPEX [ct/kWh]	2.45	2.35	2.26	2.17	2.17	2.07	2.07	1.98	1.98
Basic OPEX [ct/kWh]	2.73	2.64	2.54	2.45	2.35	2.35	2.26	2.26	2.17

Table 25. Financial data for both lifetime extension and repowering projects.

	Value
Maximum lifetime extension [years]	5
Technical lifetime extension assessment [€]	25,000, depreciated over max. extension
Operation of repowering project [years]	20
Corporate tax rate [%]	Municipal, depend on the turbine location
CAPEX - rate of growth [%/year]	-1.5%
OPEX - rate of growth [%/year]	-1.5%
Cost of debt [%/year]	3.5%
Unlevered cost of equity [%/year]	5%
Debt share [%]	Debt sculpting model
Debt service period [years]	16
Straight line depreciation [years]	16
Farm efficiency [%]	90%
Degradation [%/year]	1%
Net operating hours [h/year]	8,560
Electricity spot market price [ct/kWh]	3.68 in 2018 and 2.5% annual increase
Tendered feed-in premiums [ct/kWh]	6.28 in 2018 and 1.5% annual increase

7.3.2. Discussion of Results

The results of the spatial planning analysis preceding the economic viability analysis are shown in Figure 30. Under consideration of the characteristics of the reference repowering turbine almost one-third (33.25%) of the investigated turbine locations violate the current distance regulation in Lower-Saxony. Nevertheless, this also means that more than two-third (66.75%) and thus 1,098 wind turbines are qualified for a repowering. For the remaining 547 wind turbines a lifetime extension is the only possible end-of-funding option. As the sensitivity analysis shows, these results are robust to changes in the repowering turbine: a reduction of the hub-height by 25% would increase the share of repowerable turbines by 0.9 percentage points, while the same relative reduction in the rotor diameter would increase the share by 3.5 percentage points.

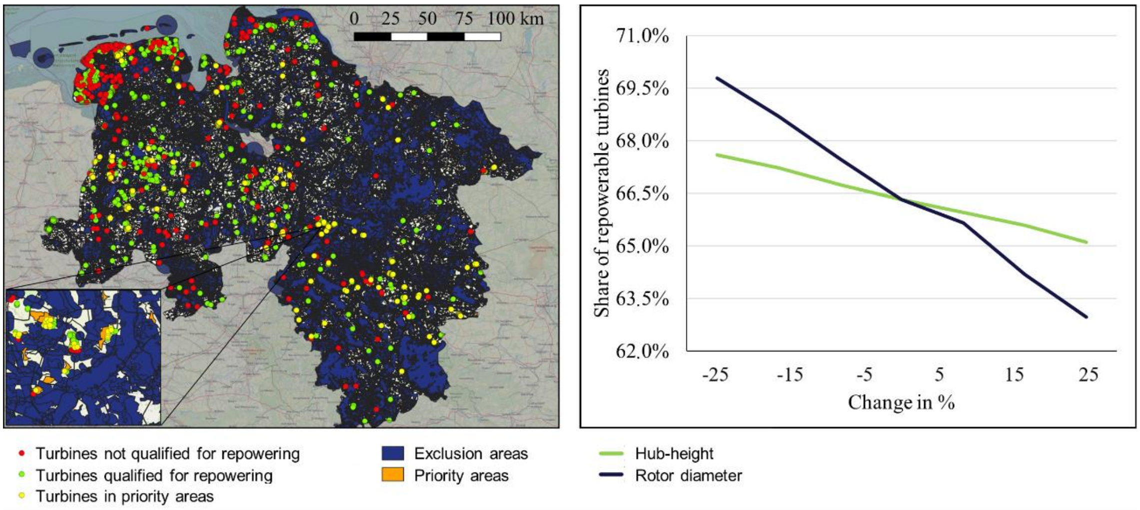

Figure 30. Results of spatial planning analysis and corresponding sensitivity analysis.

The economic viability analysis is applied to the results of the spatial planning analysis. For repowerable wind turbines the differential investment analysis is applied under consideration of the optimal stopping problem in order to determine the optimal lifetime extension and the corresponding repowering timing, while the remaining non-repowerable wind turbines are only evaluated regarding the profitability of a lifetime extension by means of a DCF analysis. Figure 31 and Figure 32 show the results of the combined modelling approach.

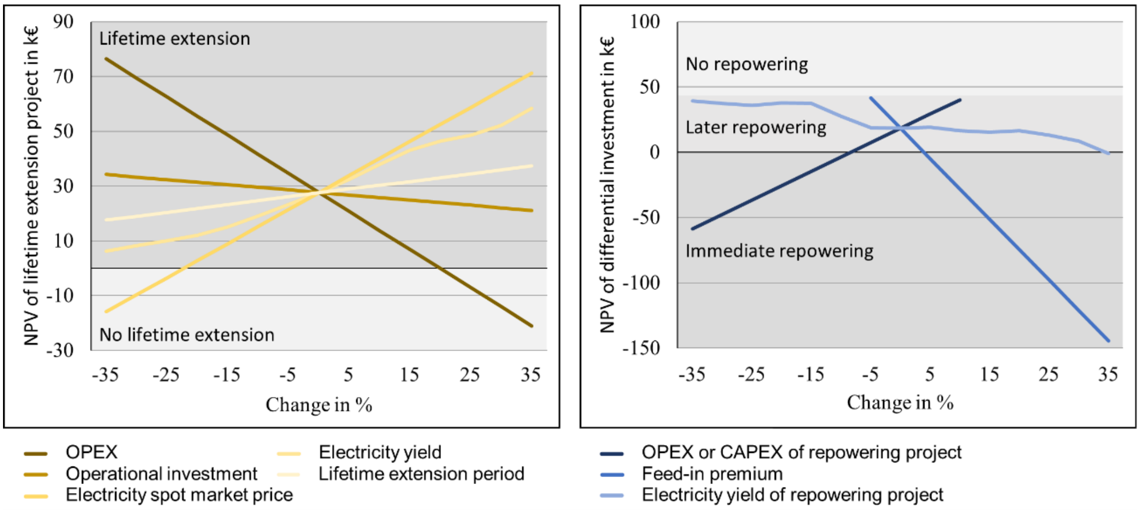

Figure 31. Sensitivity analyses of lifetime extension (left) and repowering (right) options.

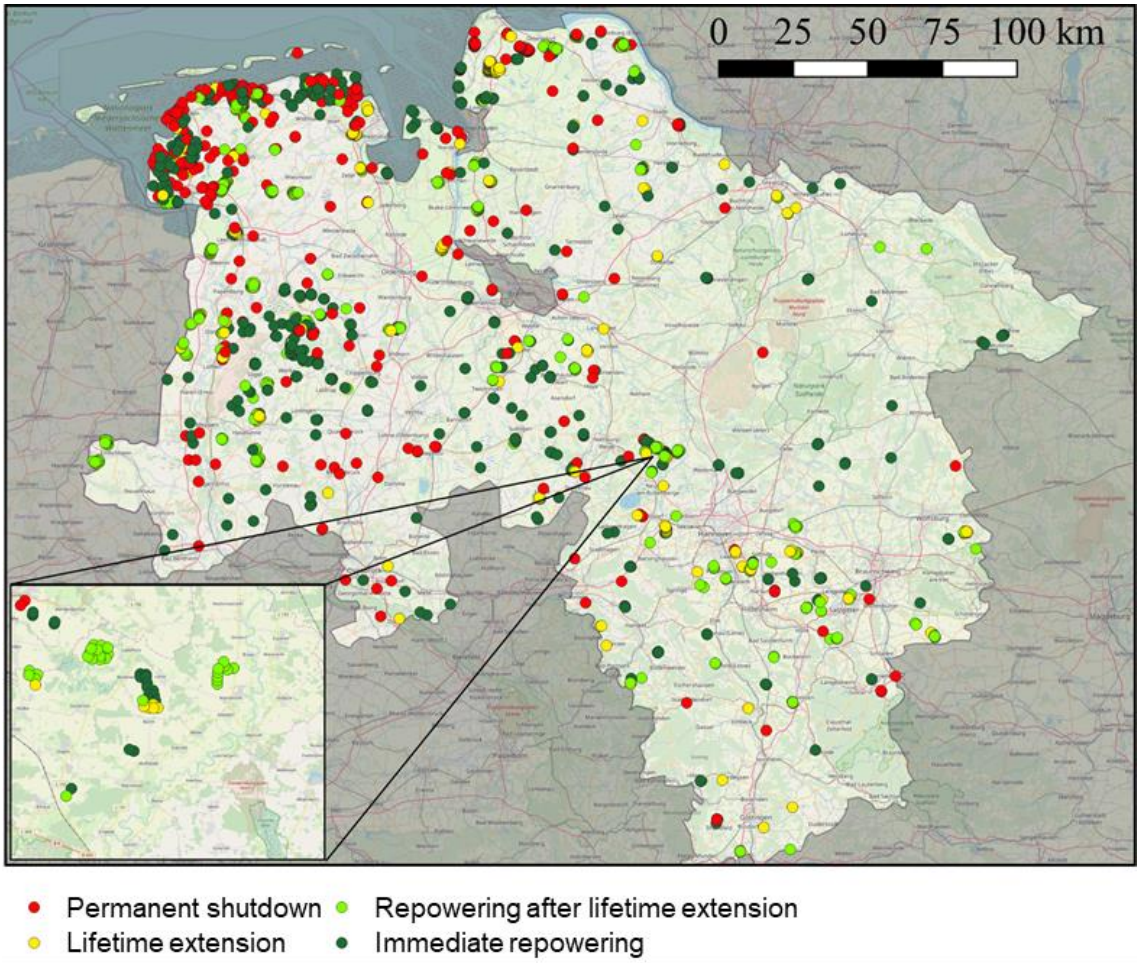

Figure 32. Optimal end-of-funding strategy for the 1,645 wind turbines under investigation.

In contrast to the sensitivity analysis of the spatial planning model, the sensitivity analysis of the economic viability model indicates a strong influence of certain model inputs. Regarding the economic viability of a lifetime extension this concerns in particular the OPEX and the electricity yield of the old turbine as well as the development of the electricity spot market prices and/or related PPA prices, while the differential investment and thus the repowering is highly dependent on both CAPEX and OPEX of the repowering project as well as the level of the feed-in tariffs tendered in the German renewable energy auctions.

For the investigated turbines, the most common optimal strategy is an immediate repowering in 2021 without a preceding lifetime extension (33.01%), followed by a lifetime extension with a subsequent repowering at a later stage after 2021 (28,51%), and a lifetime extension without a preceding repowering (17.08%). Hence, 352 wind turbines (21.4%) are neither suitable for a lifetime extension nor repowering, which implies a permanent shut-down of wind turbine operation as the only remaining option. In summary, the results primarily show a high repowering potential for Lower-Saxony, while the lifetime extension potential is also comparatively high, as it is an economically viable option for 55.75% of the turbines. However, assuming that the repowering potential would be fully exploited in 2021, the results also point to a large number of wind turbines to be decommissioned. In total, 895 wind turbines would have to be dismantled, disposed, recycled and/or resold on the secondary market only in Lower Saxony and only in 2021. For comparison: this is more or less the same number of wind turbines decommissioned throughout Germany in the past five years.

Accordingly, the wind energy market is not only faced with the challenge of profitably exploiting the large repowering and lifetime extension potentials, but market players must also urgently find sustainable and cost-efficient solutions for the imminent and large-scale dismantling and disposal of thousands of wind turbines. This is the only viable basis for ensuring that the wind energy continues to make a decisive contribution to the global energy transition and is still perceived as a sustainable and resource-saving renewable energy technology.

8. Contributions, Limitations, and Outlook

8.1. Discussion of Contributions

In this thesis several consecutive research articles are presented and discussed in the context of quantitative decision support for a variety of renewable energy market players. The specific focus is on the investigation of current challenges of these market players from the perspective of IS research and on the consecutive development of solutions based on methods well-established in IS research. The research findings essentially refer to two objectives: on the one hand, they point to the strength and necessity of IS research with regard to its integrative function between other research areas (here: renewable energy finance and policy, wind resource assessment, spatial planning, structural dynamics, and logistics). On the other hand, they respond to the need for more practical support for decision-makers in this context, as outlined by Dedrick (2010), by providing DSS specifically for practical problems of different market players (here: project developers, investors, policy makers, wind turbine manufacturers, dismantlers, waste management companies and operators). For each thematic section, the contributions and conclusions are presented in the following.

Section 2 deals with decision support for equity and debt investors regarding the valuation of investments in wind and solar farms. The global trend toward more market-based support mechanisms for these technologies leads to a compression of margins and a greater exposure to risk. Consequently, there is less room for errors when investing in in wind and solar farms, which is a major challenge, especially for smaller market players with relatively low risk-bearing capacity. If these market players are increasingly forced out of the market over the next decade, the expansion of renewable energies is likely to be at high risk in many regions due to extensive funding gaps. In order to increase the investment appetite despite the consolidating market environment, a probabilistic economic viability model for the valuation of investments in wind and solar farms under consideration of risk and uncertainty is contributed. The corresponding DSS combines a DCF calculation with MCS and IC algorithms to permit simulating the effects of individual risk factors and their correlations on profitability and financial viability

KPIs. Using the CFAR and VAR methods within the integrated debt sculpting and valuation modules, both equity and debt investors can evaluate wind and solar farms against their individual investment requirements (e.g., IRR and DSCR) and acceptable level of risk (e.g., a 90% confidence level). In this way, the DSS contributes to advanced decision-making by ensuring that more sustainable investments are conducted that match with the risk-bearing capacity of investors.

Section 3 directly follows Section 2 in terms of content and deals with decision support for project developers regarding the optimization of strategic bidding in renewable energy auctions. The previously mentioned trend to market-based support mechanisms is evidenced by the introduction of auctions for renewable energies in many countries. In most auctions, project developers compete by bidding their required sales price and a capacity to be installed and only the most cost-efficient projects with the lowest offered sales prices are granted until the auction volume is reached. The new challenge in the development of wind and solar farms within the framework of auction-based support mechanisms is therefore the precise quantification of competitive and sustainable bidding strategies. The recent past, e.g., in Germany and Mexico, has shown that project developers tend to underprice in terms of offered sales prices in order to be most competitive. Although this behavior increases the probability of being awarded, it also increases the probability that the received financial support is insufficient regarding a profitable and financially viable construction and operation of the corresponding wind or solar farm. In order to prevent this unsustainable bidding behavior and to ensure that the majority of tendered wind and solar farms can be built, marginal cost and strategic bidding models are contributed and extend the probabilistic economic viability model and corresponding DSS. Both models contribute to advanced decision-making by enabling the calculation of a lower bound for the bid price that matches the investment requirements of all stakeholders (marginal cost model) as well as the maximization of the expected profit by means of an optimized bidding strategy based on assumptions about future auction rounds.

Section 4 takes up the topic of renewable energy auctions from the perspective of policy-makers and deals with a specific external effect, which is the accumulation of wind and solar capacity at most resource-rich locations within an auction area. Although this results in a substantial reduction of the financial support for a specific technology, as only the most cost-efficient projects are granted, the highly correlated availability of wind and solar resources at these locations in combination with the spatial concentration of capacity increases the volatility of electricity supply, which negatively affects the system integration of intermittent renewable energies and corresponding electricity distribution costs. In order to promote the system integration of wind and solar farms under auction-based support mechanisms a spatial distribution model is contributed that utilizes a wind simulation as well as the extended probabilistic economic viability model from Section 3. The spatial distribution model contributes to advanced decision-making by enabling the derivation and evaluation of auction features (here: location-based incentives) that permit appropriately managing the spatial distribution of new wind and solar capacity taking the trade-off between cost-efficient renewable electricity supply and reliable and cost-efficient electricity distribution into account. In addition, it also contributes by enabling the simulation of investment/bidding behavior of investors through an economic agent, which can be transferred to similar issues regarding the design of renewable energy support mechanisms.

Section 5 focuses on decision support for wind turbine manufacturers in the optimal design of wind turbine substructures, which is a well-established research area in engineering. Most engineering models typically minimize the mass of structural designs as a cost indicator. A reduction in mass also leads to a reduction in reliability and reduces the expected lifetime of the substructure, which has a negative impact on the risk-return ratio of a wind farm due to lost revenues at the end of the life cycle. Consequently, a trade-off exists between variable lifetime and component costs of a substructure, which, however, is inadequately depicted in state-of-the-art engineering models. In order to enable analyzing the effect of design changes in wind turbine substructures on the risk-return ratio of wind farms, an interdisciplinary modelling approach is contributed, which combines an aero-elastic wind turbine model with the extended probabilistic economic viability model from Section 3. The interdisciplinary modelling approach contributes by clearly demonstrating that a change in paradigm for optimal substructure designs is needed, as more durable substructures have a more appropriate risk-return ratio over the entire lifetime than the less cost-intensive designs. Accordingly, minimizing the mass is not necessarily optimal, which is a generic research result that can also be transferred to other components.

Section 6 deals with decision support for dismantling and disposal companies in the planning of cost-efficient decommissioning processes for wind turbines. In the coming years, more and more wind turbines worldwide will reach the end of their technical and/or economic lifetime. Due to lack of historical experience the current state of the art in dismantling wind turbines is to conduct the entire process on-site (i.e., at the location of a wind turbine), although this undistributed dismantling is highly time-consuming and implies risks and challenges of ecological, economic, and logistical kind. An alternative is the dismantling in reverse logistics networks, which allow for partial dismantling of certain wind turbine components on-site and subsequent transport of the partially disassembled components to specialized dismantling factories for further handling. In order to enable designing cost-efficient dismantling networks for wind turbines another interdisciplinary modelling approach is contributed, which combines logistical and economic aspects in an optimization model. The underlying research contributes by pointing out the necessity of a change in paradigm in the dismantling and disposal of wind turbines. The results clearly indicate that a distributed dismantling in an optimally designed network has considerable cost reduction potential for the entire end-of-life handling of wind turbine rotor blades and nacelles and significantly improves the sustainability of the corresponding processes.

Section 7 deals with decision support for operators and various higher-level stakeholders concerned with the design of optimal end-of-funding strategies for ageing wind turbines. The end-of-life of many wind turbines is approaching worldwide, as a large number of wind turbines will reach the end of their funding period in the upcoming years. When designing end-of-funding strategies for affected wind turbines, current research tends to investigate spatial and economic aspects as well as the different possible strategies, including lifetime extension, repowering and decommissioning, separately. However, an optimal strategy can only be determined by comparing the different options with each other. Consequently, in order to enable selecting and designing optimal end-of-funding strategies for ageing wind turbines, an interdisciplinary modelling approach is contributed, that combines and extends the developed modelling approaches presented in the previous sections in an interdisciplinary GIS. The underlying research contributes by pointing out the high repowering and lifetime extension potentials in the German wind fleet and in particular the necessity for exploiting these potentials to the full extent in order to enable the wind industry to continue playing a pioneering role in the energy transition, despite the decreasing availability of new green field areas. The results further clearly underline the results from Section 6 that fully exploiting the repowering potential in combination with the high number of wind turbines to be decommissioned is likely to result in massive dismantling and disposal issues, which require new efficient and sustainable solutions.

Besides the contributions to the research streams corresponding to the addressed challenges and issues of the different market players, as for example energy economics or energy policy literature, this thesis further contributes to the green IS literature by addressing important issues of the transition toward sustainable energy systems. The overall findings of this thesis show that quantitative decision support based on rapidly growing volumes of data directly contributes to the needs of market players in an increasingly digitized (renewable) energy market by improving the decision-making process through aggregated information. Consequently, the underlying research directly responds to the necessity for more solution-oriented IS research on global warming mitigation and issues surrounding the transition to renewable energy, as postulated by Malhotra et al. (2013), Gholami et al. (2016), and Seidel et al. (2017). As the interaction of the developed models within the thesis shows, model approaches and nascent design theories have emerged during the research process that can be applied in terms of generalized design principles to a wide range of different challenges and issues. These design principles directly contribute to DSR in DSS research, as stated by Gregor and Hevner (2013).

8.2. Discussion of Limitations

In this section, a critical assessment of this thesis is presented. The assessment focuses in particular on the research designs used, the methods and procedures applied, and the results and conclusions generated and comprises three superordinate limitations that apply to all thematic sections. Of course, further specific limitations for the individual thematic sections exist, which are presented and discussed in the corresponding research articles.

The first main limitation refers to the partially limited accessibility to real-world cost data used for the presented case-studies. This has been less of a limitation for the micro-level analyses presented in Sections 2, 3 and 5, which focus on the evaluation of individual wind and solar farms for which sufficient cost data is available, but rather for the higher-level analyses underlying Sections 4, 6 and 7, in which large numbers of wind and solar farms in entire regions are investigated. Due to the partial lack of real-word data for entire wind and solar fleets, the research underlying these sections mainly focused on conducting simulation studies based on estimated cost data derived from a variety of different sources. Although these simulation studies enabled well-founded proofs-of-concepts based on demonstrations and evaluations of the applicability and capabilities of the developed technological artifacts, future research will have to place more emphasis on the collection of more real-world cost data in order to enable a more comprehensive validation of these models and instantiations in the long term. Besides the cost data, this also partially applies to the revenue data, which is limited in terms of access to data on renewable energy auctions and PPA. The reason for the partial lack of revenue data, however, is that these sales mechanisms are still very young and therefore very little data is publicly available. In this regard, future research will have to focus on long-term comparisons between the simulation and real-world results and regularly conduct the implementation of data and model adjustments in the case of significant divergences.

The second main limitation relates to the applied research design. The importance of relevance and rigor in thorough IS research is shown by the long-term debate on both fundamental aspects (e.g., Straub and Ang, 2011; Desouza et al., 2006; Benbasat and Zmud, 1999). Consequently, the research underlying this thesis followed a rigorous research process, although the main focus was on applying IS research to practical problems of renewable energy market players. However, the DSR approach applied in this thesis is subject to a central limitation with regard to relevance and rigor, which is the lack of extensive incorporation of stakeholders into the artifact development process. For this reason, the developed technological artifacts have a strong technical focus. Although practitioners have been involved in the model development and the design of the case studies presented, they have not been involved in the development of the corresponding DSS leading to a limitation regarding research on the actual user side of the DSS and thus evaluations of the goal of utility. Although demonstrations and evaluations of the developed models and instantiations were conducted, they mostly cover a theoretical perspective. On-site demonstrations and evaluations with concerned stakeholders were not carried out, although they potentially lead to the identification of additional issues and challenges not covered by the current status of the technological artifacts. Therefore, future research will have to place more emphasis on the collection of requirements of the relevant stakeholders of the developed models and instantiations and on the adaptation of their current designs to meet these requirements.

The third main limitation directly relates to the first and covers the strong focus on quantitative research approaches and the abstinence from systematic qualitative research. Although qualitative research was already initiated with the involvement of stakeholders in the research process, no structured survey of relevant stakeholders and corresponding systematic evaluations regarding requirements for the developed technological artifacts were conducted. In order to cope more strongly with the overarching objective of DSR, which is the contribution of highly abstract, complete, and mature knowledge by means of well-developed design theories about embedded phenomena (Gregor and Hevner, 2013), future research will have to place more emphasis on the combination of quantitative and qualitative research, as this could further improve the generalizability of the overall findings and puts the developed nascent design theories and the corresponding knowledge in the form of operational principles on more robust foundations.

Both the overarching limitations set out in this subsection and the limitations related to the specific research articles should serve as a starting point for further research. Future research efforts should focus on overcoming the outlined critical aspects and addressing them in future research projects.

8.3. Outlook

While in each research article underlying the thematic sections of this thesis implications for further research are presented in detail, a general outlook covering all thematic sections is given here.

The digitalization of the energy transition can play a key role in solving existing and future issues and challenges of renewable energy market players regarding the decentralization, flexibilization and efficient use of energy and resources and in its various forms has an impact on the entire energy sector. This can create new markets due to high potential for profound changes and innovations, which can be addressed through new business models or innovative smart services, as for example data-driven DSS. In this regard, the author of this thesis founded a university spin-off together with three co-authors of the presented research articles, André Koukal, Chris Stetter and Martin Westbomke, in September 2018 in order to transfer the joint long-term research results, in particular the developed technological artifacts, from science into practice. The associated activities remain highly research-oriented and have high potential to directly address the superordinate limitations described in Section 8.2. The explicit implementation of the developed models and instantiations in practice generates extensive real-world data on the one hand and on the other hand enables the involvement of stakeholders in the development process. Consequently, this puts future research on the developed technological artifacts in a position to place a strong focus on more data-based validations as well as a combination of quantitative and qualitative research approaches in order to increase the consideration of stakeholder requirements regarding capabilities and usability.

Regarding the superordinate role of IS research in the digitalization of the energy transition this thesis highlights in particular the importance of DSS to make solution-oriented and effective contributions to market players for current and future challenges and issues in a changing market environment. In the future, further rapidly growing volumes of data from a variety of sources in an increasingly digitalized renewable energy market will further increase this importance. Therefore, the IS research community should further intensify efforts to exploit its important integrative function between other research areas in order to provide decision-makers with highly valuable support in the transition to sustainable and efficient energy systems based on renewable energy technologies.

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Appendices

Appendix 1: Financial Decision Support System for Wind Energy – Analysis of Mexican Projects and a Support Scheme Concept

Authors: André Koukal, Jan-Hendrik Piel

Outlet: Proceedings of the 50th Hawai'i International Conference on System Sciences (HICSS), Big Island, Hawaii, USA.

Link: https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1133&context=hicss-50

Abstract: Energy consumption is constantly on the increase all over the world. Especially fast-growing economies in emerging countries contribute to this increase. Governments need to promote the expansion of renewable energies in these countries by providing adequate general conditions and suitable support schemes. We provide decision support for the assessment of wind energy projects and their financial conditions. Following design science research (DSR) principles, a discounted cash flow (DCF) model in combination with a Monte Carlo simulation (MCS) to consider project risks was created. On this basis, a decision support system (DSS) was implemented in MATLAB. The applicability of the DSS is evaluated in the course of an analysis of onshore wind projects in Mexico. Based on the analysis' results, a concept of a support scheme is designed to promote an expansion of onshore wind energy across Mexico.

Keywords: Decision support system, Computer science, Management science, Wind power

Citation: Koukal, André; Piel, Jan-Hendrik: HICSS - Financial Decision Support System for Wind Energy – Analysis of Mexican Projects and a Support Scheme Concept. In: Proceedings of the 50th Hawaii International Conference on System Sciences 2017, S. 972-981.

Appendix 2: Applying a Novel Investment Evaluation Method with Focus on Risk – A Wind Energy Case Study

Authors: Jan-Hendrik Piel, Felix J. Humpert, Michael H. Breitner

Outlet: Operations Research Proceedings 2016, Hamburg, Germany.

Link: https://link.springer.com/chapter/10.1007/978-3-319-55702-1_27

Abstract: Renewable energy investments are typically evaluated using traditional discounted cash flow (DCF) methods, such as the net present value (NPV) or the internal rate of return (IRR). These methods utilize the discount rate as an aggregate proxy for risk and the time value of money, which leads to an inadequate modeling of risk. An alternative to these methods represents the decoupled net present value (DNPV). Instead of accounting for risk in the discount rate, the DNPV utilizes so-called synthetic insurance premiums. These allow for the individual and disaggregate pricing of risk and can enhance the quality of investment decisions by facilitating a more detailed and comprehensive representation of the underlying risk structure. To reliably estimate and forecast synthetic insurance premiums requires the availability of appropriate data and expertise in interpreting this data. Thus, the practicality of the results calculated based on the DNPV depends on the quality of the inputs and the expertise of the analyst. After reviewing the main theory of the DNPV, we apply the method to a wind energy investment case to demonstrate its applicability and prospects. To illustrate the calculation of the synthetic insurance premiums, selected risk factors are modeled with probability distributions via Monte Carlo simulation (MCS). Our results show that the DNPV's seamless integration of risk assessment with investment evaluation is a promising combination and warrants further research.

Keywords:

Citation: Piel, JH., Humpert, F.J., Breitner, M.H. (2018). Applying a Novel Investment Evaluation Method with Focus on Risk—A Wind Energy Case Study. In: Fink, A., Fügenschuh, A., Geiger, M. (eds) Operations Research Proceedings 2016. Operations Research Proceedings. Springer, Cham.

Appendix 3: Promoting the System Integration of Renewable Energies: Toward a Decision Support System for Incentivizing Spatially-Diversified Deployment

Authors: Jan-Hendrik Piel, André Koukal, Julian F. Hamann, Michael H. Breitner

Outlet: Journal of Management Information Systems (JMIS), 34(4).

Link: https://www.tandfonline.com/doi/abs/10.1080/07421222.2017.1394044

Abstract: The system integration of intermittent renewable energies (RE) poses an important challenge in the transition toward sustainable energy systems. Their intermittency introduces variability into electricity generation, leading to high ancillary service costs and technical issues impairing grid stability and supply reliability. These issues can be mitigated through spatially diversified capacity deployment, as RE intermittency can be geographically smoothed over sufficiently large regions. Following a design science research approach, we develop a model for the quantification of location-based investment incentives in RE support mechanisms to foster spatially diversified capacity deployment. We evaluate the modeling approach in a simulation study with focus on diversifying wind energy deployment in Mexico under an idealized auction mechanism and demonstrate how location-based investment incentives reduce resource-dependent competition among projects. Our research contributes a nascent design theory that combines the kernel theories for identifying favorable spatial distributions of RE capacity with current policy designs to support capacity expansion management.

Keywords: Design science, energy policy, green information systems, policy decision support, renewable energy, renewable energy auctions, sustainable energy planning, wind energy

Citation: Jan-Hendrik Piel, Julian F.H. Hamann, André Koukal & Michael H. Breitner (2017) Promoting the System Integration of Renewable Energies: Toward a Decision Support System for Incentivizing Spatially Diversified Deployment, Journal of Management Information Systems, 34:4, 994-1022.

Appendix 4: Decoupled Net Present Value – An Alternative to the Long-Term Asset Value in the Evaluation of Ship Investments?

Authors: Philipp Schrader, Jan-Hendrik Piel, Michael H. Breitner

Outlet: Operations Research Proceedings 2017, Berlin, Germany.

Link: https://www.springerprofessional.de/decoupled-net-present-value-an-alternative-to-the-long-term-asse/15793512

Abstract: The aftermath of the financial crisis has threatened the stability of several financial institutions over the past years. Most heavily hit were banks with a notable exposure to ship finance, who saw the collateral value of many loans being diminished. Industry observers trace back the rare occurrence of actual defaults of ship loans to the use of the Long-Term-Asset Value (LTAV), a valuation method explicitly designed for ship investments. As the LTAV is based on a discounted cash-flow approach, it accounts for investment risks in the discount rate. The LTAV bundles the time value of money and risk in a single value, which begs the question if this method oversimplifies the incorporation of risk in the evaluation of ship investments. In the context of infrastructure investments, the Decoupled Net Present Value (DNPV) has recently been proposed as an alternative method that addresses the problem of using risk-adjusted discount rates. It separates the time value of money from risks by quantifying risk factors individually and treating them as costs to the investment. We provide a proof-of-concept regarding the applicability of the DNPV in the context of ship investments. To this end, we develop a DNPV valuation model and instantiate a prototype in Python. We then perform a simulation study that evaluates a ship investment using both the LTAV and the DNPV. The results of our study confirm the applicability of the DNPV to ship investments and point to both its advantages and limitations compared to the LTAV.

Keywords:

Citation: Schrader, P., Piel, JH., Breitner, M.H. (2018). Decoupled Net Present Value – An Alternative to the Long-Term Asset Value in the Evaluation of Ship Investments? In: Kliewer, N., Ehmke, J.F., Borndörfer, R. (eds) Operations Research Proceedings 2017. Operations Research Proceedings. Springer, Cham.

Appendix 5: An Optimization Model to Develop Efficient Dismantling Networks for Wind Turbines

Authors: Martin Westbomke, Jan-Hendrik Piel, Michael H. Breitner, Peter Nyhuis, Malte Stonis

Outlet: Operations Research Proceedings 2017, Berlin, Germany.

Link: https://www.springerprofessional.de/en/an-optimization-model-to-develop-efficient-dismantling-networks-/15793502

Abstract: In average, more than 1,275 wind turbines were installed annually since 1997 in Germany and more than 27,000 wind turbines are in operation today. The technical and economic lifetime of wind turbines is around 20 to 25 years. Consequently, dismantling of aging wind turbines will increase significantly in upcoming years due to repowering or decommissioning of wind farms and lead to millions of costs for operators. An option to supersede the costly and time-consuming dismantling of wind turbines entirely on-site is to establish a dismantling network in which partly dismantled wind turbines are transported to specialized dismantling sites for further handling. This network requires an optimization model to determine optimal locations and an appropriate distribution of disassembly steps to dismantling sites. The challenge is to consider the networks dependency on the trade-off between transportation and dismantling costs which, in turn, depends on the selection of dismantling depths and sites. Building on the Koopmans-Beckmann problem, we present a mathematical optimization model to address the described location planning and allocation problem. To permit a proof-of-concept, we apply our model to a case-study of an exemplary wind farm in Northern Germany. Our results show that the model can assist dismantling companies to arrange efficient dismantling networks for wind turbines and to benefit from emerging economic advantages.

Keywords:

Citation: Westbomke, M., Piel, JH., Breitner, M.H., Nyhuis, P., Stonis, M. (2018). An Optimization Model to Develop Efficient Dismantling Networks for Wind Turbines. In: Kliewer, N., Ehmke, J.F., Borndörfer, R. (eds) Operations Research Proceedings 2017. Operations Research Proceedings. Springer, Cham.

Appendix 6: Lifetime Extension, Repowering or Decommissioning? Decision Support for Operators of Ageing Wind Turbines

Authors: Jan-Hendrik Piel, Chris Stetter, Max Heumann, Martin Westbomke, Michael H. Breitner

Outlet: Journal of Physics: Conference Series (JOP), 1222 (2019).

Link: https://iopscience.iop.org/article/10.1088/1742-6596/1222/1/012033

Abstract: In Germany, more than one third of the installed wind energy capacity will leave the feed-in tariff funding between 2021 and 2025. Operators of affected turbines are therefore increasingly concerned with the design of profitable end-of-funding strategies. This requires feasibility analyses of both lifetime extension and repowering options and entails the subsequent challenge to determine the optimal lifetime extension and corresponding repowering timing. To support operators and other stakeholders dealing with wind turbines' end-of-life issues, this study presents a geographic information system that permits evaluating optimal end-of-funding strategies at different spatial scales reaching down to detailed analyses on individual turbine level. The decision support system processes topographic, wind, turbine, and finance data in an integrated system of resource simulations, spatial planning analyses and economic viability assessments. Case-study results show that a uniform end-of-funding strategy cannot be applied to all ageing turbines. Conducted sensitivity analyses rather indicate that the best strategy highly depends on various turbine-specific aspects, especially the location, type and maintenance costs as well as exogenous factors, including the developments of electricity spot market prices and tendered feed-in premiums. In light of latest trends regarding the exogenous factors, lifetime extension and repowering potentials increase. However, the results also indicate that dismantling, disposal and recycling of numerous ageing turbines will become a major challenge for the wind energy sector in the next decade.

Keywords:

Citation: JH Piel *et al* 2019 *J. Phys.: Conf. Ser.* 1222 012033.

Appendix 7: Influence of Structural Design Variations on Economic Viability of Offshore Wind Turbines: An Interdisciplinary Analysis

Authors: Clemens Hübler, Jan-Hendrik Piel, Chris Stetter, Christian G. Gebhardt, Michael H. Breitner, Raimund Rolfes

Outlet: Renewable Energy, 145

Link: https://www.sciencedirect.com/science/article/abs/pii/S0960148119309474

Abstract: Offshore wind energy is a seminal technology to achieve the goals set for renewable energy deployment. However, today's offshore wind energy projects are mostly not yet sufficiently competitive. The optimization of offshore wind turbine substructures with regard to costs and reliability is a promising approach to increase competitiveness. Today, interdisciplinary analyses considering sophisticated engineering models and their complex economic effects are not widespread. Existing approaches are deterministic. This research gap is addressed by combining an aero-elastic wind turbine model with an economic viability model for probabilistic investment analyses. The impact of different monopile designs on the stochastic cost-efficiency of an offshore wind farm is investigated. Monopiles are varied with regard to diameters and wall thicknesses creating designs with increased lifetimes but higher capital expenditures (durable designs) and vice versa (cheaper designs). For each substructure, the aero-elastic wind turbine model yields distributions for the fatigue lifetime and electricity yield and different capital expenditures, which are applied to the economic viability model. For other components, e.g., blades, constant lifetimes and costs are assumed. The results indicate that the gain of increased stochastic lifetimes exceeds the benefit of reduced initial costs, if the overall lifetime is not governed by other turbine components' lifetimes.

Keywords: Offshore wind energy, Substructure design, Economic viability, Stochastic cost-efficiency, Lifetime distribution

Citation: Hübler, C., Piel, JH., Stetter, C., Gebhardt, C.G., Breitner, M.H., Rolfes, R. (2020) Influence of Structural Design Variations on Economic Viability of Offshore Wind Turbines: An Interdisciplinary Analysis, Renewable Energy, 145, 1348-1360.

Appendix 8: Enhancing Strategic Bidding Optimization for Renewable Energy Auctions: A Risk-Adequate Marginal Cost Model

Authors: Chris Stetter, Jan-Hendrik Piel, André Koukal, Michael H. Breitner

Outlet: Operations Research Proceedings 2018, Dresden, Germany

Link: https://link.springer.com/chapter/10.1007/978-3-030-18500-8_28

Abstract: The shift toward auction mechanisms for renewable energies has introduced competitive price discovery of financial support levels for new projects. The starting point of finding an optimal bidding strategy in these auctions must always be a reliable determination of the marginal cost, which is the minimum sales price per unit of electricity required to permit an economically viable project realization at an acceptable level of risk. We focus on enhancing strategic bidding by introducing a holistic financial modeling approach for a risk-adequate quantification of the marginal cost, which serves as the basis for strategic bidding optimization models. In order to permit a proof-of-concept and in-depth understanding of our model enhancement, we conduct a simulation study of an onshore wind farm in Germany. The results of our study show that our modeling approach enables quantifying bid prices that are both cost-competitive and sustainable in terms of a likely project realization.

Keywords: Renewable energy auctions, Strategic bidding, Competitive bidding, Valuation, Discounted cash flow, Risk analysis

Citation: Stetter, C., Piel, JH., Koukal, A., Breitner, M.H. (2019). Enhancing Strategic Bidding Optimization for Renewable Energy Auctions: A Risk-Adequate Marginal Cost Model. In: Fortz, B., Labbé, M. (eds) Operations Research Proceedings 2018. Operations Research Proceedings. Springer, Cham.

Appendix 9: Competitive and Risk-Adequate Auction Bids for Onshore Wind Projects in Germany

Authors: Chris Stetter, Jan-Hendrik Piel, Julian F. Hamann, Michael H. Breitner

Outlet: Energy Economics, 90

Link: https://www.sciencedirect.com/science/article/pii/S0140988320301894?via%3Dihub

Abstract: In recent years, auction mechanisms have gained in significance in the context of renewable energy deployment. An increasing number of countries have adopted auctions for the allocation of permits and financial support for renewable energy projects, thereby increasing competition among project developers. As a result, profit margins have decreased significantly while sensitivity to risks and uncertainty has increased. The adequate quantification of bid prices is a key challenge. We present a modeling approach to determine competitive and risk-adequate auction bids. The contribution of this paper is an improved method for quantifying marginal cost, which is the minimum sales price per unit of electricity through which the investment criteria of all project stakeholders are fulfilled. In our financial model, the risk-adequateness is determined through the investment criteria of equity investors by means of the adjusted present value, and those of debt investors by means of the debt service cover ratio, through Monte Carlo simulations. The resulting marginal cost serves as the starting point for strategic bidding optimization, regardless of the pricing rule in the contemplated auction design. To demonstrate the integrability of our mathematical model with strategic bidding optimization, we check its applicability in a case study, which shows how a German project developer should bid to realize an onshore wind farm project. We show that our model enables the quantification of bid prices that are both competitive and risk-adequate.

Keywords: Renewable energy auctions, Competitive bidding, Adjusted present value, Debt service cover ratio, Risk analysis, Onshore wind energy

Citation: Stetter, C., Piel, JH., Hamann, J.F., Breitner, M.H. (2020) Competitive and Risk-Adequate Auction Bids for Onshore Wind Projects in Germany, Energy Economics, 90, 104849.