# Development of Feedback Control for Energy Policy Design to Guarantee Sustainable Solar and Wind Power Investment Growth

Dissertation for the acquisition of the academic degree

Doktor der Ingenieurwissenschaften (Dr.-Ing.)

Submitted to the

Faculty of Electrical Engineering and Computer Science

of the University of Kassel

By

**Do, Thi Hiep**

from Hanoi, Vietnam

Kassel, November 2021

**Referees:**

Prof. Dr. rer. nat. Clemens Hoffmann

Prof. Dr.-Ing. Kurt Rohrig

**Day of defence:**

26 November 2021

# Acknowledgments

To finish this dissertation, first and foremost, I would like to express heartfelt thanks to my supervisor, Prof. Dr. rer. nat. Clemens Hoffmann, Head of Department of Integrated Energy Systems (INES), University of Kassel; Former Director of the Fraunhofer Institute for Energy Economics and Energy System Technology (Fraunhofer IEE), Kassel, Germany. I am greatly indebted to him for his time, advice, and support. Our conversations have been a great source of motivation and inspiration.

I am grateful to my second referee Prof. Dr.-Ing. Kurt Rohrig who accepted to jon the examination board without hesistation.

I would like to express my kind thanks to all colleagues at the INES: Annette Petrat, Friedrich Krebs, Sascha Holzhauer, Lukas Nacken, Geo Kocheril, and Alexander Basse for their supports, advices during my time at the INES.

Also, I would like to express my thanks to colleagues at the Fraunhofer IEE: Ulrike Fuchs, Jan von Appen, Helen Ganal, Philipp Härtel, Michael von Bonin for their supports.

In 2018, I was given the opportunity to do a four-month internship at the German Corporation for International Cooperation GmbH (GIZ) in Vietnam. I would like to thank my colleagues at the GIZ energy team for their supports, suggestions, and insights into the renewable power investment markets in Vietnam.

I also thank organizations that give me the financial supports for my Ph. D study: Ministry of Education and Training of Vietnam (MoET), the German Academic Exchange Service (DAAD), and the University of Kassel.

Finally, I wish to give the greatest thanks to the love of my life, Pham Van Tin, who has supported me, beside me in both happy and sad times, gone through many challenges together with me. I also thank my parents and my family for their enormous supports and love. The work would not have been finished without their constant encouragement.

I thank you all.

# Zusammenfassung

Die Energiewende im Stromsektor ist einer der wichtigsten Wege zur Erreichung der Klimaziele. Um den Ausbau erneuerbarer Energien zu stimulieren, spielt die Regulierungspolitik eine entscheidende Rolle. Diese Politiken haben jedoch aufgrund der ungeeigneten Designs bisher nur Teilergebnisse oder unerwartete Folgen erzielt. Daher geht die Studie der Frage nach: "Wie muss die Regulierungspolitik gestaltet werden, um ein günstiges Umfeld für den Ausbau erneuerbarer Energien zu schaffen?"

Diese Arbeit schlägt vor, die Feedback-Control-Theorie für die Gestaltung der Energiepolitik zu verwenden, konzentriert sich auf die Gestaltung von Preismechanismen, um ein nachhaltiges Wachstum der Investitionen in erneuerbare Energien zu gewährleisten. Der Feedback-basierte Preismechanismus (FPM) wird regelmäßig auf Basis des beobachteten Investitionsvolumens und nicht des prognostizierten angepasst. Aufgrund der Popularität und Anwendbarkeit des Proportional-Integral-Derivative-Reglers (PID) in Ermangelung eines Systemmodells wird diese Technik für den Preismechanismusentwurf gewählt. Dementsprechend minimiert der Regler die Abweichung zwischen der gewünschten installierten Leistung und dem tatsächlichen Volumen durch Anwendung von Proportional-, Integral- und Differentialtermen.

Der zukunftsweisendste und wertvollste Beitrag dieser Dissertation ist die Entwicklung mathematischer Modelle rückkopplungsbasierter Preismechanismen. Konkret werden die PID-basierten Preismechanismen in diskreten ökonometrischen Modellen formuliert. Die Reglerparameter werden durch historische Analysen am historischen Beispiel der Erneuerbaren-Politik in Deutschland als Fallbeispiel realisiert. Wir kommen zu dem Schluss, dass Häufigkeit und Höhe der Preisanpassungen für einen effektiven Feedback-basierten Preismechanismus entscheidend sind. Die Ergebnisse dieser Studie bieten politischen Entscheidungsträgern eine gute Referenz für die Gestaltung der Energiepolitik und die Durchführung entsprechender Studien.

**Schlüsselwörter:** *Preismechanismen, Rückkopplungsregelung, PID-Regler, Investition in erneuerbare Energien.*

## Abstract

Energy transition in the power sector is one of the main pathways to achieving the climate targets. In order to stimulate renewable power development, regulatory policies play a vital role. However, these policies have so far attained only partial results or unexpected consequences due to the unsuitable designs. Therefore, the study addresses the question, "How do regulatory policies have to be designed in order to create a favorable environment for renewable power development?"

This work proposes to use feedback control theory for energy policy design, focuses on price mechanism design to guarantee sustainable renewable power investment growth. The feedback-based price mechanism (FPM) is regularly adjusted based on the observed investment volume rather than the predicted one. Due to the popularity and applicability of the proportional-integral-derivative controller (PID) in the absence of a system model, this technique is chosen for price mechanism design. Accordingly, the controller minimizes the deviation between the desired installed capacity and the actual volume by applying proportional, integral, and derivative terms.

The most forward-looking and valuable contribution of this dissertation is the development of the mathematical models of feedback-based price mechanisms. Specifically, the PID-based price mechanisms are formulated in discrete econometric models. The controller parameters are realized through historical analysis using the historical example of renewable policy-making in Germany as a case study. We conclude that frequency and level of price adjustment are crucial for an effective feedback-based price mechanism. The results of this study provide a good reference for policymakers for designing energy policies and conducting relevant studies.



**Keywords:** *price mechanisms, feedback control, PID controller, renewable power investment.*

# Graphical Abstract

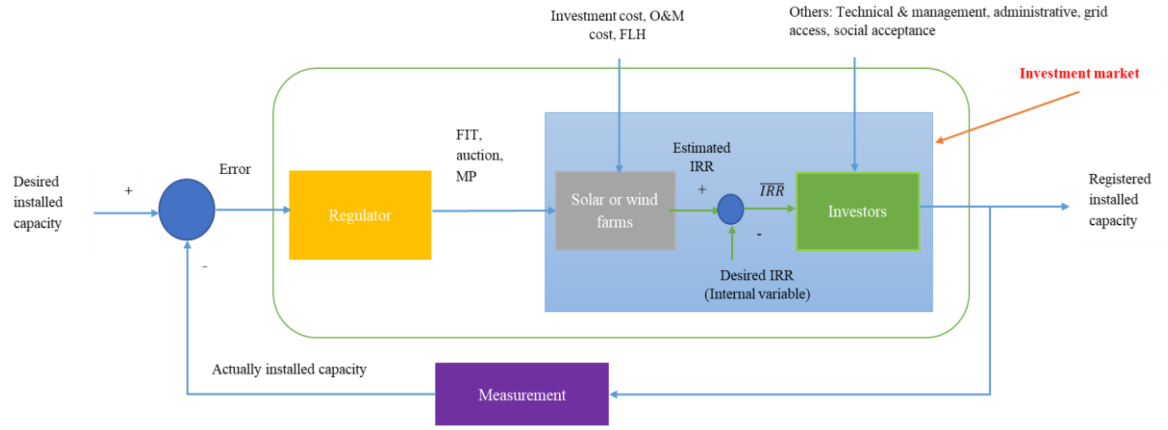



Figure 0.1. Graphical Abstract

# Table of Contents

# List of Tables

# List of Figures

# List of Abbreviations

| | |
|---|---|
| AC | Alternating current |
| ADB | Asian Development Bank |
| AFD | Agency of French Development |
| ASEAN | The Association of Southeast Asian Nations |
| BOT | Build – operate – transfer |
| BMWi | Bundesministeriums für Wirtschaft und Energie (Federal Ministry for Economic Affairs and Energy of Germany) |
| BNEF | Bloomberg New Energy Finance |
| CAPEX | Capital expenditure |
| CGEM | Competitive generation electricity market |
| COD | Commercial operation date |
| CO2 | Carbon dioxide |
| CREM | Competitive retail electricity market |
| CWEM | Competitive wholesale electricity market |
| DC | Direct current |
| DPPAs | Direct power purchase agreements |
| EBRD | European Bank for Reconstruction and Development |
| ECGM | Entirely competitive generation market |
| FDR | Feedback-based degression rate |
| EIB | The European Investment Bank |
| EPBP | Entirely price-based pool |
| EPC | Engineering, procurement, and construction |
| EREA | Electricity and Renewable Energy Authority |
| EU | European Union |

| | |
|---|---|
| EVN | Electricity of Vietnam |
| EVN NPT | National Power Transmission Corporation of Vietnam |
| FPM | Feedback-based price mechanism |
| FIT | Feed-in tariff |
| FIP | Feed-in premium |
| GDP | Gross domestic product |
| GHGs | Greenhouse gases |
| HPM | Hybrid price mechanism |
| IDR | Initial degression rate |
| IE | Institute of Energy of Vietnam |
| IEA | International Energy Agency |
| IRENA | International Renewable Agency |
| IRR | Internal rate of return |
| IPCC | Intergovernmental Panel on Climate Change |
| IPPs | Independent power producers |
| IPT | Independent power transmission |
| JICA | Japanese International Cooperation Agency |
| KfW | German Development Bank |
| LCOE | Levelized cost of electricity |
| LPG | Liquefied petroleum gas |
| LQR | Linear quadratic regulator |
| MP | Market premium |
| EMPC | Economic model predictive control |
| MAC | Marginal abatement cost |
| MoIT | Ministry of Industry and Trade of Vietnam |
| MoNRE | Ministry of Natural Resources and Environment of Vietnam |

| | |
|---|---|
| NLDC | National Load Dispatch Center of Vietnam |
| NPV | Net present value |
| NREL | US National Renewable Energy Laboratory |
| PPM | Prediction-based price mechanism |
| PDP | Power development plan |
| PID | Proportional-integral-derivative |
| PID-BPM | Proportional-integral-derivative-based price mechanism |
| PP | Premium price |
| PPP | Public-private partnership |
| RE | Renewable energy |
| RECs | Renewable energy certificates |
| REN21 | Renewable energy policy network for the 21$^{st}$ century |
| RESs | Renewable energy standards |
| ROA | Real options analysis |
| SCC | Social cost of carbon |
| SMP | Spot electricity market price |
| UNFCCC | United Nations Framework Convention on Climate Change |
| VAT | Value-added tax |
| VND | Vietnam dong |
| VINACOMIN | Vietnam National Coal Company of Vietnam |
| VREs | Variable renewable energies |
| USA | United States |
| WB | World Bank |

# List of Measures

| | |
|---|---|
| BTU | British thermal unit |
| EUR | Euro |
| GW | Giga Watt |
| GWh | Giga Watt-hour |
| KTOE | Thousand tons of oil equivalent |
| kWh | Kilo Watt-hour |
| MW | MegaWatt |
| MWh | Mega Watt-hour |
| TOE | A ton of oil equivalent |
| TWh | Tera Watt-hour |
| USD | United States dollar |

# Chapter 1. Introduction

## 1.1. Motivations

The awareness of the enormous impact of energy production on the global climate has increased over the last decade (European Environment Agency, 2017). Despite the recurring fierce denial of climate research results, this increasing awareness puts the energy economy under increasing pressure for calling for fundamental reform. The energy transition from fossil-based to low-carbon-based energy generation has become a global trend. The technological development of renewable energy production promises to offer a complete solution to achieve climate targets. The energy transition in the power sector has achieved remarkable results. As of 2019, the global solar and wind power installed capacity reached around 627 GW and 651 GW. China, the United States, Brazil, and Germany are the leading countries producing electricity from renewable resources (Renewable Energy Policy Network for the 21st century (REN21), 2020). In 2019, renewable energy contributed 27% to the total electricity generation in China (Hove *et al.*, 2020), about 17% in the United States (U.S Energy Information Administration, 2020). In the first half of 2019, Germany reached a record of 55.8% electricity generation from renewable resources, 30.6% from wind energy, and 11.4% from solar energy (Fraunhofer Institute for Solar Energy Systems (Fraunhofer ISE), 2020).

Renewable energy targets are part of the legal basis for renewable power expansion. National renewable power targets are formed in terms of installed capacity, electricity generation, electricity consumption, investment budget, or carbon reduction (REN21, 2020). According to the Federal Government of Germany (2019), Germany aims to achieve a renewable energy share of 65% in the total electricity consumption in 2030. The total installed capacities of solar power, onshore wind power, and offshore wind power are expected at 98 GW, 65–71 GW, and 20 GW, respectively.

In order to create a favorable environment for renewable power development, various energy policies have been adopted (REN21, 2020). Regulatory policies such as feed-in tariff (FIT) (Couture and Gagnon, 2010; Klein *et al.*, 2010), auction (IRENA and CEM, 2015; Kitzing *et al.*, 2016), and market premium (MP) (Kreiss, Ehrhart and Hanke, 2017) mechanisms have been expected to stimulate renewable power development. However, these mechanisms have so far attained only partial results or even negative consequences due to the unsuitable pricing approaches.

One popular pricing approach is based on predicted values (later defined as a *prediction-based price mechanism* (PPM)). The price level depends on the electricity generation costs, considering the predicted investment costs, operation and maintenance costs, generated electricity, estimated full-load hours, and profitability (Klein et al., 2010). Another approach is based on predicted values and actual market responses (later defined as a *hybrid price mechanism* (HPM)). The actual market responses are reflected by the deviation between the desired investment volume and the actual one (Hiep and Hoffmann, 2018). Because these two approaches depend either totally or partially on predicted values, they are sensitive to unpredictable factors. As a result, the actual impacts of price mechanisms deviate far from the expectations. Specifically, the solar power overinvestment in Germany caused social inequality (higher renewable power surcharge was shouldered by electricity consumers, while investors got high profit) (Thure, Claudia and Jochen, 2011; Grau, 2014). In addition, the overinvestment in Vietnam has created challenges for system and transmission grid operations (Sanseverino *et al.*, 2020). In contrast, the wind power underinvestment failed to achieve the wind power development corridor (Sach, Lotz and Bluecher, 2019).

This work proposes to use feedback control theory for energy policy design, focusing on price mechanism design (later defined as a *feedback-based price mechanism* (FPM)) to guarantee sustainable renewable power investment growth. It is noted that feedback control theory has been used in macroeconomics (Taylor, 1993; Neck and Karbuz, 1997; Onatski and Stock, 2002; Zhang and Semmler, 2003; Hawkins, Speakes and Hamilton, 2015; Alexeenko, 2017; Kostarakos and Kotsios, 2017; Shepherd, Torres and Saridakis, 2018). However, research on applying this approach to design price mechanisms for renewable power investment is unavailable. The price following the feedback approach is regularly adjusted based on the observed investment volume instead of the predicted one, providing a higher degree of robustness against unpredictable factors.

Regulations in general, particularly price mechanisms, often take mathematical shapes. However, the past shows that little attention was put to study the dynamical consequences of a particular mathematical rule to ensure that this dynamic approaches the desired behavior. In control theoretical language, it can be said that the rules were designed without having a sufficiently precise system model (or a control path). This shortcoming is the opportunity for this research.

## 1.2. Research aims

On the background explained above, this study addresses the question how regulatory policies have to be designed in order to create a favorable environment for renewable power development. Accurately, we aim to **rigorously develop mathematical forms of price mechanisms focusing on feedback control systems' architecture that guarantees sustainable solar and wind power investment growth**. The term "*sustainable*" in this context means that the growth is upheld over a long period, and at the same time, avoids over or under-investment, overpayment, and high curtailment. Sustainable solar and wind power investment growth contributes to economic and environmental sustainability in the long run.

Figure 1.1 depicts a feedback control system of price mechanisms for renewable power investment with three main components: investment market, regulator, and measurement. The political entity *regulator* is identified with the theoretical control concept as the controller. It generates the appropriate price signal under the FIT, auction, or MP mechanisms to steer the investment market to achieve the targeted investment growth. The price is updated regularly based on the deviation between the desired installed capacity and the actual volume.

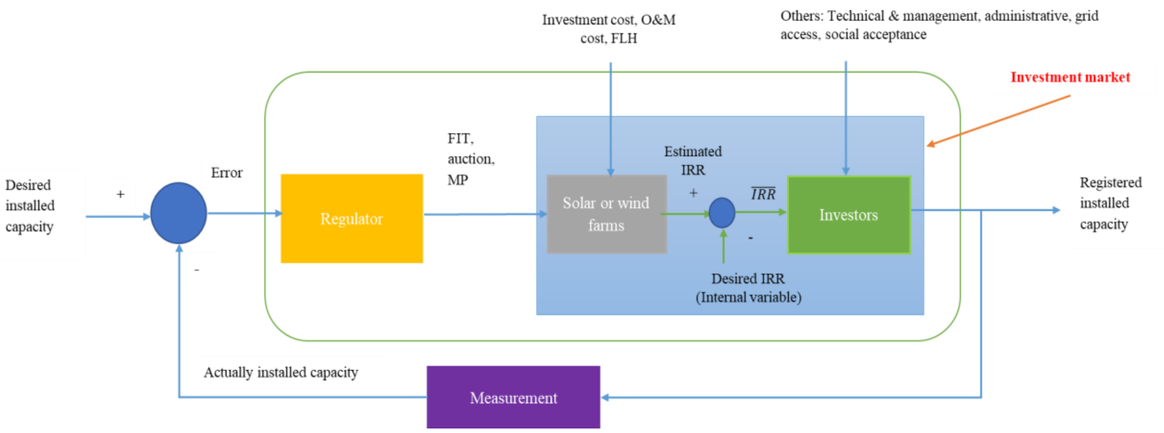



Figure 1.1. Block diagram of a feedback control system of price mechanisms for renewable power investment

In order to achieve the research aim, this study is conducted with the following objectives:

- Taking a satellite perspective on the different approaches to regulation policies that have been tried in the past with more or less success.
- Systematizing the various approaches by analyzing them in the framework of feedback control theory which has been successfully applied for decades to technical systems.

- Rigorously developing mathematical forms of price mechanisms that should guarantee sustainable solar and wind power investment growth.
- Using historical example of renewable policy making in Germany to test and parametrize different control mechanisms. Germany went through different phases of refinement of renewable energy policies including good success and bad failure and offers indeed a copies study ground. Historical data from Germany allows the author to identify the action-response behavior of Germany's energy economy and to infer optimal parameters for improved regulatory schemes.
- As the author is from Vietnam, the findings are applied to the Vietnam energy economy giving valuable advice for Vietnamese policy makers how to devise sustainable regulatory schemes for a successful energy system transformation in Vietnam.

### 1.3. Research questions

The mentioned research aim leads to the following main research question: **How is the feedback control's mathematical method of price mechanisms designed to help achieve sustainable solar and wind power investment growth?** This question needs further specifications.

In renewable power investment markets, the government sets the renewable power investment targets; investors decide the actual investment flows. Therefore, the understanding of investor characteristics and behavior plays a crucial role in policymaking. It is a fact that investors in renewable power investment markets are various and diverse. In order to comprehend them, the following questions will have to be answered:

- Who are investors in solar and wind power investment markets?
- What are their investment motivations?
- What are their finance, land, and human resources?
- How are the investors affected by external factors?

This study focuses on the relationship between energy policies and renewable power investment growth. The questions are:

- What policies are available to promote renewable power investment?
- How do the energy policies affect investor behavior?

In rigorously applying control theory for renewable power investment markets, mathematical models of investor behavior should be constructed. During the modeling, the following questions will be addressed:

- How should investor behavior in solar and wind power investment markets be modeled?
- How suitable are the constructed models for prediction?

As mentioned in Section 1.2, this work aims to develop a feedback control system architecture for price mechanism design. Therefore, the following questions will be answered:

- Which mathematical shapes can be used to design price mechanisms to achieve the targeted renewable power investment volume?
- How are the architected feedback-based price mechanisms applied to the solar and wind power investment markets in Germany and Vietnam?

## 1.4. Research methods

In order to achieve the research objectives mentioned in Section 1.2 and answer the research questions in Section 1.3, a literature review will be conducted, combined with historical analysis.

The literature review provides knowledge of the impacts of energy policies, particularly price mechanisms, on investor behavior. It also allows identifying available approaches to investor behavior modeling and their limitations.

Furthermore, by exploring the literature, we can determine the available pricing approaches and identify their drawbacks. Finally, the literature review provides references for constructing new mathematical models of investor behavior and developing mathematical forms of price mechanisms.

The historical analysis strategy is also used reasonably in this dissertation. First of all, this method explores the negative consequences of conventional pricing approaches in renewable power investment markets in Germany and Vietnam. Secondly, the constructed models of investor behavior are tested, the parameters of the price mechanism models are realized through an empirical analysis of the historical data of the price mechanisms and solar power investment in Germany.

## 1.5. Dissertation structure

The dissertation is organized into eight chapters. The introductory chapter lays out the research motivations, research aims, research questions, research methods, and dissertation structure. Chapter 2 describes technology diffusion phases, corresponding price mechanisms, and possible renewable power diffusion scenarios. Then, a systematic analysis of the impacts of energy policies on investor behavior is provided. In control system designs, system modeling and controller selection are two crucial steps. The emphasis of Chapter 3 is on modeling investor behavior. Firstly, available approaches to mathematical modeling of investment growth are reviewed. Then the dynamic and time-variant features of investor behavior are reflected in our new models. Because feedback control theory is still unknown to many economists and policymakers, an overview of this theory is described in Chapter 4. Subsequently, the application of feedback control techniques to economic policy is reviewed to acknowledge the potential technique for price mechanism design. Because the accurate model of investor behavior is unavailable while the work of PID control relies on the response of the controlled output, not on knowledge or a model of the system, the PID controller is selected for price mechanism design. Chapter 5 devotes the development of mathematical shapes of the PID-based price mechanisms. Application of the PID-based price mechanisms to Germany and Vietnam is presented in Chapter 6 and Chapter 7. Finally, we arrive at some research conclusions and suggestions for future works in Chapter 8.

Figure 1.2 illustrates the outline of the dissertation structure.

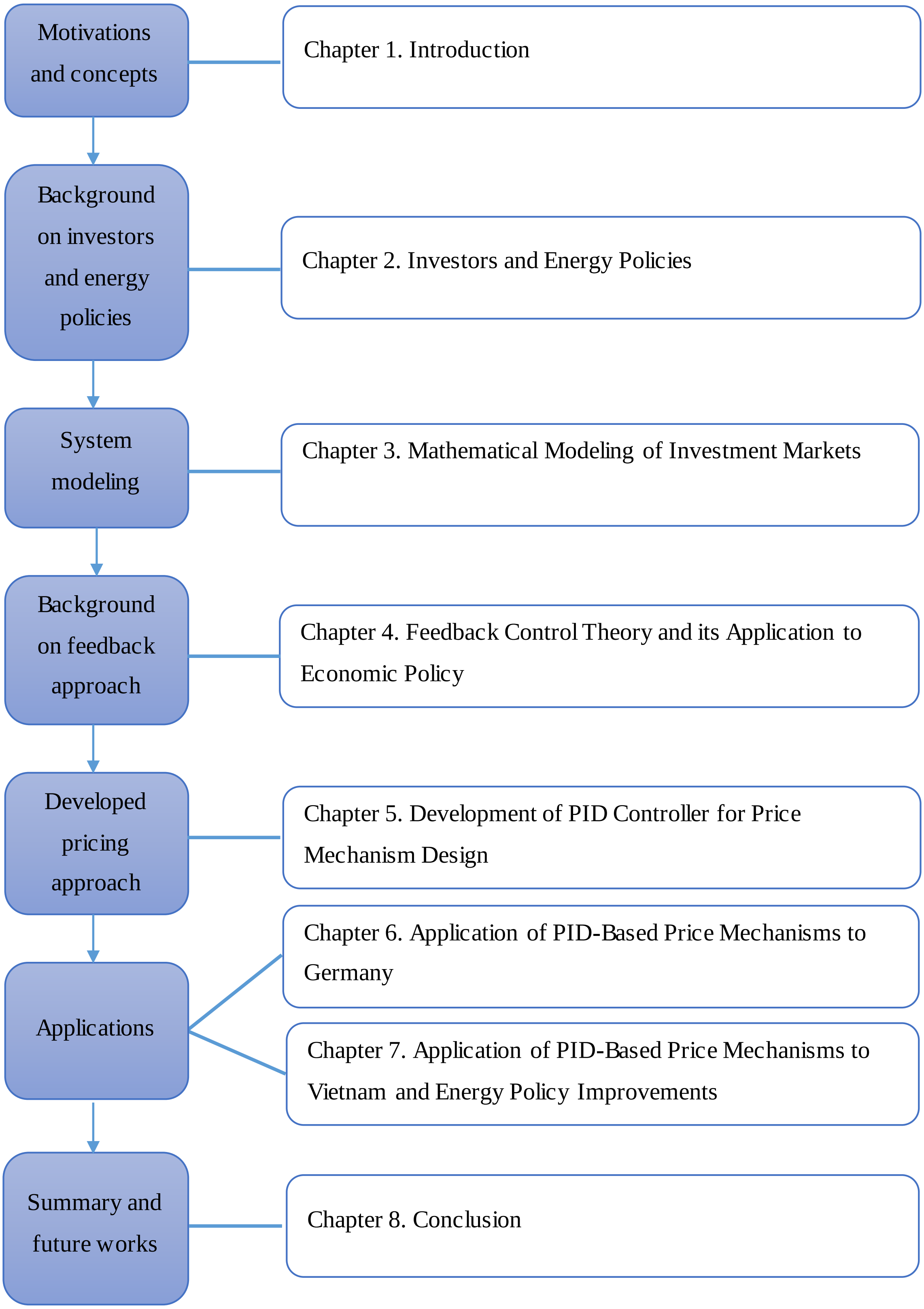



Figure 1.2. The outline of the dissertation structure

# Chapter 2. Investors and Energy Policies

## 2.1. Introduction

Investors decide the actual amount of renewable power investment in terms of installed capacity volume. Rational energy policies stimulate renewable power investment. Therefore, comprehending renewable power investor behavior helps policymakers construct and adjust energy policies effectively to achieve the intended effects.

Renewable power investors are diverse. Some investors enter the renewable power investment markets from very the beginning; others are interested in the markets as they mature. This fact is due to their different investment motivations and internal resources. Clearly, diverse investors require diverse and flexible energy policies.

Energy policies are economic policies related to the development of the energy sector. Various financial and fiscal incentives and regulatory policies have been adopted to support renewable power investment (REN21, 2020). Such policies provide critical signals for investment decisions in renewable power investment markets.

This chapter will provide a comprehensive understanding of investors and study the impacts of energy policies on investor behavior in renewable power investment markets. The work is organized as follows. Section 2.2 describes phases of technology diffusion, particularly the renewable power investment path. Then, possible scenarios of renewable power investment growth are characterized. Section 2.3 analyzes investment motivations, investors' internal resources, and the effects of micro and macro factors on investor behavior. Section 2.4 investigates the role of energy policies in investment decisions. Finally, Section 2.5 concludes the chapter.

## 2.2. Renewable power diffusion

### *2.2.1. Phases of technology diffusion*

Rogers (1983) describes an idealized technology diffusion that follows an S-shape curve over time. The adopters' distribution follows the bell curve with five adopter categories (Figure 2.1). Innovators account for about 2.5% of the adopters. They are risk-takers, have financial resources, and try new things regardless of the consequences. 13.5% of the adopters are early adopters who are at a higher social status, have financial liquidity and advanced education, but more careful about adoption choices than the innovators. 34% of the adopters are early majority adopters who are more risk-averse than the innovators and the early adopters. They observe and then follow the early adopters. Late majority adopters account for 34% of the population who spend their money on new technology when it becomes standard practice. Finally, laggards with social contact limitations are the last adopters.

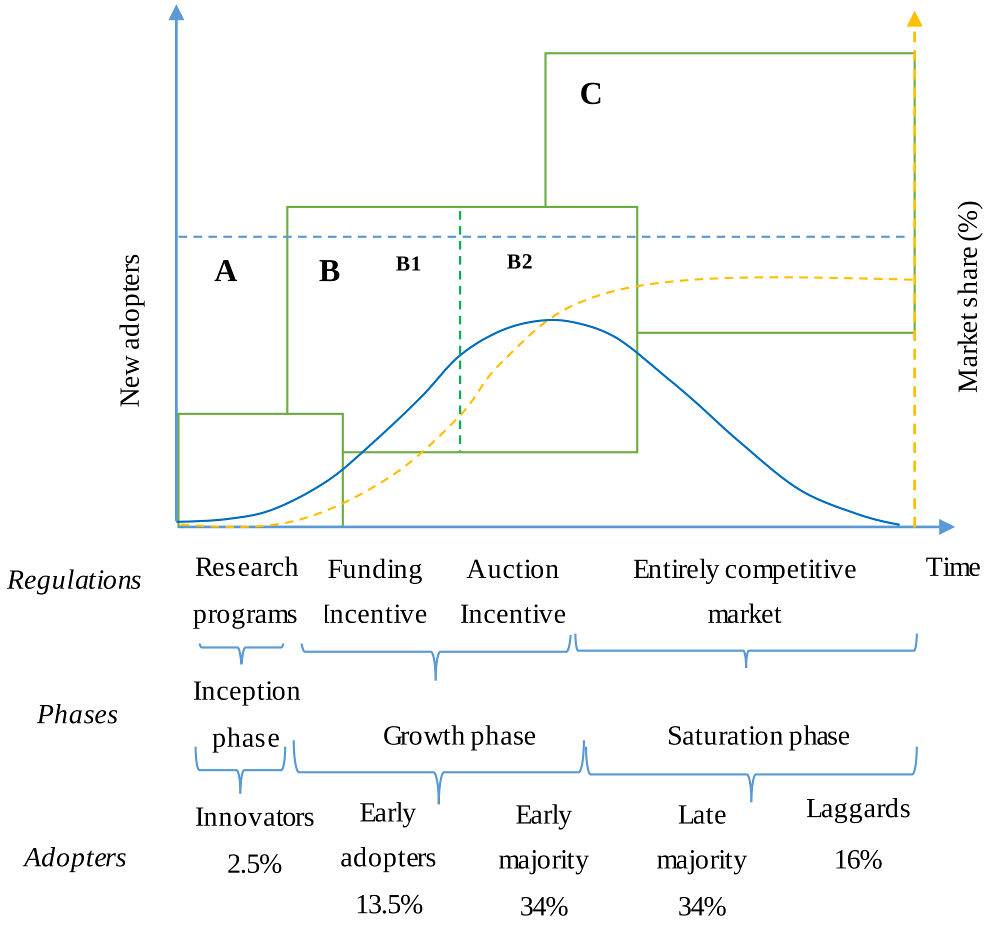



Figure 2.1. Three phases of technology diffusion

In terms of diffusion maturity, technology diffusion can be divided into three distinct phases: an *inception phase*, a *growth phase*, and a *saturation phase* (Grubler and Nakicenovic, 1991). Regarding diffusion speed, we distinguish them as an *initial slow growth*, a *rapid take-off period*, and a fl*attening growth*. The regulations corresponding with the above diffusion phases may be (A) research programs, (B) market incentives, including (B1) funding incentives and (B2) auction incentives, and (C) entirely competitive markets

In the early phase, the development must be supported by research funding to demonstrate practical feasibility. First functional proofs are provided by prototypes whose costs are far from economic viability. During the growth phase, market incentives stimulate a large market and leverage economies of scale, for example, to lower the cost. The cost reductions not only depend on technological breakthroughs but the further development and automation of production. The creation of automated production is only possible if sales markets are created. In the third phase, the technology becomes mature and can support itself in a much freer market force game. Real competition can intervene in the market, which is no longer specific to a specific technology and allows free competition to optimize it further. It should be noted that a combination of regulations is employed in the transition periods.

### *2.2.2. Phases of renewable power diffusion*

This section describes phases of renewable power diffusion following the pattern of technology diffusion as illustrated above. Accordingly, during the inception phase, the appropriate financing scheme is research programs. Then, political authorities introduce the FIT mechanism to attract investors, therefore, leads to a robust increase in renewable power installations. The experience in Germany indicates that the change from the FIT mechanism towards the auction mechanism is necessary to limit the financial burden on electricity consumers. In the saturation phase, both renewable and conventional power plants participate in an entirely competitive electricity market. The market premium mechanism is adopted in the transition period between the auction mechanism and an entirely competitive electricity market. Accordingly, apart from the revenue from the spot electricity market, renewable power plants may receive additional revenues due to the difference between the long-term contract price and the spot electricity market price. The contract price is either the FIT or the accepted auction price.

Although power investment markets and electricity markets exist simultaneously, the above analysis indicates that the investment markets need considerable attention during the growth phase. In contrast, the competitive electricity markets play a crucial role in the saturation phase.

Figure 2.2 depicts the general relationship between stakeholders in power investment markets and electricity markets. Policymakers create legal frameworks in terms of constitutions, codes, laws, resolutions, ordinances, decisions, and circulars. Investors, power plant owners, consumers, and service providers behave following these legal frameworks. Most investors expect a certain profit level when they spend their money on investment projects. Price mechanisms are a part of the legal frameworks, which directly affect project revenue. Therefore, they indirectly affect investment decisions. Because of lacking experience in power plant operations, investors may sell power plants to others after the plants are put into operation. Therefore, investors and power plant owners may be the same or different legal persons. The generated electricity is sold to buyers. In competitive generation electricity markets, the buyer is a single buyer. There are wholesale buyers in competitive wholesale electricity markets

(CWEMs). In competitive retail electricity markets (CREMs), consumers have opportunities to buy electricity directly from power plants through direct power purchase agreements (DPPAs).

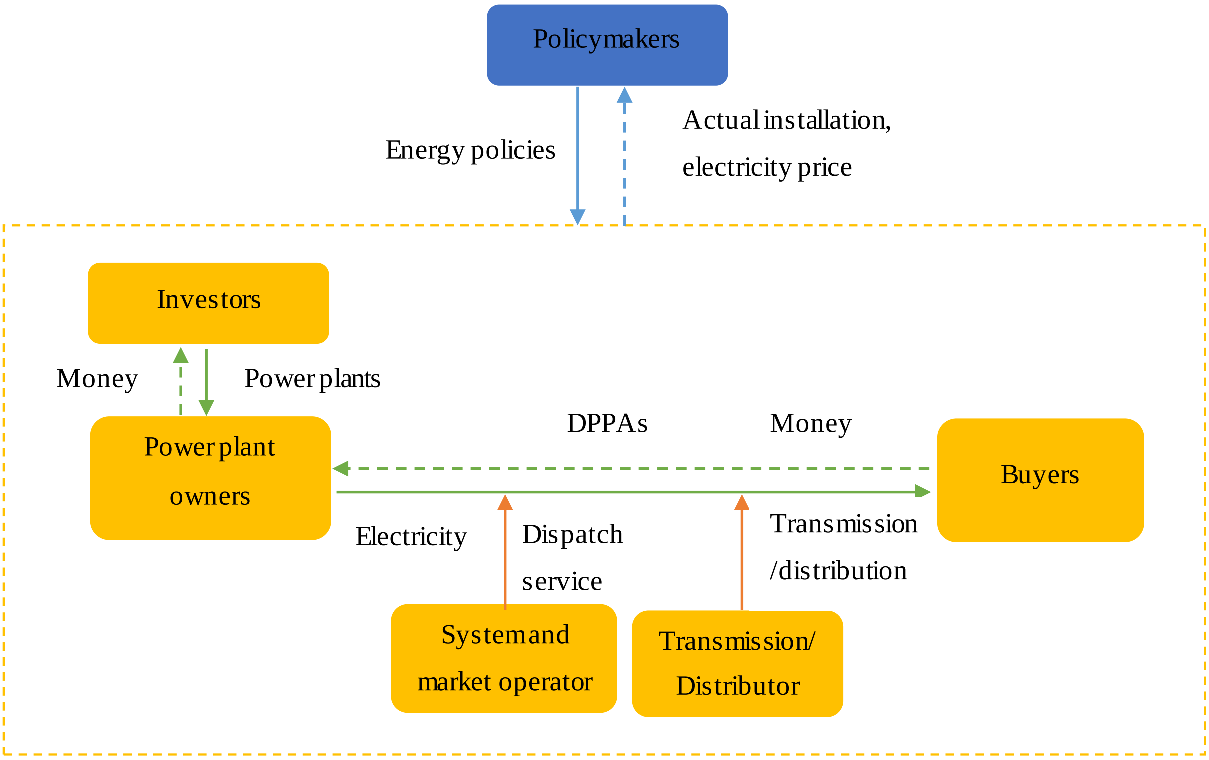



Figure 2.2. Stakeholders in power investment markets and electricity markets

The generated electricity is transferred from renewable power plants to consumers through dispatch and transmission, implemented by service providers. Money flows from buyers to power plants. The policymakers get feedback from the stakeholders about actual investment, electricity generation, transmission congestion, electricity price, and other information. Then, they adjust the energy policies based on the deviation between the targeted indicators and the actual ones.

### *2.2.3. Possible scenarios of renewable power diffusion*

Energy transitions differ from country to country. Looking globally, we realize that countries started energy transformation at different time points. For example, Germany is about 20 years ahead of Vietnam in the energy transition in the power sector. This country introduced the first Renewable Energy Sources Act to incentivize renewable power development in 2000. Currently, the solar and wind power diffusions in Germany are at the later growth phase. In contrast, not until 2011, Vietnam approved the first support mechanism for wind power development. Currently, Vietnam is at the early growth phase of solar and wind power diffusion.

This section addresses possible renewable power diffusion scenarios starting from the growth phase (Figure 2.1). The S-shape curve of renewable expansion can only be realized if sufficient time is given. Under the high time pressure of fighting climate change, other scenarios of renewable power development are possible. Looking globally from country to country, we see early reactors and later ones. Table 2.1 describes four principle scenario classes that are identified.

Table 2.1. Characteristics of possible scenarios of renewable power diffusion

| Scenario | Name of the scenario | Characteristics |
|---|---|---|
| A | Early reaction | a smooth ramp-up of installation at the growth phase and a constant speed at the saturation phase |
| B | Practical latest reaction | a steeper ramp-up of installation at the growth phase and a constant speed at the saturation phase |
| C | Theoretical latest reaction | depending on ramp-up pace, "perpendicular" ramp-up of installation (within one year) while keeping massive installation rate |
| D | Beyond latest reaction | either over-healing of renewable installation or otherwise violating emission target |

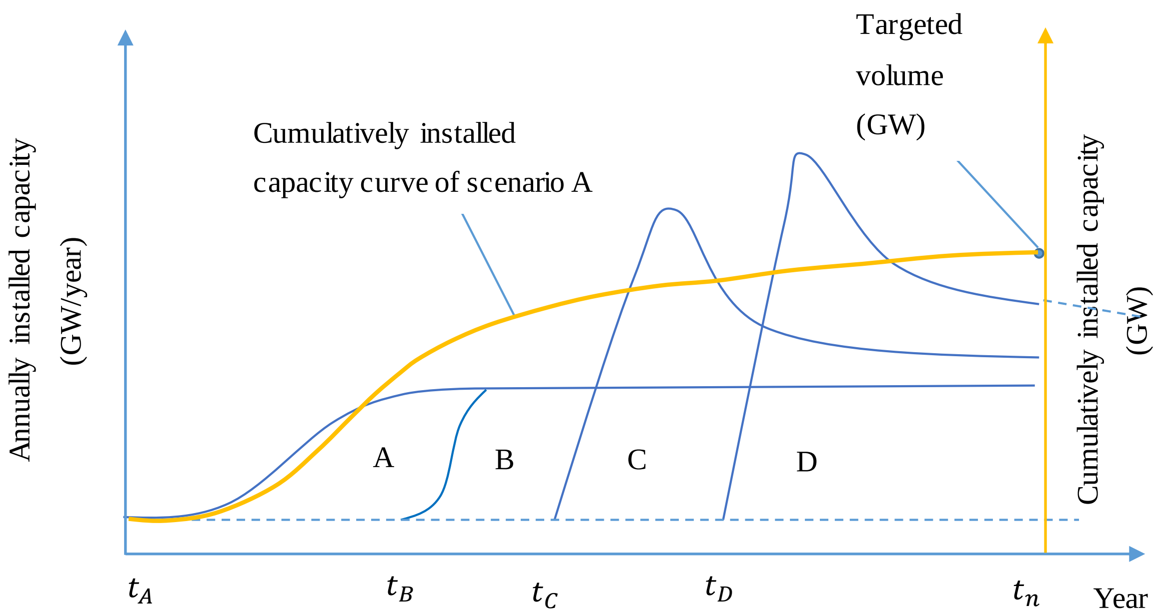



Figure 2.3. Possible scenarios of renewable power diffusion

The government coordinates the renewable energy diffusion path by setting energy targets (e.g., a specific cumulatively installed capacity by the year $t_n$). In order to achieve that aim, measures to start the diffusion can be implemented starting from the year $t_A$ (scenario A), $t_B$ (scenario B), $t_C$ (scenario C), or $t_D$ (scenario D). Figure 2.3 depicts that the later the diffusion starting point, the higher the annually installed capacity needed. The curves are constructed so that the integral under the curves is the same – equivalent to the targeted cumulatively installed capacity. However, with scenario D, the targeted installation volume is not achieved by the end of the year $t_n$.

## 2.3. Investor comprehension

### *2.3.1. Investor classification*

In contrast to conventional power investment markets, where most investors are utilities, renewable power investors are diverse. Investors can be classified based on ownership, central business area, or experience (Masini and Menichetti, 2012; Bergek, Mignon and Sundberg, 2013). In terms of ownership, they are distinguished as publicly and privately owned. Public investors include companies and organizations owned or controlled by municipal, regional, or national governments, while private investors use private capital resources. According to the International Renewable Energy Agency (IRENA) (2016), private entities globally owned over 85% of solar and wind power projects, while the state sector was less than 15%.

Private investors are divided into several types based on the main business area. Power project developers participate in electricity production by combining it with project development. Finance organizations, organized investors take advantage of holding funds to invest in renewable power assets. Independent power plants specialize in electricity production. Finally, end-users take advantage of owning roofs or spaces for renewable power installations. Table 2.2 classifies renewable power investors in Germany.

Table 2.2. Renewable power investor groups in Germany (Climate Policy Initiative, 2016; Werner and Scholtens, 2017)

| Investor groups, Level 1 | Investor groups, Level 2 | Examples |
|---|---|---|
| Utilities | Big power companies | EON, RWE, EnBW |
| | Local power companies | MVV Energy, Munich City Utilities, Hamburg City Utilities |
| Developers | International developers | DONG Energy, Vattenfall, Iberdrola |

| **Investor groups, Level 1** | **Investor groups, Level 2** | **Examples** |
|---|---|---|
| | National developers | PNE, wpd, Energiekontor, juwi |
| Finance organizations | International banks | German Federal Bank, Commercial bank, Morgan Stanley |
| | Local banks | Commercial bank, Bayern LB, LBBW, DZ Bank |
| Organized investors | Insurance companies | Allianz, MEAG |
| | Pension funds | VBL |
| | Foundations | |
| Independent power companies | Independent power plants | RE IPP |
| End-users | Industrial | |
| | Commercial | |
| | Residential | |

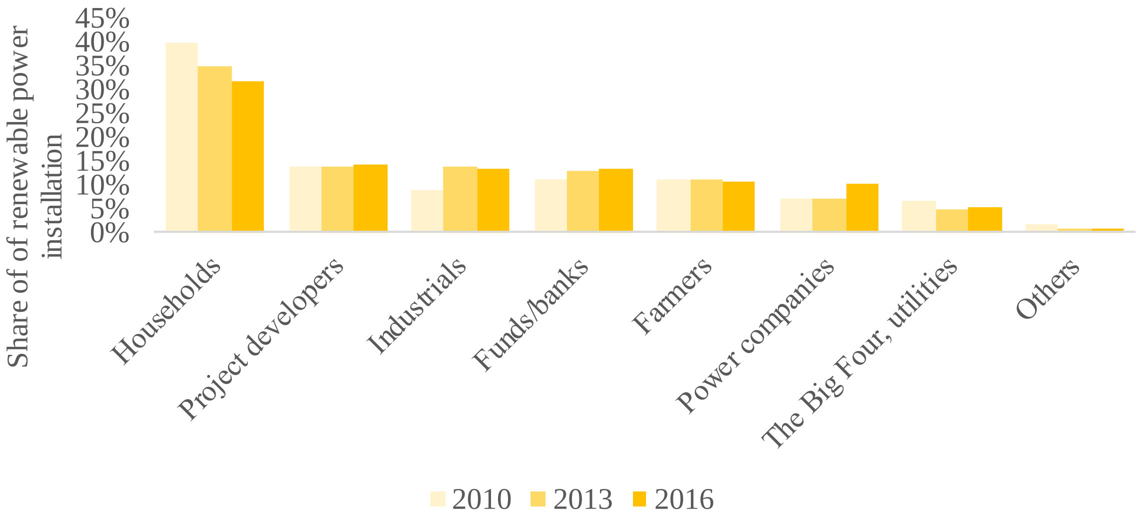



Figure 2.4. The ownership structure of renewable power installed capacity in Germany

(Source: Data from Morris, 2018)

Households and farmers contributed more than 50% to the total renewable power investment in Germany. However, recent years have seen a gradual decreasing share by these investors. In contrast, the investment by project developers and financial organizations increased slightly between 2010 and 2016. Despite having advantages in the electric power sector, the "Big Four"

– the German utilities, including RWE, EnBW, E. ON, and Vattenfall - accounted for only 5.6% of the total renewable power installed capacity in 2016. (Figure 2.4).

Heiskanen *et al.* (2017) indicate that 90% of renewable power investors in Finland in 2013 were utilities and project developers. However, households made up 67% of the total solar power investment flow.

In conclusion, the contribution of utilities in the total renewable power investment varies from country to country. Households play a crucial role in increasing the share of solar power in the total power supply.

### *2.3.2. Investment motivations*

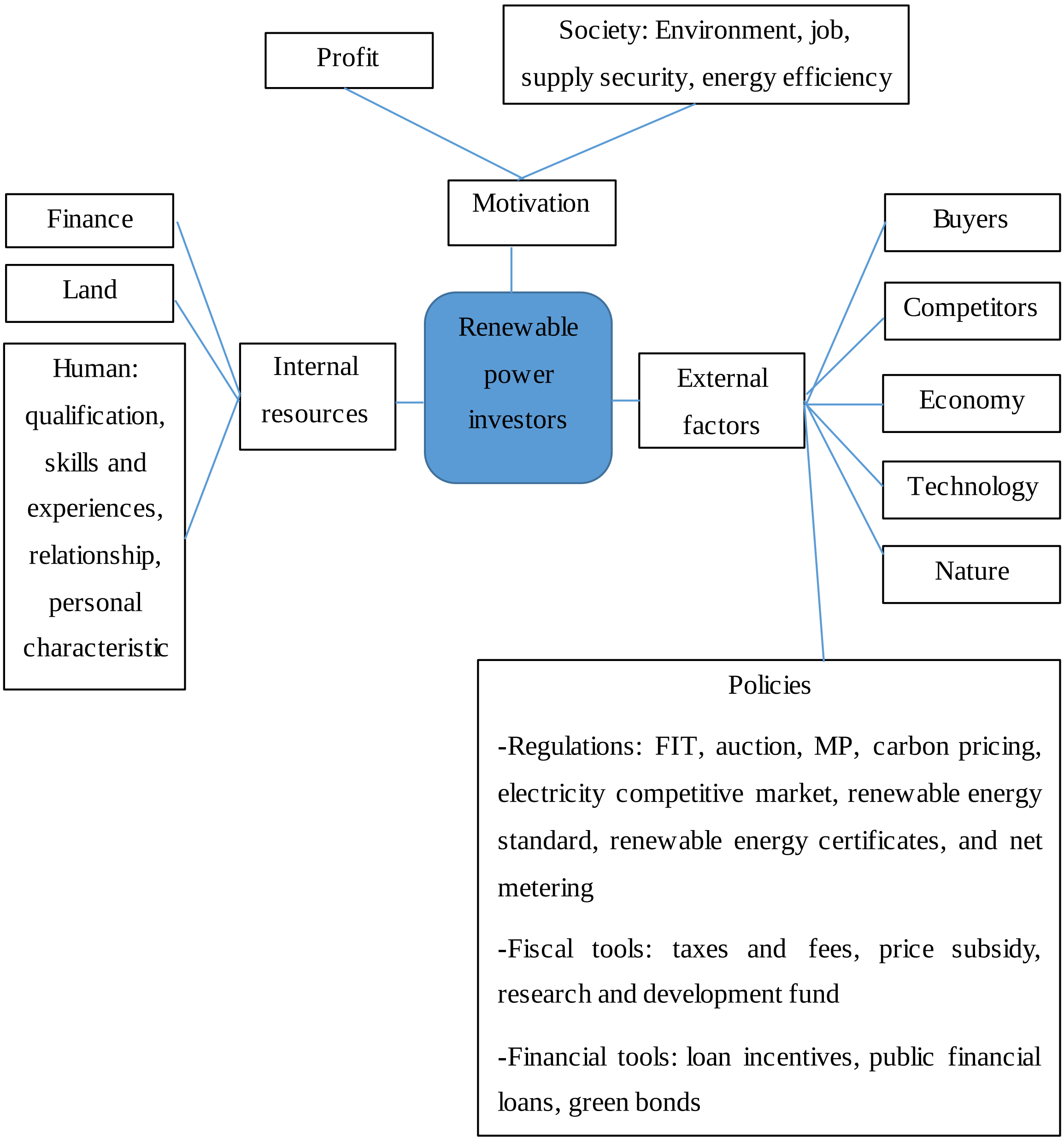


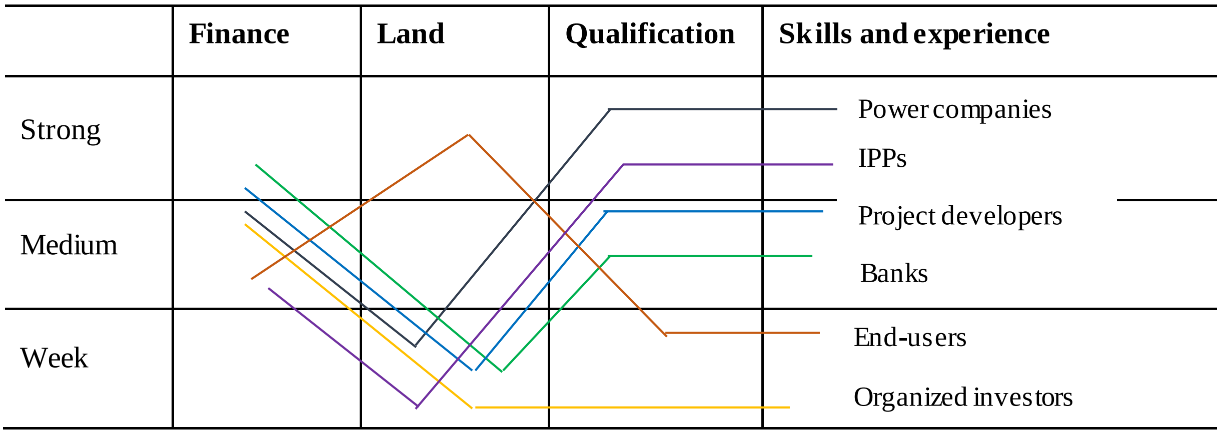

Figure 2.5. Motivations, internal resources, and external environment of renewable power investors

It is noteworthy that investors have different investment motivations. Most investors are profit-seeking players. From our observation and logical analysis, IPPs who spend all their resources on green power plants expect high profitability. Because of owning investment portfolios, private diversified companies and public-owned non-energy companies consider investment choices carefully. Utilities may spend their money on solar and wind power investment projects simply because green electricity generation is a part of their service chain to meet customer needs. They are also subjects of renewable energy standards (RESs) or renewable energy certificates (RECs) (see Section 2.4.6). Most end-users spend their money on rooftop solar PV systems or wind farms for self-consumption achievement rather than profit. Furthermore, some investors are willing to spend their money on green projects because they would like to contribute to social development, such as job creation, electricity supply security improvement, or environmental protection (Figure 2.5).

### *2.3.3. Internal resources*

Internal resources include capabilities related to capital and human. Capital is represented by finance and land resources, while human resources are characterized by educational background, skills, experiences, relationships, and personal characteristics (Figure 2.5). The internal capabilities are either strengths or weaknesses of investors.

Table 2.3. The internal resource matrix of investor groups




Utilities, IPPs have the advantages of internal capital, substantial qualification, skills, and experiences. However, because of not owning land, the project implementation depends on external land resources. By contrast, end-users have weak qualifications, skills, and expertise. However, they own the roofs, spaces, and land for installing solar panels or wind turbines. Banks have capital from low-interest deposits. Organized investors, households, and farmers own specific savings (Bergek, Mignon and Sundberg, 2013; Darmani, Niesten and Hekkert, 2014; Werner and Scholtens, 2017). The strengths or weaknesses of investors can be illustrated in a matrix, as shown in Table 2.3.

### *2.3.4. External environment*

The external environment includes micro and macro factors that affect investors' decisions. The micro-environmental forces consist of buyers and competitors, while the macro-environment comprises economic, technological, natural, and legal factors (Figure 2.5). Thus, the external surroundings are either opportunities or challenges for investors.

Depending on the electricity market design, electricity buyers are single buyers, wholesale buying companies, or end-users (see Section 2.2.2). In the inception and growth phases, electricity from renewables is prioritized to dispatch (German Federal Parliament, 2017; Prime Minister of Vietnam, 2017a). However, renewable power plants may be required to reduce their generation due to technical reasons. If renewable power plants participate in an entirely competitive electricity market, electricity from these power plants is only bought if the submitted price is lower or equal to the market-clearing price.

Competitors of solar and wind power farms are conventional power plants and other renewable power plants. The competitive level mainly depends on the electricity generation cost gap among technologies. The average electricity generation cost of utility-scale solar PV and onshore wind in Germany in 2018 was lower than most high-emitting technologies (Kost *et al.*, 2018). The average cost to produce a unit of electricity is called the "Levelized cost of electricity (LCOE)." The LCOE of a 1 MW project is determined using the following formula:

$$LCOE = \frac{I_0 + \sum_t^n \frac{C_t}{(1+WACC)^t}}{\sum_t^n \frac{E_t}{(1+WACC)^t}} \tag{2.1}$$

$LCOE$: levelized cost of electricity of a 1 MW project (Euro cents/kWh).

$I_0$: investment expenditure (million Euro).

$C_t$: operation and maintenance cost in year t (million Euro/year).

$E_t$: electricity generation in year t (MWh/year).

WACC: weighted average cost of capital (%).

n: a lifetime of the project.

Due to the uncertain nature, solar and wind energies are called "variable renewable energies (VREs)." Electricity generation from solar power plants depends on solar radiation. Accurately, more electricity is produced when the sun shines, while no electricity is generated at night. The electricity generation from wind power plants varies depending on wind speed, air density, and turbine characteristics. Without blowing wind, wind turbines cannot generate electricity. Figure 2.6 shows the electricity generation curves from solar and wind energy in Germany on a summer day, a winter day. Electricity generation from solar power plants follows parabolic curves with the generation period from 7 to 17h in winters and 5 to 20h in summers. In contrast, wind turbines produce electricity much more on a summer day than on a winter day. However, electricity generation from wind energy fluctuates significantly within a short period.

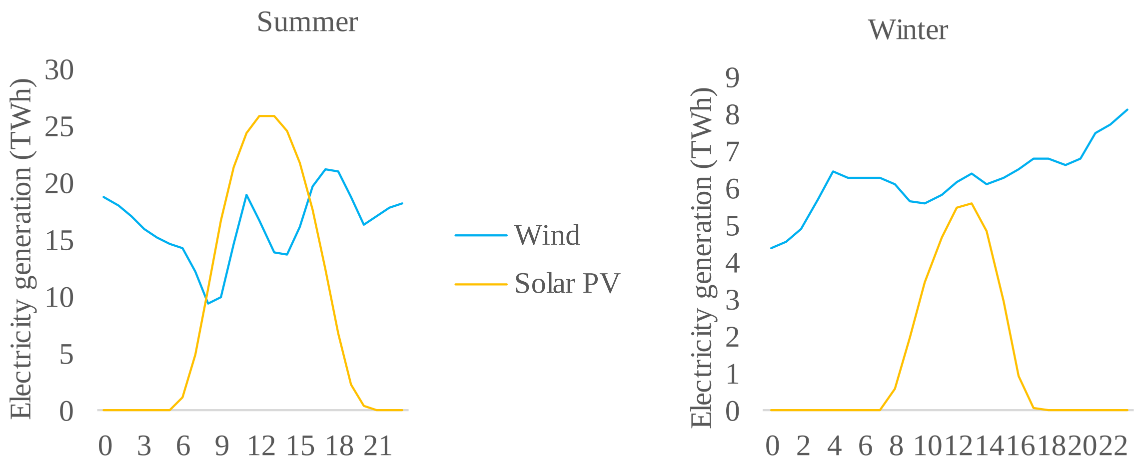



Figure 2.6. Electricity generation from solar and wind in Germany on typical days

Scientific and technological advances reduce renewable electricity generation costs; they improve the competitive ability of renewable resources compared with fossil fuels. The investment costs are forecasted to drop sharply between 2018 and 2030 from the average of 1,210 USD/kW to the range of 340 to 834 USD/kW for solar power (IRENA, 2019a), from 1,497 USD/kW to the range of 800 to 1,350 USD/kW for onshore wind, and between 1,700 and 3,200 USD/kW for offshore wind power (IRENA, 2019b).

## 2.4. Energy policies and their effects on investor behavior

This section aims to give readers an overview of energy policies and analyze the effects of these tools on investor behavior.

### *2.4.1. Feed-in tariff mechanism*

A feed-in tariff (FIT) is a fixed electricity price paid for electricity generated by renewable power plants and fed into the electricity grid. Usually, the tariff differs by technology (e.g., rooftop, ground-mounted, or floating systems for solar power, onshore or offshore systems for wind power), scale (e.g., residential, commercial, industrial, or utility-scale), and location (depending on wind speed, solar radiation). The FIT mechanism is a price commitment for investment projects over their power plants' lifecycle. The tariff does not depend on spot electricity market prices (Couture and Gagnon, 2010). If a project is paid with the FIT, the annual revenue is determined as follows:

$$R = \sum_{h=1}^{8760} E_h * FIT \tag{2.2}$$

R: annual revenue of the project (million Euro).

$E_h$: commercial electricity from the project at hour h (MWh).

$FIT$: feed-in tariff for the project (Euro cents/kWh).

Determining the FIT level is challenging. Traditionally, it is calculated based on renewable electricity generation costs (Klein *et al.*, 2010). The investment costs account for a majority, while operation and maintenance costs make up a small proportion of the renewable electricity generation costs. Accurately, PV module cost accounts for 50-60% of the solar power investment cost. Inverters converting DC power into AC power constitute 10–15%. System balance cost represents 5–10%. For wind power projects, capital costs include wind turbine costs, grid connection costs (substations, buildings, cablings), construction costs (roads, site preparation), and others (development and engineering costs such as licensing procedures, consultancy, and monitoring systems). Turbine cost accounts for 65–84% of the total capital cost of onshore wind power projects, while this cost defines 30–50% of the total investment expenditure of offshore wind power projects. Offshore wind power projects face high grid and construction charges due to required foundation structures, maintenance, and cabling. These costs vary according to plant geographical location (depending on wind speed, water depth, distance from shore) (IRENA, 2018).

If renewable power plants do not exist, the electricity will have to be generated by conventional power plants with high external costs. From this identification, the approach to the avoided external cost-based FIT mechanism is developed. Apart from electricity generation costs, policymakers in Portugal have also considered carbon emission costs (Klein *et al.*, 2010).

The FIT mechanism is original to support new technologies with high investment costs. As the investment costs of solar and wind power have decreased significantly, the FIT mechanism is now limited to be applied in new renewable power investment markets (e.g., in Vietnam). For the mature markets (e.g., in Germany), the FIT mechanism remains only for small-scale projects to promote investments by end-users. According to the REN21 (2021), by the end of 2020, 116 countries applied the FIT mechanism.

### *2.4.2. Auction mechanism*

Auction is a quantity-based price mechanism (Finon, Menanteau and Lamy, 2002). Solar and wind power investors submit bids that include installed capacity volume and electricity price to an auction agency. Bids with lower prices are accepted first until reaching the desired installation volume. Such a winner selection follows the *merit-order effect* principle (Figure 2.7).

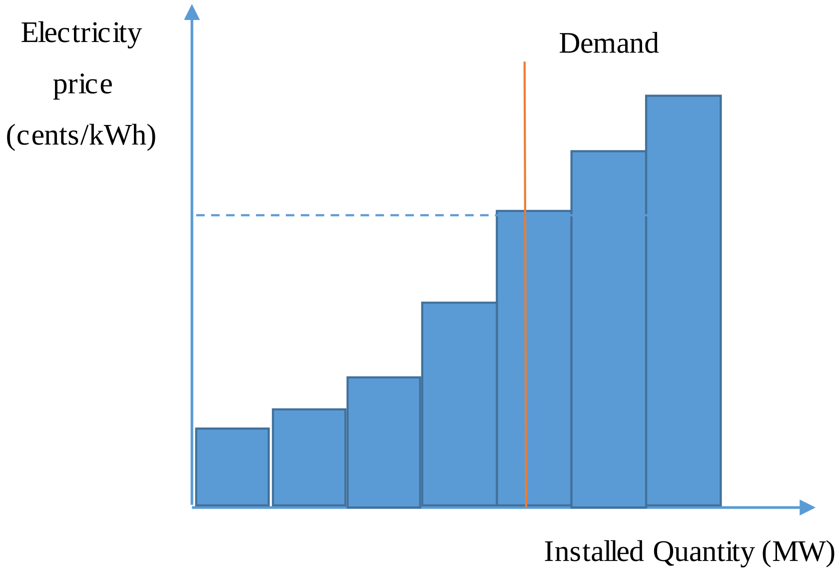



Figure 2.7. The merit-order effect principle of the auction mechanism

Both installed capacity and electricity price are determined through the bidding process before projects are implemented. Thus, the auction mechanism commits the revenue for accepted investment projects.

Depending on the auction design, the selected bids are paid with a *uniform price or pay-as bid*. A uniform price is the highest price of accepted bids and is paid for all winning bids. If the pay-as bid auction is applied, the winning bids are paid with their submitted prices. The formula of the annual project revenue is as follows:

$$R = \sum_{h=1}^{8760} E_h * AP \qquad (2.3)$$

$AP$: accepted auction price.

Using the auction mechanism, the government can orient the investment market through auction frequency, auction volume, and ceiling price regulations. Auction frequency is selected based on a market scale represented by targeted investment volume: the larger the market, the more regular the auction. The auction frequency varies from country to country, from technology to technology (Kitzing *et al.*, 2016). For example, Germany has organized 3 - 7 auction rounds of solar power or wind power each year. Auction volume is represented by electricity generation, installed capacity, or budget cap. Most governments set power targets in installed capacity; whereby, the auction volume is also installed capacity. The ceiling price is the maximum awarded value that a bidder can receive, regulated to prevent collusion from pushing the price up while controlling policy costs (IRENA and CEM, 2015). Determining the ceiling price is challenging. It is recommended that the ceiling price should reflect market conditions and technology costs.

Regarding the auction format, policymakers choose either a sealed-bid auction or a descending clock mechanism. With the *sealed-bid auctions*, bidders do not know the bidding price of their competitors. The bids are selected based on the merit-order effect principle (Figure 2.7).

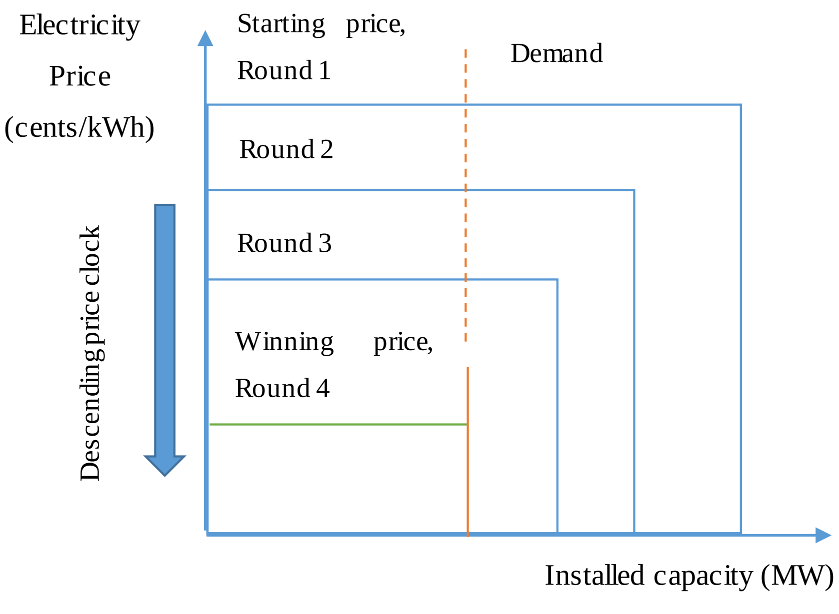



Figure 2.8. Principle of a descending clock auction

In contrast, with the *descending clock* or *iterative auctions*, bidders do not have information about the targeted volume. An auction agency sets a ceiling price and calls for bids. Then, the agency observes the volume of bids at that price. After that, the price is reduced, and the agency calls for the next bidding rounds until achieving the targeted volume (Figure 2.8). The descending clock means that the price is reduced gradually over time. This auction format is challenging to implement and only useful in markets with high competition (e.g., in Brazil and Mexico) (Hochberg and Poudineh, 2018).

The competitive auction mechanism affects differently on investors. Utilities and IPPs with good expertise may benefit from this mechanism. In contrast, the complicated auction mechanism may become a barrier for investor groups with no expertise and experience in offering a good bid strategy. It is also tricky for small-scale investors due to the high transaction cost and risk. By the end of 2020, more than 86 countries worldwide introduced the auction mechanism (Renewable Energy Policy Network for the 21st century (REN21), 2021).

### *2.4.3. Market premium mechanism*

Market premium (MP) is a partial electricity market-dependent price mechanism. It represents a hybrid structure that combines the FIT mechanism or auction mechanism and the spot electricity market. Apart from the market price, renewable power plant owners receive a premium according to the transaction period.

$$PP_h = SMP_h + MP_h \tag{2.4}$$

$PP_h$: premium price at hour h (cents/kWh).

$SMP_h$: system marginal price (or marginal market price) at hour h (cents/kWh).

$MP_h$: market premium at hour h (cents/kWh).

The system marginal price is the last generating unit’s submitted price dispatched in the spot electricity market. The market premium is either be fixed or sliding. Fixed MP is the same MP at different transaction periods and determined in advance independently from the market price (e.g., a given MP is 2 cents/kWh, no matter how much the market price is). The fixed MP is simple; however, it poses risks to consumers (when the market price is high) and renewable power plants (when the market price is low). In contrast, a sliding MP varies following the market price. At periods of high market price, the MP is low (even zero), and vice versa. The sliding MP is preferred over the fixed MP because it reflects the market conditions (Couture and Gagnon, 2010). The annual project revenue with the MP mechanism is determined as follows:

$$R = \sum_{h=1}^{8760} E_h * PP_h \tag{2.5}$$

According to the BMWi (2012), a monthly sliding MP in Germany is the difference between the reference value and the average monthly market price.

$$MP_m = RP - \overline{SMP}_m \tag{2.6}$$

$MP_m$: the market premium for a specific technology in month m (Euro cents/kWh).

RP: the reference price for a specific technology (FIT or accepted auction price) (Euro cents/kWh).

$\overline{SMP}_m$: the average monthly market price for a specific technology (Euro cents/kWh).

$$\overline{SMP}_m = \frac{\sum_{h=1}^{720} E_h * SMP_h}{\sum_{h=1}^{720} E_h} \tag{2.7}$$

With a given FIT of 11 Euro cents/kWh for solar power, the calculated average monthly market price of 9 Euro cents/kWh, the monthly MP for solar power is determined at 2 Euro cents/kWh. Figure 2.9 illustrates the prices for solar power at 12 transaction periods in a month. This design shows an hourly fixed MP but monthly sliding MP.

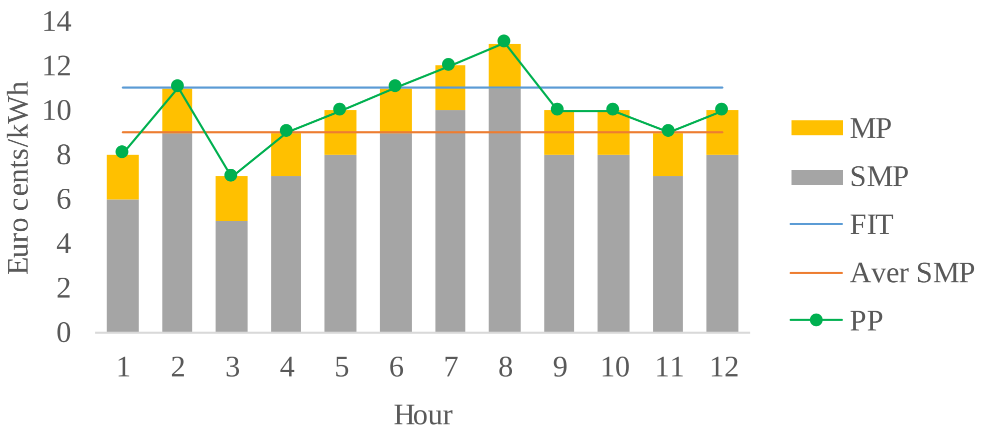



Figure 2.9. An example of the market premium mechanism

Thus, we have a "FIT-based market premium mechanism" if the reference price is FIT and an "auction-based market premium mechanism" if the reference price is accepted auction price.

From (2.7), we identify that the monthly MP is zero if the reference price is lower than the average monthly market price. The first offshore wind power auction round in Germany shows a surprising result. Three of four projects submitted the bids with a price of 0 Euro cents/kWh. The zero-price bids mean that the investors accept to be paid with only the spot electricity market price, no market premium (Kreiss, Ehrhart and Hanke, 2017).

With the high penetration of renewable power, the MP mechanism increases the competitiveness among power generation technologies. Therefore, it forces power plants to reduce electricity generation costs. Moreover, the hybrid mechanism reduces financial risks for both power plant owners and electricity buyers. When the electricity market price is lower than the contract price, the investor's revenue is lower than that paid with the market price but higher than that paid with the contract price, and vice versa.

The MP mechanism is too complicated for small-scale investors. However, it may be suitable for utilities, project developers, and IPPs.

### *2.4.4. Entirely competitive generation market*

An entirely competitive generation market (ECGM) is an entirely market-dependent price mechanism. In this market, a bidder offers a total price based on the electricity generation cost. Therefore, the ECGM is also known as an entirely price-based power pool (EPBP). Project revenue depends entirely on the dispatched quantity and the accepted price. Renewable power plants are paid with either a uniform price or a pay-as bid depending on the market design. There is no long-term contract between power plants and buyers. The annual project revenue with the ECGM is determined:

$$R = \sum_{h=1}^{8760} E_h * EMP_h \tag{2.8}$$

$EMP_h$: entirely market price for a specific bidder at hour h.

Without price commitments, renewable power plant owners face high market risk. This mechanism is applicable only when renewable power resources are highly competitive with traditional ones. So far, no ECGMs are available.

### *2.4.5. Carbon price mechanisms*

According to the Intergovernmental Panel on Climate Change (IPCC) (2018), "a carbon price is the price for avoided or released carbon dioxide or carbon dioxide-equivalent emissions." The carbon charge aims to reduce carbon emissions by making fossil fuels-based power production more expensive; therefore, green power sources more attractive.

There are two main carbon price mechanisms: carbon taxes and emissions trading systems (ETS). A carbon tax is a price-based mechanism that the government sets the carbon price directly. Traditionally, the carbon tax is determined based on the social cost of carbon (SCC). According to Yohe *et al.* (2007), "the social cost of carbon is the marginal cost of the impacts caused by emitting one extra tonne of carbon dioxide at any point in time, inclusive of non-market impacts on the environment and human health." Briefly, the SCC reflects the damage cost if the emissions continue. Integrated Assessment Models (IAMs) are well-known for estimating the SCC. These models result in an SCC from 13.36 to 2,386.91 USD/t$CO_2$, a mean value of 54.70 USD/t$CO_2$ (Wang *et al.*, 2019). The SCC varies from country to country. It is high in India, China, Saudi Arabia, and the United States (Ricke *et al.*, 2018).

Another carbon pricing approach is based on the marginal abatement cost (MAC) – the cost of reducing one more unit of emissions. It is also known as the final average cost of reducing carbon emission after a set of carbon reduction policies is applied. Because the cost of curbing a one-carbon unit differs among countries, the MAC varies by country accordingly. Taking advantage of the FIT mechanism's popularity, Bakhtyar *et al.* (2017) suggest carbon price determination based on the substitute price of avoiding carbon emissions (SPAC). This research results in a carbon price of 63 to 2,951 Euro/t$CO_2$ in European countries. Because the FIT level varies over time, the SPAC is time-variant accordingly.

In contrast with the carbon tax, an ETS, or a cap-and-trade system, is a market-based mechanism. The government regulates the number of carbon allowances per period and defines polluters who have to hold emissions permits. The tradings can be transacted privately or in international markets. In other words, the emissions permits can be bought and sold through bilateral contracts or centralized markets.

As of April 2019, 29 carbon taxes and 28 emission trading systems have been employed worldwide, equal to around 20% of carbon emissions. The carbon price ranges from 1 to 127 USD/t$CO_2$ (Ramstein et al., 2019). Werner and Scholtens (2017) indicate that carbon price significantly affects utilities' investment decisions in Germany.

### *2.4.6. Other regulatory policies*

*Renewable energy standards (RESs)* require utilities to spend at least a specific investment share of the total investment amount on renewable power projects. The USA's mandatory RES is from 5 to 40% by 2025, differentiating states (US Environmental Protection Agency, 2016). According to the Prime Minister of Vietnam (2015), large power generation companies in Vietnam will have to reach 3%, 10%, and 20% of renewable power installed capacity in the total investment by 2020, 2030, and 2050. In conclusion, the RESs directly affect utilities' investment selection.

*Renewable energy certificates (RECs)* are a type of green certificate. One unit of electricity from renewable energy sources is equivalent to one certificate. Utilities, if not adequately invest in renewable energy, can purchase this certificate from remaining investors. Thus, this mechanism allows utilities to be more flexible in choosing electricity generation technologies. As of March 2015, 29 states in the USA applied the RECs (Cox and Esterly, 2016).

*Net metering* is a billing mechanism applied for rooftop solar systems that are invested by end-users. It measures the electricity added to the grid when the generation by rooftop solar systems is excess, the electricity taken from the grid when deficient. Cox and Esterly (2016) indicate that if the FIT level is equal to or higher than the electricity generation cost from rooftop solar systems, this mechanism will stimulate new installations by end-users.

### 2.4.7. Financial instruments

*Loan incentives* are instruments related to loan time, lending interest rates, and grace periods. Generally, the investment capital is structured by equity and debt liability, popularly with a ratio of 20/80 or 30/70. In other words, most investment capital comes from external sources. Therefore, lending incentives are vital supports for many investors. There are several accessible loan sources, such as on-lending, co-lending, and subordinated debts. On-lending is also known as intermediary financial lending, whereby capital intermediaries borrow funds from organizations and on-lend them to renewable power investors. Co-lending is established by a group of commercial banks and oriented to provide capital for large-scale projects. Subordinated debts are the loans ranked after other loans if a company falls into liquidation or bankruptcy. Investors have opportunities to access different loans with different interest rates and grace periods. According to the IRENA (2016), international power project developers can quickly access domestic and international credit institutions. Utilities, IPPs can borrow money from local banks. Responding to the Government of Vietnam's green energy development orientation, commercial banks in Vietnam have introduced special loan packages with low interest rates and long grace for end-users (Viet, 2021).

Another financial source is public funding, contributing 15% to the renewable investment budget (IRENA, 2016). This financial source comes from international, national, and local public finance institutions. International financial institutions such as the World Bank (WB), European Investment Bank (EIB), European for Reconstruction and Development (EBRD), KfW Development Bank (KfW), and Asian Development Bank (ADB) have been active in the renewable energy sector. Besides, export credit agencies supply government-backed loans, guarantees, and insurance to corporations from their home country, aiming to do business in developing countries.

*Green bonds* are bonds issued for green energy projects with long grace periods and low-interest rates. EIB and WB initiated and introduced green bonds in 2007. However, not until 2014, this type of bond has reached a rapid growth rate. According to the IRENA (2020), in 2018, a total green bond value of 167 billion USD was raised, mainly in the USA, China, and France. In principle, public or private institutions can issue this type of bond if the green bond principles and climate bonds standards are satisfied. However, history shows that only pensions and insurance companies can use green bonds as capital mobilization channels. In Vietnam, pilot projects for the green bonds were implemented in Ho Chi Minh City and Ba Ria Vung Tau province, with a total value of 603.5 billion VND (equivalent to 27.7 million USD). However, the official green bond market has so far been unavailable (Anh Tu, Sarker and Rasoulinezhad, 2020).

#### *2.4.8. Fiscal instruments*

*Taxes and fees* such as import tax, corporate income tax, and land fee are included in the business cost. A higher tax or fee rate leads to a higher cost, and therefore a lower profit. In Vietnam, preferrable taxes, even exempted, are applied to green power projects. For example, according to the Ministry of Finance of Vietnam (2019), rooftop PV installations of no more than 50kW are entitled to import tax exemption within five years. Also, special projects may enjoy the exemption of corporate income tax. Similarly, exemption and reduction of land use fees and water surface rents are stimulating renewable power investment.

*Price subsidy* is a support mechanism that governments pay producers enough money to compensate for the loss of selling products at low prices. In many countries, governments derive from the government budget to pay renewable power plant owners.

*The research and development fund* is a government budget devoted to scientific and technological research projects. For example, Korea spent USD 20,000/year/research on solar and wind power (Chang, Fang and Li, 2016). According to the BMWi (2020), the amount of 6.5 billion Euros is planned to support companies and research establishments in research and develop energy technologies.

Despite the expected good impacts on renewable power investment markets, the taxes, subsidies, and research and development funds do not significantly affect private investment (Azhgaliyeva, Kapsalyamova and Low, 2019).

### *2.4.9. Procedures*

*Document systems* related to renewable power project development and implementation include investment licenses, loans, land leasing, and power purchase agreements. Without experience in preparing these documents, investors may encounter difficulties. Therefore, simplifying the document systems contributes to the success of renewable power diffusion.

*Processing duration* is the time for granting the mentioned documents: the shorter the processing duration, the more attractive the investors.

Table 2.4 presents regulatory policies, fiscal and financial incentives for renewable energy development in Germany and Vietnam in 2019.

Table 2.4. Policy systems for renewables in Germany and Vietnam in 2019 (REN21, 2020)

| **Policy** | **Tool** | **Germany** | **Vietnam** |
|---|---|---|---|
| Renewable energy targets | | E, P, HC, T | E, P, T |
| Renewable energy in national power development planning | | | X |
| Regulatory Policies | FIT | X | X |
| | Auction | X | |
| | RESs/ RECs | | X |
| | Net metering | | |
| | Biofuel blend obligation | X | X |
| | Renewable heat obligation | X | |
| | Tradable REC | X | X |
| | Market premium | X | |
| Fiscal incentives | Tax incentives | X | X |
| | Investment or production tax credits | X | X |
| | Reductions in sales, energy, carbon emission, VAT, or other taxes | X | X |
| Financial incentives | Public investment, loans, grants, capital subsidies, or rebates | X | X |

Note: E: energy (final or primary); P: power; HC: heating or cooling; T: transport.

## 2.5. Chapter conclusion

The results of studying investor behavior and the impacts of energy policies on investment decision-making provide policymakers inputs for policy design.

This chapter describes three phases of technology diffusion, here concretely renewable power diffusion. These phases comprise a gradual introduction of research programs, funding and auction incentives, and finally arriving at entirely competitive markets. This three-phase approach is recommended to create rational regulatory frameworks for the inception, growth, and saturation phases. In the transition period between phases, different price mechanisms should be combined. For renewable power diffusion, after the financing scheme for research programs, the FIT mechanism, which commits revenue for investors, is suggested to stimulate the solar and wind power investment volume. At the later growth phase, the auction mechanism and market premium mechanism are alternatives to limit the financial burden on consumers and gradually drive to an entirely competitive electricity market.

Moreover, we argue that there are various scenarios of renewable power development to achieve a particular renewable power target. In other words, the curve of renewable power diffusion can be in various forms, not only the S-shape. The later the diffusion starting point, the higher the annually installed capacity needed. Besides, a country may not achieve renewable energy development goals because of late adoption.

It is identified that renewable power investors are diverse. Apart from profit, green power projects may attract economic sectors simply because of job creation, electricity supply security improvement, or environmental protection. Utilities, IPPs have the advantages of human and finance resources but depend on external land resources. By contrast, end-users own the roofs, spaces, and land but lacking skills and expertise in project implementation.

Furthermore, this chapter points out that investors are affected at different levels by energy policies. The FIT mechanism has strongly forced private investment. In contrast, utilities and IPPs with good expertise may benefit from the auction mechanism and market premium. Carbon price mechanisms, other regulatory policies, loan incentives, green bonds, preferred taxes, and fees are also favorable instruments for stimulating renewable power investments.

# Chapter 3. Mathematical Modeling of Investment Markets

## 3.1. Introduction

According to Barbosa (2003), the mathematical formulation of the system provides a quantitative understanding of the system, predicts the future, and quantifies prediction uncertainty. Models of investment markets are crucial in the control system design of price mechanisms for renewable power investment. However, modeling investor behavior is challenging for a variety of reasons. First of all, investors in renewable power investment markets are diverse. They are different in investment aims, have different internal resources, and are affected differently by the investment environment (see Chapter 2, Section 2.3, and Section 2.4 for more details).

Figure 3.1 defines a renewable power investment market as a system that consists of assets (solar or wind farms) and investors (organizations and individuals). In contrast to the straightforward calculation of the profitability of renewable power farms (see Section 3.3 for the formulations), the estimation of a mathematical model of investor behavior that yields renewable power investment volume as a function of profitability is a much more arduous effort.

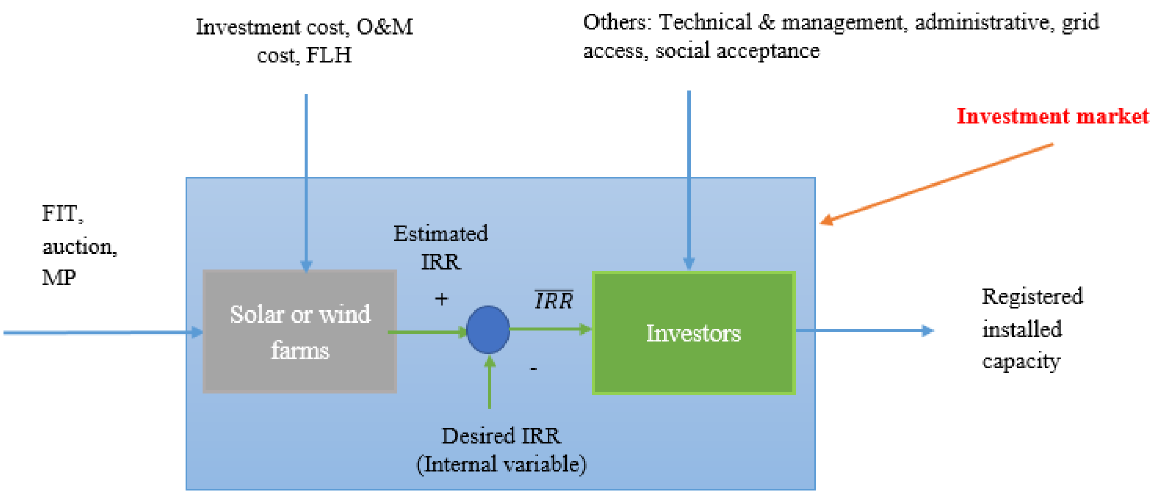



Figure 3.1. Block diagram of a solar and wind power investment market

This chapter is organized as follows: Section 3.2 reviews models of the investment market to acknowledge the current approaches and identify their limitations. Our own approach is started by separating an investment market into assets and investors. Section 3.3 describes the formulation of profitability. Then, based on observation, speculation, and mathematical language, we construct several investor behavior models in Section 3.4. Finally, Section 3.5 highlights the chapter conclusions.

## 3.2. Literature review of investment market models

Mathematical models of the renewable power investment market can be grouped into three types: econometric models, diffusion models, and learning curve models.

### *3.2.1. Econometric models*

Econometric models use statistical approaches to quantify the relationship between economic variables and a particular economic phenomenon (Shalabh, 2018). This approach has been widely used for investigating the factors affecting investment decisions.

Before making investment decisions, an investor considers whether the investment project will satisfy his goals (e.g., desired profitability) and whether the internal resources meet the project implementation requirements. In addition, a careful evaluation of the impacts of the micro and macro environment on the investment is also necessary (Georgakellos and Macris, 2009).

Clearly, most investors make investment decisions based on profitability. Various indicators are used for project financial performance assessment, such as the net present value (NPV), the internal rate of return (IRR), the ratio of benefit to cost (B/C), and the payback time (Tpb) (Rehber, 1999). NPV is the most widely and classically used for evaluating profitability, and it is not excepted for green power projects. The NPV is calculated using a predefined return rate (or risk-adjusted discount rate). An investor only implements an investment project if the estimated NPV is positive. However, despite the popularity of NPV, numerous researchers have recently criticized that using the classical NPV to evaluate the financial performance of renewable power investments is insufficient (Masini and Menichetti, 2012; Barcelona, 2015). They argue that the standard NPV is based on static assumptions while the future is uncertain. Masini and Menichetti (2012), Barcelona (2015) indicate that an investment portfolio is preferred over a singular investment with uncertainty. These studies specify a positive correlation between the investment portfolio and investment performance. Another approach to overcome the limitations of static NPV is through the real options analysis (ROA). Accordingly, an investment is only undertaken if the NPV of the current investment exceeds or equals the value of later investment opportunities (Zhang *et al.*, 2016; Kim, Park and Kim, 2017). Futhermore, Drury, Denholm and Margolis (2011), De Boeck *et al.* (2016) criticize that the NPV cannot compare the profitability of projects with different investment costs and that the IRR can be a helpful tool.

Regarding the investment models, Grau (2014) assumes that the project deployment increases proportionally to the NPV of the project. Segmented regression models are suggested to quantify investor behavior according to the investment market's maturity. Klein and Deissenroth (2017) indicate that the investment is a time-invariant exponential function of IRR. Profitability directly affects investment decisions. However, the profitability varies depending on revenue and cost factors, which are affected partially by energy policies. Masini and Menichetti (2012) indicate a preference for the FIT mechanism rather than the tax incentives, investment grants, tender schemes, tradable green certificates, and renewable portfolio standards. Also, this study argues that venture and private investors prefer short-term policies to substantial financial incentives. Yang et al. (2019) show a more significant tax incentive effect over monetary subsidies in China. Werner and Scholtens (2017) argue that wind energy investment drivers differ according to the investor group. The FIT mechanism changes do not affect the behavior of large utilities in a statistically significant way. Large utilities have still preferred investing in fossil fuel-based power projects. In contrast, the FIT mechanism adjustments are vital signs for small private investors, diversified companies, and independent power producers. Carbon price makes utilities consider the investment between high-emitting technologies and low-emitting ones more carefully.

In summary, the previous econometric models provide a simple knowledge about the factors affecting investment decisions. They are limited to describe the dynamic and time-variant characters of investor behavior.

### *3.2.2. Diffusion models*

Bass's model is one of the well-known diffusion models built on the assumption that two communication channels influence potential adopters. Mass media is supposed as an external influence factor (or innovators), while word of mouth is an internal influence factor (or imitators) (Bass, 1969). The Bass model formula applied to renewable power diffusion with discrete analog data would look like:

$$v_t = V_t - V_{t-1} = p(m - V_{t-1}) + \frac{q}{m} V_{t-1}(\mathrm{m} - V_{t-1}) \tag{3.1}$$

$$v_t = (p + \frac{q}{m} V_{t-1})(m - V_{t-1}) \tag{3.2}$$

$v_t$: additionally installed capacity in year t (MW/year).

$V_t$, $V_{t-1}$: cumulative installed capacity in year t, t-1 (MW).

m: total potential installed capacity (MW).

p: external influence coefficient (coefficient of innovation).

q: internal influence coefficient (coefficient of imitation).

Equation (3.2) can be rewritten in the form of a non-linear regression model as follows:

$$v_t = pm + (q - p)V_{t-1} + \frac{q}{m} V_{t-1}^2 \quad (3.3)$$

The Bass model to investigate renewable power investment growth has been studied (Ostojic, 2010; Paschalia, 2012). However, Rao and Kishore (2010) indicate the limitations of this model for renewable power diffusion. The main reason is that the Bass model works with the assumption of time-invariant coefficients, while the renewable power investment environment varies over time. Moreover, there is an increasing trend in the total potential installed capacity in most countries. For instance, an annual electricity consumption growth rate of 13% required a considerable increase in the installed capacity from 27 to 48 GW between 2000 and 2018 in Vietnam (Le, 2019). In addition, unlike the diffusion of other commercial products, solar and wind power development has been stimulated mainly by support policies that are renewed or replaced over time. Besides, historical data indicates a significant decrease in renewable power investment costs. The changes in energy policies and investment costs require a time-variant external coefficient. Furthermore, it is a fact that the impact of past investments on current investments varies over time. In other words, the internal coefficient is time-variant.

All in all, the Bass diffusion model is successfully applied to the diffusion of consumer goods diffusions such as televisions, automobiles, and information technology products. However, it is limited to investigate the diffusion of renewable power.

### *3.2.3. Learning curve models*

Recently, Learning Curves have attracted attention. They are the foundation of the push or pull policy approach, whereby policy adjustments drive technology diffusion along their development curves (Wiesenthal *et al.*, 2012). Learning curves for solar or wind power technologies illustrate the relationship between electricity generation cost and cumulative installed capacity (Grafström, Fellow and Poudineh, 2021). Accurately, they define the decrease rate of renewable investment cost every time the cumulative installed capacity doubles. The mathematical formulation of a basic LC is as follows:

$$LCOE_t = LCOE_0\, V_t^{-E} \quad (3.4)$$

$LCOE$: levelized cost of electricity (cents/kWh).

$V_t$: cumulative installed capacity in year t (MW).

E: positive experience parameter. The higher the parameter, the steeper the learning curve.

Logarithming both two sides of (3.4), we obtain:

$$\log(LCOE_t) = \log(LCOE_0) - E\log(V_t) \tag{3.5}$$

$$E = \frac{\log(LCOE_0) - \log(LCOE_t)}{\log(V_t)} \tag{3.6}$$

Two essential indicators of the learning curve are progress rate and learning rate. A progress rate (PR) demonstrates the percentage value of the technology cost compared to its previous level when the cumulative installed capacity doubles.

$$PR \equiv \frac{LCOE_{t_2}}{LCOE_{t_1}} = 2^{-E} \tag{3.7}$$

Where $\frac{V_{t_2}}{V_{t_1}} = 2$

Contrary, a learning rate (LR) signifies the cost reduction percentage compared to its previous level when the cumulative installed capacity doubles.

$$LR \equiv \frac{LCOE_{t_1} - LCOE_{t_2}}{LCOE_{t_1}} = 1 - PR \tag{3.8}$$

The investment cost is the main cost component of renewable power investment projects. The operation and maintenance costs account for a small proportion of the LCOE and vary slightly over time. Therefore, the LC can be formed purely based on the investment cost.

Figure 3.2 illustrates the learning curve of solar power investment in Germany. The specific solar power investment cost was 5.91 and 0.88 million Euro/MW in 2000 and 2020. Likewise, the cumulative installed capacity in 2020 was 53,848 MW. Accordingly, the LR of solar power in Germany in this period is estimated:

$$E = \frac{\log(5.91) - \log(0.88)}{\log(53{,}848)} = 0.175$$

$$LR = 1 - 2^{-0.175} = 0.114$$

A learning rate of 11.4% means that during this period, the solar power investment cost in Germany decreased by 11.4% compared to its previous level every time the cumulative installed capacity doubles.

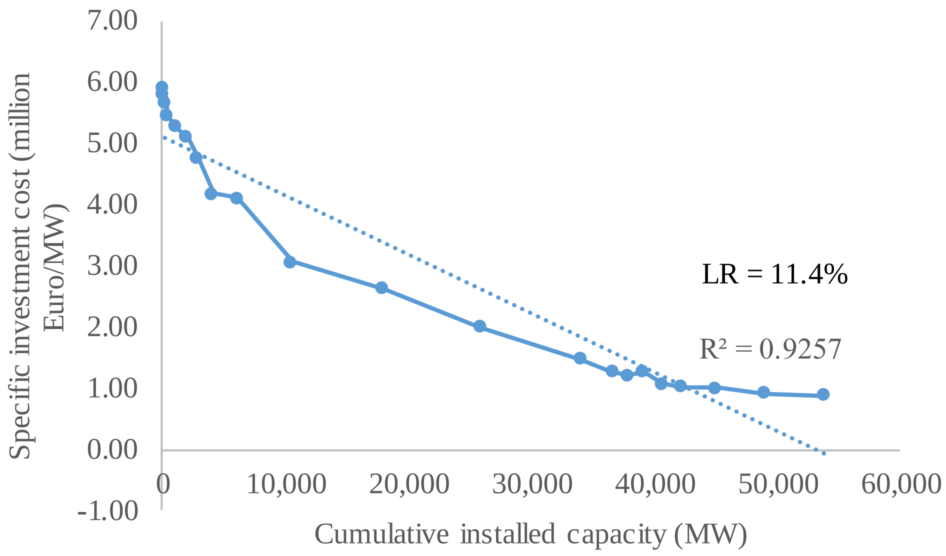



Figure 3.2. The learning curve of solar power investment in Germany between 2000 and 2020

(Source: Data from BMWi and AGEE-Stat, 2021)

The estimation of the learning curve requires observed data for an extended period. In other words, this approach applies to mature technologies. The learning curve has appeared to be a proper method for explaining solar power cost changes (Kersten *et al.*, 2011). However, it is less applicable for studying wind power diffusion. This limitation is due to the average global wind turbine price increase between 2004 and 2009, which violates the learning curve's assumption. The wind turbine cost increased for a variety of reasons. According to Lantz, Wiser and Hand (2012), the raw material price of wind turbines such as steel, iron, copper, aluminum, and fiberglass, increased substantially due to the financial crisis in late 2008. Besides, a robust growth of wind power installed capacity resulted in significant supply constraints. The increase in profitability and labor costs of component manufacturers and supply chain bottleneck also contributed significantly to the increase in wind turbine prices.

Della, Gryglewicz, and Kort (2012) indicate two investment scenarios depending on the learning curve's shape regarding the investment model. If the learning curve is flat, investors prefer spending their money on later projects with larger scales. Otherwise, the investments are implemented earlier.

### 3.3. Model of profitability

This section describes the formulations to determine the profitability of renewable power projects. Figure 3.3 illustrates the inputs and output of the formulations.

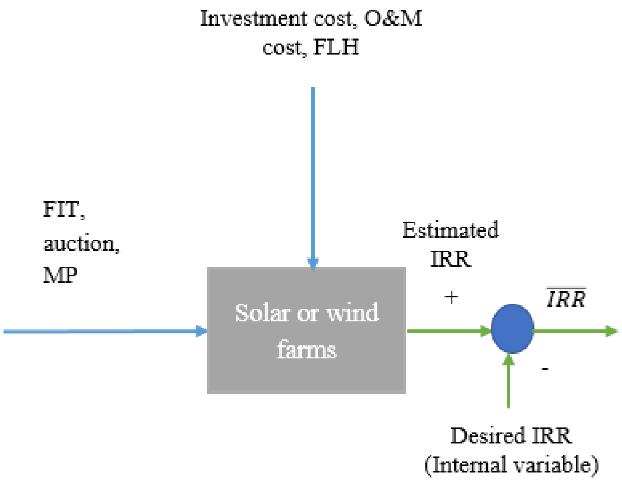



Figure 3.3. Block diagram of the renewable power farms

IRR is the discount rate at which the NPV of all cash flows from a project equals zero. The IRR of a 1 MW project is determined as follows:

$$0 = \sum_{t=1}^{n} \frac{R_t - C_t}{(1 + IRR^{estimated})^t} - I_0 = \sum_{t=1}^{n} \frac{FLH_t * p_t - OM_t}{(1 + IRR^{estimated})^t} - I_0 \qquad (3.9)$$

$IRR^{estimated}$: estimated IRR of the project (%).

$R_t$,$C_t$: predicted revenue, cost of the project in year t (million Euro/year).

$I_0$: estimated specific investment cost of the project (million Euro/MW).

$FLH_t$: expected full-load hours of the project in year t (hours).

$p_t$: electricity price of the project in year t (Euro cents/kWh).

$OM_t$: predicted operation and maintenance cost of the project in year t (million Euro/year).

n: the life cycle of the project.

When planning investment projects, investors establish a targeted profit rate or a desired IRR that reflects the minimum acceptable return percentage that the investment must earn to undertake it. A new project is profitable and should be pursued if the estimated IRR is higher than the desired IRR. The desired IRR is the capital cost in which each category of money is proportionally weighted (Investopedia, 2021).

$$IRR^{desired} = \text{WACC} = E * Re + D * Rd * (1 - Tc) \qquad (3.10)$$

$IRR^{desired}$: desired internal rate of return of the project (%).

Re, Rd: cost of equity, debt (%).

E, D: share of financing equity, financing debt (%).

Tc: corporate tax rate (%).

$$\text{Set } \overline{IRR} = IRR^{estimated} - IRR^{desired} \tag{3.11}$$

$\overline{IRR}$: the deviation between the estimated IRR and the desired IRR (later defined as the $profitability$). If $IRR_t^{estimated} > IRR^{desired}$, the investment is valuable enough to be undertaken.

## 3.4. Development of mathematical models of investor behavior

This section translates beliefs about factors and patterns that influence investor behavior into mathematical formulations. The constructed models are tested against actual observations to see how suitable they are for prediction. On this basis, the potential application of the designed models is discussed.

### *3.4.1. Building models*

We aim to model investor behavior in renewable power investment markets as the basis to design control systems of price mechanisms. Therefore, price mechanisms have to be direct or indirect inputs of constructed models. Moreover, because price mechanisms indirectly affect investment decisions through profitability, this section will translate the beliefs about the effects of profitability on investor behavior into mathematical formulations. In a general formulation, the additional investment is a function of profitability variable and a "profitability coefficient" that can be tuned to adapt the model to observed data.

$$v_t = f(\overline{IRR}, \beta) \tag{3.12}$$

$\overline{IRR}$: profitability.

$\beta$: profitability coefficient.

It is a fact that renewable power investors are heterogeneous, and the investment environment varies over time. Therefore, it is not easy to comprehend the investors' responses to the changes in price mechanisms. Although a mathematical formulation of a credible and complete model is highly demanding, identifying several characteristics and quantifying them is still meaningful. This research will not look at individual behavior but construct the aggregate investor behavior models.

#### *3.4.1.1. Threshold regression model*

A first specialization of the general model (3.12) is the so-called "threshold model," which consists of a single or a set of threshold values that distinguish the value range where the behavior predicted by the model varies in some critical way (Zapata and Gauthier, 2003). A threshold regression model is a type of threshold model that uses time-series data (Hurlin, 2018). The attractiveness of renewable power investment can be formulated as a threshold regression model in the following way.

$$v_t \begin{cases} \leq \varphi & \text{If } \overline{IRR}_t \leq 0 \\ = \beta\overline{IRR}_t + e_t & \text{If } \overline{IRR}_t > 0 \end{cases} \tag{3.13}$$

$\varphi$: maximum renewable power investment if profitability is less than or equal to zero.

$\overline{IRR}_t$: threshold variable.

$e_t$: model error at time t.

Equation (3.13) describes that the additionally installed capacity follows a monotonically increasing function if the profitability is positive; otherwise, it is less than or equal to $\varphi$. The correlation between profitability and the additionally installed capacity is illustrated in Figure 3.4.

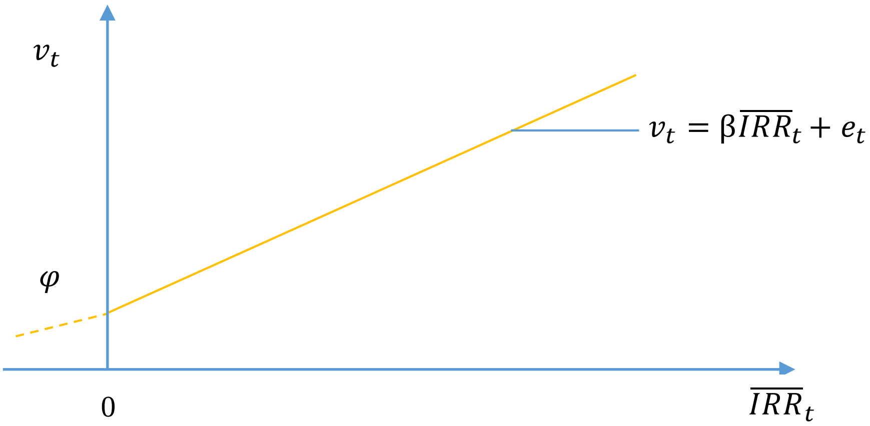



Figure 3.4. Correlation between profitability and additionally installed capacity

Equation (3.13) is a static and time-invariant model. There is no memory. Although nonlinear representation may be more realistic to describe the relationship between profitability and additional installed capacity, this study assumes that investor behavior follows a linear threshold regression model.

According to Kotler (1996), innovators also accept negative profitability. However, later adopters expect positive profitability. Figure 3.5 illustrates the change in profitability over the diffusion phases.

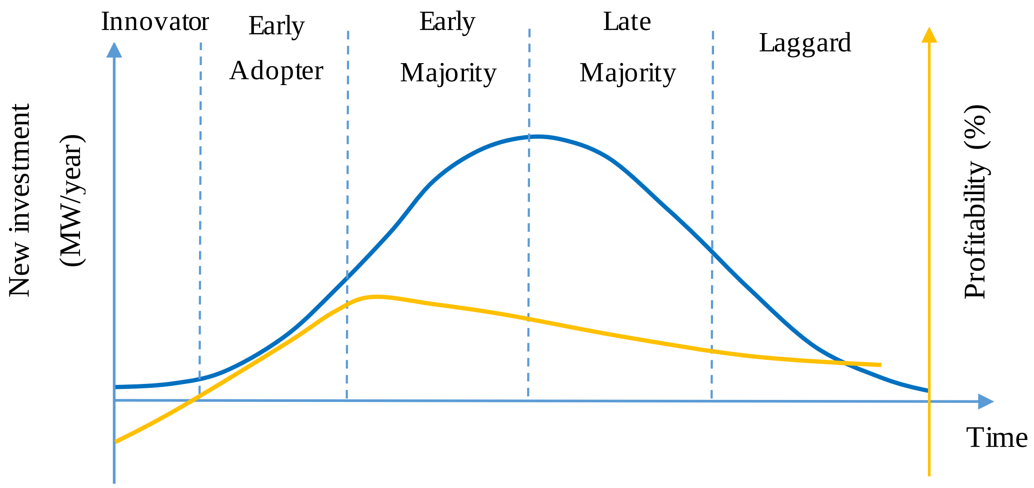



Figure 3.5. Profitability variability over the diffusion phases

There is no exact solution for (3.13). Instead, we estimate the coefficient β, which fits the equation "best." In other words, we solve the optimization problem, which minimizes the sum of the squares of the errors.

$$\sum_{t=1}^{n} \hat{e}_t^2 = \sum_{t=1}^{n} (v_t - \hat{\beta}\overline{IRR}_t)^2 \rightarrow min \tag{3.14}$$

The method to solve (3.14) is called Ordinary Least Square (OLS) (Hayashi, 2000).

*3.4.1.2. Adaptive model*

An equation with parameters varying to adapt to the changing context is called an "adaptive model." Because of the variability of the investment environment, the impact of profitability on investors' decisions changes over time. Mathematically, the profitability coefficient should then be updated at each time of the investment decision. The adaptive model reflecting investor behavior would look like this:

$$v_t = \beta_t \overline{IRR}_t + e_t \tag{3.15}$$

$\beta_t$: time-variant profitability coefficient.

Equation (3.15) is a static and time-variant model. To solve this model, we can apply the feedback approach proposed by Mahajan, Bretschneider, and Bradford (1980). Accordingly, before making the investment decision at time t, renewable power investors compare the previous period's actually installed capacity with the predicted value and then adjust the profitability coefficient based on the deviation.

$$\hat{\beta}_{t+1} = \hat{\beta}_t + A(e_t) \tag{3.16}$$

$A(e_t)$: Feedback filter.

The feedback filter produces a time-variant profitability coefficient and allows the investment model to adapt to changing data patterns. Applying the feedback filter proposed by Carbone and Longini (1977) to the problem, we have:

$$A(e_t) = |\hat{\beta}_t| \left[ \frac{v_t - \hat{v}_t}{\hat{v}_t} \frac{\overline{IRR}_t}{\overline{\overline{IRR}}_t} K \right] \tag{3.17}$$

$\hat{v}_t$: predicted installed capacity at time t.

$0 \leq K$: learning factor which reflects the adaptation speed. If $K = 0$, the profitability coefficient is constant.

$\overline{\overline{IRR}}_t$: an updated average of the profitability. The present value of the profitability variable is scaled by its smoothed mean and the forgetting factor. The formula of an exponential smoothing scheme is as follows:

$$\overline{\overline{IRR}}_t = w\overline{IRR}_t + (1 - w)\overline{\overline{IRR}}_{t-1} \tag{3.18}$$

$0 < w < 1$: smoothing factor.

The feedback approach requires selecting the initial profitability coefficient, the learning factor, and the smoothing factor suitably. Manual tuning is one method to select parameters.

*3.4.1.3. Distributed-lag model*

A *distributed-lag model* is a regression equation that predicts the current value of the dependent variable based on both current and past (lagged) values of independent variables (Baltagi, 2008). Due to the fluctuating nature of solar and wind power resources, the grid constraints, the variability of the spot electricity market, and the impacts of many other factors, profitability is uncertain.

Figure 3.6 illustrates the change in revenue commitment according to the price mechanism. The FIT mechanism is the highest revenue commitment for solar and wind power investments. Under the auction mechanism, the winning bidders are awarded a uniform price or submitted price over the project lifecycle. With the market premium mechanism, the power plant owners may receive a market premium depending on the deviation between contract and market prices. If an entirely competitive generation market is employed, the revenue depends totally on the competitive electricity market.

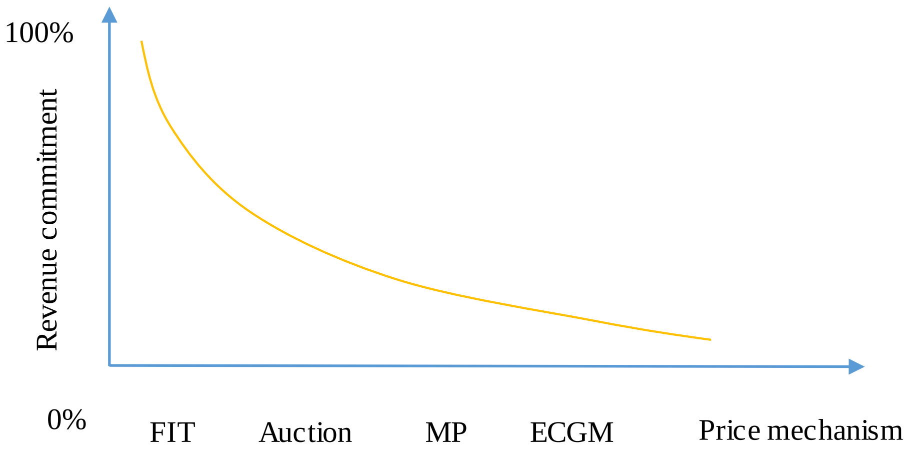



Figure 3.6. Correlation between price mechanisms and revenue commitment

Under the profitability uncertainty, the investors may take the current profitability and lagged profitability into decision-making consideration. The linear infinite distributed lag model (IFDL) of investor behavior would look like:

$$v_t = \beta_0 \overline{IRR}_t + \beta_1 \overline{IRR}_{t-1} + \beta_2 \overline{IRR}_{t-2} + \cdots + e_t \tag{3.19}$$

$$v_t = \sum_{\tau=0}^{+\infty} \beta_\tau \overline{IRR}_{t-\tau} + e_t \tag{3.20}$$

$\beta_\tau$: current or lagged weighting coefficients.

$\overline{IRR}_{t-\tau}$ : profitability at time t-τ.

Equation (3.20) is a dynamic and time-invariant model. The memory is included in the model.

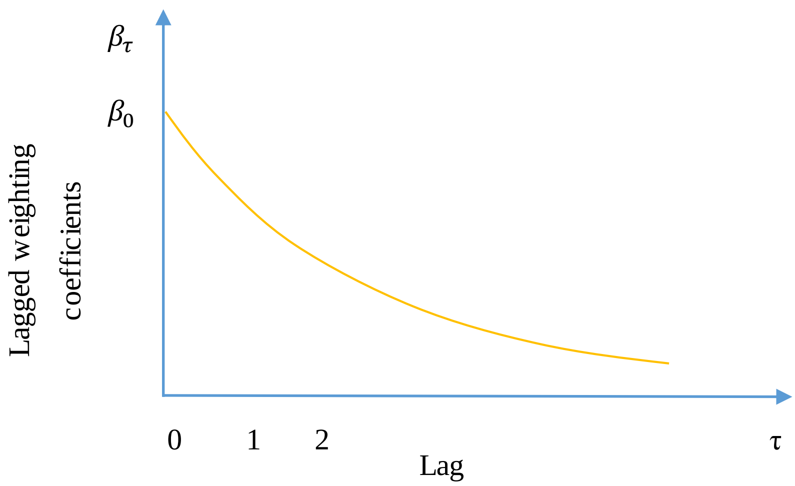



Figure 3.7. Lag weight curve

The additionally installed capacity is specified when the current and lagged weighting coefficients are known. However, estimating an infinite number of lag weights in (3.20) is impossible. With the assumption that the further the profitability information, the lower its influence on the instant decision ($\beta_\tau > \beta_{\tau+1}$), Baltagi (2008) suggests using a functional form that allows the lag distribution to decay gradually to zero to limit the lagged weights. The geometric lag model (also known as Koyck lag) is a well-known infinite lagged weighting coefficient model. According to Koyck (1954), the lag weights follow an exponential decline (Figure 3.7).

The lag weight at time $t - \tau$ is defined:

$$\beta_\tau = \beta_0 \lambda^\tau \tag{3.21}$$

$\beta_0$: scale factor.

$0 \leq \lambda < 1$: decay rate.

Substitution of (3.21) into (3.19), we obtain:

$$v_t = \beta_0 \overline{IRR}_t + \beta_0 \lambda \overline{IRR}_{t-1} + \beta_0 \lambda^2 \overline{IRR}_{t-2} + \cdots + e_t \tag{3.22}$$

$$v_t = \beta_0 \sum_{\tau=0}^{+\infty} \lambda^\tau \overline{IRR}_{t-\tau} + e_t \tag{3.23}$$

For constant profitability, the infinite geometric sum can be summed, leading to $\beta_0 \frac{1}{1-\lambda}$, then (3.23) can be rewritten as:

$$v_t = \beta_0 \frac{1}{1-\lambda} \overline{IRR}_t + e_t \tag{3.24}$$

Equation (3.24) can be solved using the OLS.

For profitability varies over time, because of the infinite number of terms and non-linear higher order of λ in (3.23), it is impossible to use the OLS to solve the model.

*3.4.1.4. First-order autoregressive model*

A *first-order autoregressive model* is a model that includes one lagged value of the dependent variable. The first-order autoregressive model is achieved by applying the Koyck transformations proposed by Koyck (1954) to (3.21). The Koyck transformations include the following steps:

Firstly, lagging (3.22) one period, we have:

$$v_{t-1} = \beta_0 \overline{IRR}_{t-1} + \beta_0 \lambda \overline{IRR}_{t-2} + \beta_0 \lambda^2 \overline{IRR}_{t-3} + \cdots + e_{t-1} \tag{3.25}$$

Secondly, multiply the coefficient $\lambda$ to both sides of (3.25), we obtain:

$$\lambda v_{t-1} = \beta_0 \lambda \overline{IRR}_{t-1} + \beta_0 \lambda^2 \overline{IRR}_{t-2} + \beta_0 \lambda^3 \overline{IRR}_{t-3} + \cdots + \lambda e_{t-1} \quad (3.26)$$

By subtracting (3.25) from (3.22) and doing several conversions, the first-order autoregressive model of the infinite distributed lag model is achieved:

$$v_t = \beta_0 \overline{IRR}_t + \lambda v_{t-1} + \epsilon_t \quad (3.27)$$

$$\epsilon_t = e_t - \lambda e_{t-1} \quad (3.28)$$

$\beta_0$: current profitability coefficient.

$\lambda$: retention coefficient.

Equation (3.27) shows that the current investment is influenced by the current profitability and the carryover from past profitability. The model has two parameters and looks much more straightforward than the distributed-lag model. However, the correlation between $v_{t-1}$ and $e_{t-1}$ in (3.27) violates one assumption of the OLS application (Hayashi, 2000). The direct application of the OLS will carry out bias and inconsistent estimation. In order to remove that correlation, we employ the instrumental variables estimator (IVE) proposed by Liviatan (1963). Specifically, because $\overline{IRR}_{t-1}$ correlates with $v_{t-1}$ but does not correlate with $e_{t-1}$, we chose $\overline{IRR}_{t-1}$ as an instrumental variable of $v_{t-1}$. The IVE is carried out using two-stage OLS. Firstly, $v_{t-1}$ in (3.27) is replaced by $\hat{v}_{t-1}$.

$$v_t = \beta_0 \overline{IRR}_t + \lambda \hat{v}_{t-1} + \varepsilon_t \quad (3.29)$$

$$\hat{v}_{t-1} = \emptyset \overline{IRR}_{t-1} \quad (3.30)$$

The parameter $\emptyset$ is estimated using the OLS. There is no correlation between the independent variable and the error term in (3.29). Therefore, the OLS can be applied directly to estimate parameters.

Thus, we have four different models of investor behavior, as summarized in Table 3.1.

Table 3.1. Different variants of models of investor behavior

| **Model** | **Formula** | **Characteristics** |
|---|---|---|
| Threshold regression model | $v_t = \beta \overline{IRR}_t + e_t$ | Static and time-invariant |
| Adaptive model | $v_t = \beta_t \overline{IRR}_t + e_t$ | Static and time-variant |

| Model | Formula | Characteristics |
|---|---|---|
| Distributed-lag model | $v_t = \sum_{\tau=0}^{+\infty} \beta_0 \lambda^{\tau} \overline{IRR}_{t-\tau} + e_t$ | Dynamic and time-invariant |
| First-order autoregressive model | $v_t = \beta_0 \overline{IRR}_t + \lambda v_{t-1} + \epsilon_t$ | Dynamic and time-invariant |

***3.4.2. Testing models***

The designed models could be extended to examine further the detailed influences of the current profitability, past profitability, time factor on investor behavior in different investment markets. However, the most relevant manner to demonstrate and illustrate their impact is through a historical analysis. The applicability of the constructed models is tested against the historical data of the German investment market

*3.4.2.1. Data analysis*

The German energy transition was kicked off in 2000 thanks to the introduction of the Renewable Energy Source Act (German Federal Parliament, 2000). With several amendments (German Federal Parliament, 2004, 2009, 2012, 2014, 2017), the law has created a highly effective policy framework for accelerating renewable power deployment. Along with the wind power investment market, the solar power investment market has become dynamic and attractive.

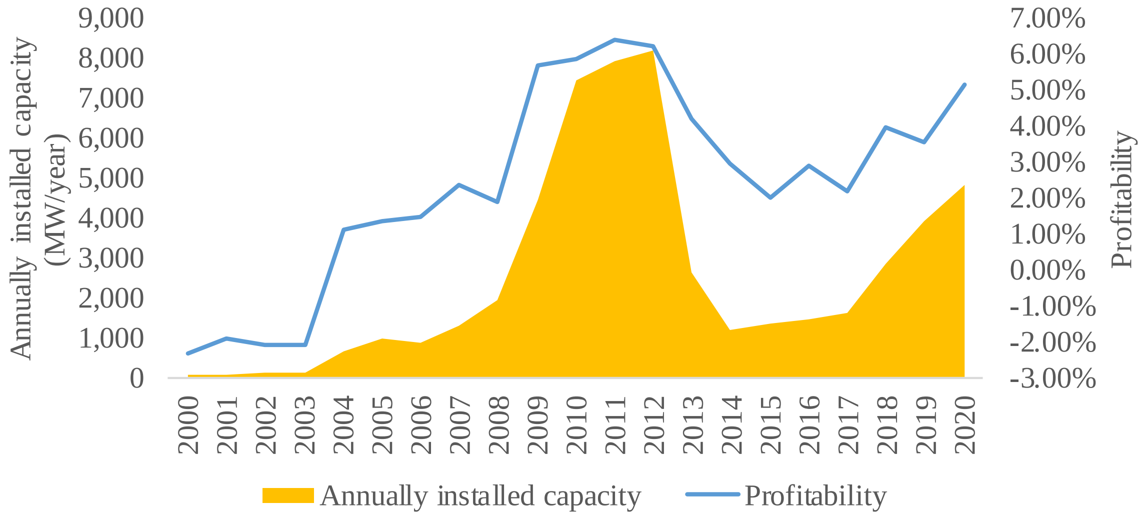



Figure 3.8. The correlation between profitability and the annually solar power installed capacity in Germany between 2000 and 2020

The law amendments have caused profitability variability, which created a structural shift in the annually installed capacity. Four periods of solar power price mechanisms can be identified: 2000 – 2003, 2004 – 2008, 2009 – 2012, 2013 – now (Figure 3.8) (see the detailed data in Appendix 1 and Appendix 2). Because of negative profitability (Figure 3.8), the data between 2000 and 2003 is removed in this test.

Table 3.2. Descriptive statistics of profitability and the annually solar power installed capacity in Germany between 2004 and 2020

| | **Mean** | **Standard Error** | **Minimum** | **Maximum** | **Count** |
|---|---|---|---|---|---|
| Profitability | 3.48% | 0.44% | 1.13% | 6.37% | 17 |
| Annually installed capacity (MW/year) | 3,141 | 621 | 670 | 8,161 | 17 |

Table 3.2 shows a profitability range from 1.13% to 6.37%, an average of 3.48% for solar power investment projects. The annually installed capacity reached 3,141 MW/year on average and a maximum of 8,161 MW/year.

*3.4.2.2. Model estimation*

In order to estimate the models and study the prediction accuracy, we divide the dataset into training data (2004 – 2012) and validation data (2013 – 2020). This section estimates model parameters.

Applying the OLS to the training data results in the estimated parameter of the threshold regression model, as shown in Table 3.3.

Table 3.3. Estimated parameter of the threshold regression model

| | **Period** | **Number of Observation** | **β** | **P-value** | $\boldsymbol{R^2}$ |
|---|---|---|---|---|---|
| Threshold regression model | 2004 - 2012 | 9 | 1,123 | $1.26*10^{-6}$ | 95.39% |

The R-squared of 95.39% reveals the high correlation between profitability and the annually installed capacity. The findings also indicate that an increase of 1% in profitability leads to an average increase of 1,123 MW/year in the installed capacity.

By applying the feedback approach to the training data with the selected initial K, w and $\beta_0$ values of 0.4, 0.5, and 595, the estimated parameter of the adaptive model is achieved, as reported in Table 3.4.

Table 3.4. Estimated parameter of the adaptive model

| **Year** | $\boldsymbol{\beta_t}$ |
|---|---|
| 2004 | 595 |
| 2005 | 595 |
| 2006 | 639 |
| 2007 | 611 |
| 2008 | 575 |
| 2009 | 736 |
| 2010 | 764 |
| 2011 | 971 |
| 2012 | 1,084 |
| 2013 | 1,175 |
| 2014 | 997 |
| 2015 | 801 |
| 2016 | 754 |
| 2017 | 635 |
| 2018 | 675 |
| 2019 | 698 |
| 2020 | 848 |

The findings show that there is an increasing trend in profitability coefficient in the period from 2008 to 2013. The profitability coefficient decreases significantly in the following years and then increases again in 2020. The maximum value of the profitability coefficient is for 2013, and the minimum value for 2004.

The estimated parameters of the first-order autoregressive model are determined by employing the instrumental variables estimator to the training data. The findings in Table 3.5 indicate that both the current profitability coefficient and the retention coefficient are statistically significant at 5%. Moreover, the current and lagged profitability explain 97.82% of the change in the annually installed capacity.

Table 3.5. Estimated parameters of the first-order autoregressive model

| | Period | Number of Observation | β | P-value (of β) | λ | P-value (of λ) | $R^2$ |
|---|---|---|---|---|---|---|---|
| First-order autoregressive model | 2004 - 2012 | 9 | 713 | 0.003 | 0.45 | 0.03 | 97.82% |

The high R-squared values of the designed models show a good match between model predictions and data. However, the estimated parameters do not ensure a good fit for the latter. Therefore, we should use different data for assessing model performance.

*3.4.2.3. Model performance*

This section tests the predictability of the models through two steps. Firstly, the estimated models in Section 3.4.2.2 are used to predict the annually installed capacity from 2013 to 2020. Then, the model performance metrics are evaluated. Figure 3.9 illustrates the predicted annually installed capacity using different models.

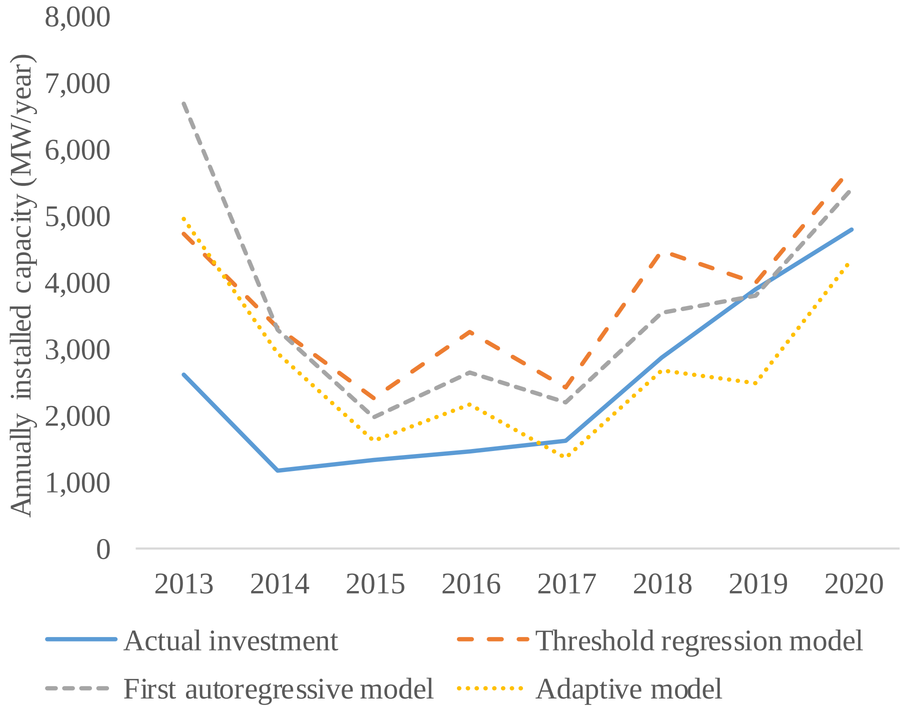



Figure 3.9. Actual and predicted solar power installed capacity in Germany between 2013 and 2020

The four main metrics for regression model evaluation are R-squared, bias, mean absolute error, and root mean square error (Rayner and Bender, 2008). The formulation and role of each metric are described in Table 3.6.

Table 3.6. Four main metrics of model performance

| Metric | Formulation | Role |
|---|---|---|
| R-squared | $R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$ | The closer $R^2$ is to 1, the better the prediction. |
| The bias | $Bias = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)}{n}$ | The bias describes how well the model matches the validation dataset. The smaller the bias is, the better the prediction is. |
| The mean absolute error (MAE) | $MAE = \frac{\sum_{i=1}^{n}\lvert\hat{y}_i - y_i\rvert}{n}$ | It indicates the mean of the absolute values of the individual prediction errors on the validation dataset's overall values. |
| The root mean square error (RMSE) | $RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}$ | It indicates an absolute number on the deviation between the prediction and the observation. The closer the RMSE and the observation, the less variant the prediction is. |

Thus, each of the metrics reveals different aspects of the prediction; therefore, using all of them provides a better understanding of the prediction accuracy.

The model performance metrics are obtained by applying the metrics to the validation dataset, as shown in Table 3.7.

Table 3.7. Calculated metrics of model performance

| | Threshold regression model | Adaptive model | First-autoregressive model |
|---|---|---|---|
| R-squared | 92.93% | 84.75% | 87.11% |
| Bias | -1,303 | -350 | -1,226 |
| Mean absolute error | 1,303 | 925 | 1,243 |
| Root mean square error | 1,467 | 1,194 | 1,727 |

Some findings are drawn from the results:

Firstly, despite the high R-squared of 92.93%, the threshold regression model has poor prediction accuracy because the values of other metrics are high compared to the average investment volume of 2,471 MW/year from 2013 to 2020.

Secondly, although the R-squared of the adaptive model is the lowest with 84.75%, this model is more accurate for prediction due to the lower values of the other performance metrics. This finding is suitable because the investment environment varies over time, indicating that profitability's impact on investors' decisions changes over time.

Thirdly, although the adaptive model is better than the two other models for prediction, it is still not good enough for prediction due to the high root mean square of 1,194 MW/year compared to the average investment volume of 2,471 MW/year. One reason for the high error is because the effects of technical and management factors, administrative, grid access, and social acceptance are ignored in this model.

It should be noted that the above findings are only correct for the solar power investment market in Germany. The predictability of the constructed models for various investment markets is not yet evaluated.

### 3.5. Chapter conclusion

Investors play a crucial role in renewable power development paths. Accurately mathematical modeling of investor behavior contributes to the success of energy policy design.

This chapter indicates that even though investor behavior may be dynamic and time-variant, there is a surprising lack of models reflecting these characteristics. The literature shows that most previous econometric models, diffusion models, and learning curve models are static and time-invariant. However, dynamic and time-variant models may be more realistic due to the investor behavior and investment environment variability.

The attraction of renewable power investment is reflected in the threshold regression, the adaptive, the distributed-lag, and the first-order autoregressive models. Testing the four constructed models against observed data of solar power investment in Germany between 2004 and 2020 shows better predictability of the adaptive model than the threshold regression model and the first autoregression model. However, it could be argued whether the predictive power, particularly the adaptive model, should be viewed as a success or failure. On the one hand, it captures the dynamics of the actual investment, which is much more than just a trend prognosis. This is undoubtedly a success. On the other hand, the mean absolute error is significant compared to the absolute values, which could be seen as a failure. We still think that modeling investment behavior is meaningful and that there are still several ways to improve it. On the other hand, this result motivates us to reach out for the feedback control method that does not rely on an exact prognosis and will work on it in the following chapters.

# Chapter 4. Feedback Control Theory and Its Application to Economic Policy

## 4.1. Introduction

According to Leff (2000), “a feedback control system is a system whose output is controlled using its measurement as a feedback signal. This feedback signal is compared with a reference signal to generate an error signal filtered by a controller to produce the system’s control input.” Control theory deals with dynamical systems’ behavior to design a control model that ensures control stability, accurately and quickly settling to steady-state values (Abdelzaher *et al.*, 2008). Feedback control theory is initially applied in physical, mechanical, and electrical systems and has tremendous success. The applications in space technologies, weapon systems, power systems, robotics, ship stabilization systems, temperature control systems, and sun-tracking control of solar collectors are well-known (Dorf and Bishop, 2011). This approach is also expanded to be employed in social sciences (Gupta, 1979; Robinson, 2007), medicines (Ledzewicz and Schättler, 2004), and economic policy design (Taylor, 1993; Onatski and Stock, 2002; Zhang and Semmler, 2003; Hawkins, Speakes and Hamilton, 2015; Alexeenko, 2017; Kostarakos and Kotsios, 2017).

Economic policy refers to actions by governments to influence economies. Such actions can be grouped into fiscal policies, financial (or monetary) policies, and regulatory systems. The fiscal policies are represented by taxes, fees, and government spending, while the monetary policies aim to adjust the money supply through interest rates and reserve requirements. In addition, particular regulatory systems are adopted to drive specific economic sectors (Benassy-Quere *et al.*, 2019). The economic policies’ objective is to ensure that the economic systems respond as closely as possible to the desired paths through appropriate manipulations. In order to achieve that objective, the feedback control theory may help.

Although numerous feedback control approaches have been studied and applied to analyze economic policy problems, they are still unknown to many economists and policymakers. Section 4.2 presents the basic knowledge and some critical aspects of the feedback control theory. In Section 4.3, the developed feedback control approaches to economic policy are reviewed, and known applications are investigated. Realizing the potential of the proportional-integral-derivative (PID) controller for price mechanism design, Section 4.4 presents its basic principles and properties. Some conclusions and implications are discussed in the last section.

## 4.2. Feedback control theory

### *4.2.1. Components and principles*

Many dynamical systems require control mechanisms to perform stably and accurately. System control can be implemented with or without feedback. However, most control mechanisms are based on feedback, whereby the actual output value is returned and compared with the desired value. The error between those two is the basis for computing the corrective control action (Doyle, Francis and Tannenbaum, 1990).

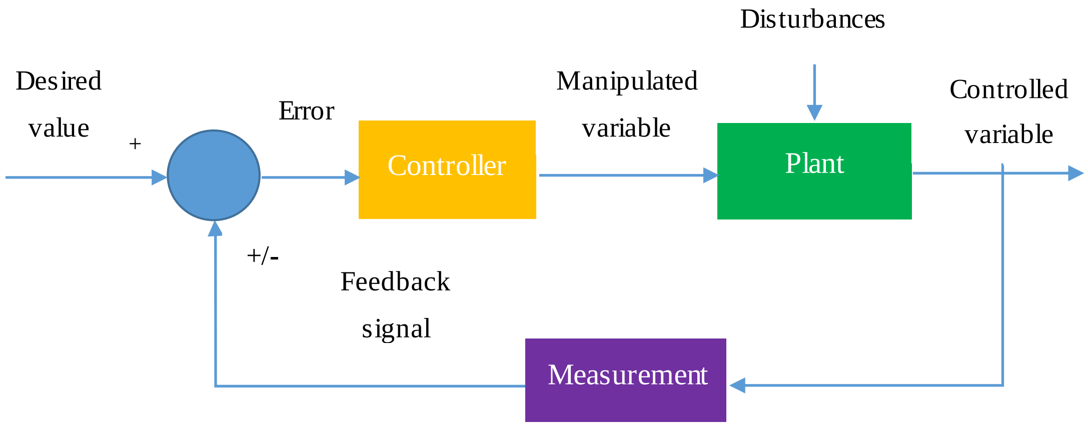



Figure 4.1. Block diagram of a feedback control system

A feedback control system can be illustrated as a closed-loop block diagram, as illustrated in Figure 4.1. The plant (or controlled system) is the system that is affected. The input into the plant is called the manipulated variable, and the plant's output is the controlled variable. A control system aims to determine how to quantify an appropriate manipulated variable such that the system will output the controlled variable with the desired value. Measuring the output or controlled variable can be challenging because, in particular, there may be delay time in identifying the actual output in economic systems. The desired value (set point or reference signal) is given independently from the feedback control system. Disturbances are uncontrollable input signals that upset the controlled system. An error constitutes the control loop's control action and equals the algebraic difference between the desired value and the feedback signal.

Two types of feedback are positive feedback and negative feedback. Positive feedback is a process to increase the change in the system over time. In contrast, negative feedback decreases the system deviation; therefore, it is preferred in mechanical and electronic engineering and economic policy designs.

### *4.2.2. Control system design*

According to Dorf and Bishop (2011), "control system design is to obtain the configuration, specifications, and identification of the key parameters of a proposed system to meet an actual need." The steps of a control system design are illustrated in Figure 4.2.

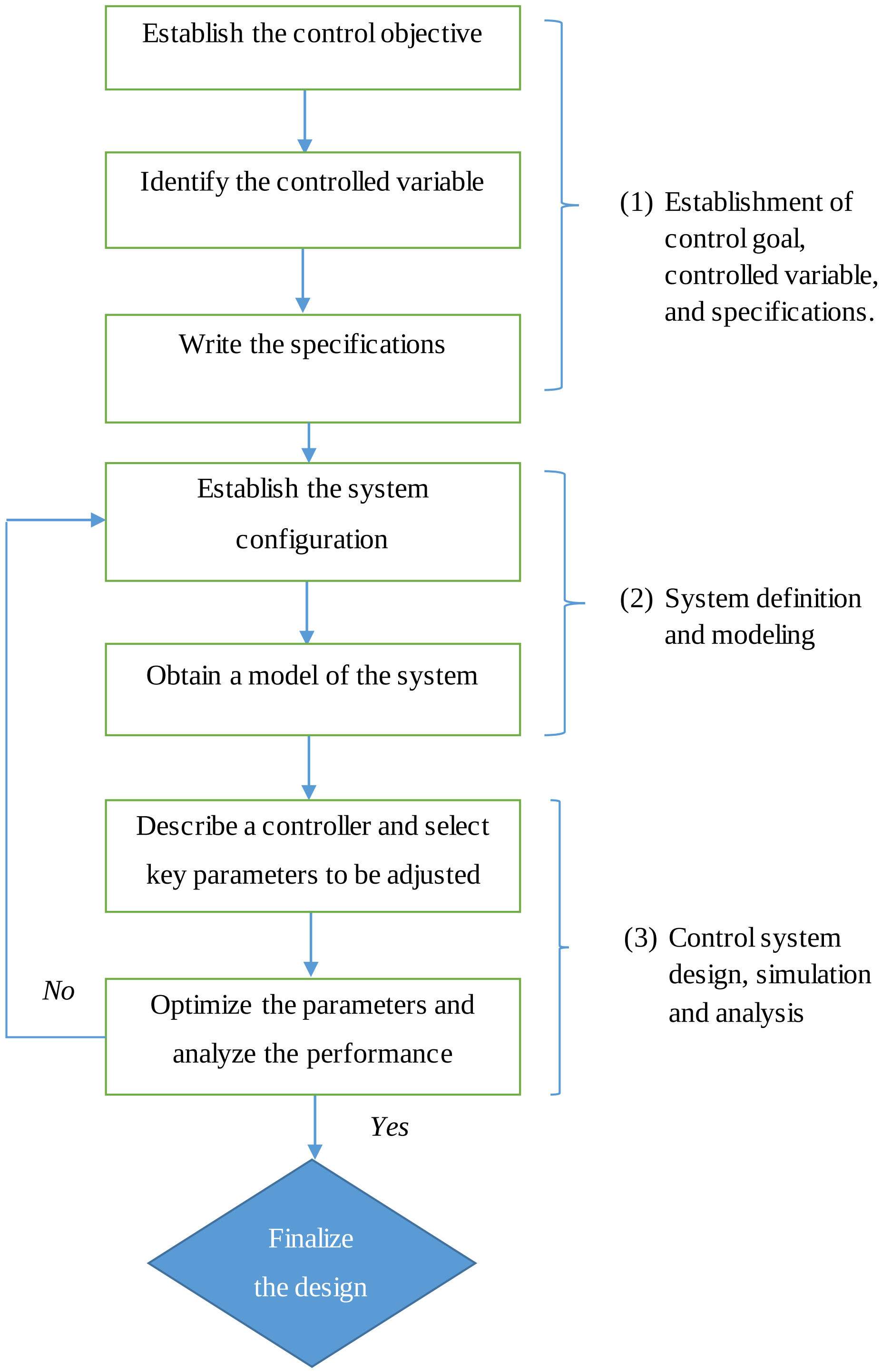



Figure 4.2. Steps of control system design (Dorf and Bishop, 2011)

First, we define the control objective (e.g., control the solar power investment volume accurately). Then we identify the variables that we want to control (e.g., the annually installed capacity). The next step is to write the performance specifications that describe how the feedback system should perform. Stability is the most critical performance specification. Other specifications involve the time-response, such as the first peak time, maximum peak time, rise time, settling time, maximum overshoot, and maximum undershoot (see Section 4.2.3 for more details). Next, we configure the system to a control system with components and principles, as described in Figure 4.1.

A system model is obtained by one of two underlying approaches: theoretical modeling and empirical modeling. *Theoretical models* are based on physical laws such as Newton's or electrical laws like Kirchhoff's. The theoretical models work with certain assumptions. If the assumptions are unsatisfied, the models cannot predict the output accurately. Unlike the theoretical approach, *empirical models* are extracted from experimental data, actual observation, and experience. This method is employed for complex systems or systems with unknown governing laws. For engineering systems, experiments are implemented, and the measurement data of relevant quantities are recorded. A model structure is then specified, and the model parameters are adjusted to minimize the error. For economic systems, the *empirical econometric models* are constructed based on historical evidence.

The controller selection is a crucial step in the control system design. The feedback controller uses the deviation between the desired output and the actual one to quantify the manipulated variable.

The final step is optimizing the controller parameters and analyze the control performance (see Section 4.4.2 for the methods to choose controller parameters). If the desired performance specifications are satisfied, the design will be finalized. Otherwise, the system is reconfigured, and the design steps are repeated until the desired performance specifications are achieved.

### *4.2.3. Control specifications*

Control specifications are performance indicators that we would like the system to achieve. Every control system must first guarantee the *stability* of the closed-loop behavior. A system is stable if, with a bounded input, the system produces a bounded output (known as BIBO stable) (Gy and Gerencser, 2002). A bounded variable is a variable whose range is limited between minimal and maximal values. Specifically, an arbitrary input u bounded by two finite constants M and L ($M < u \leq L$) is applied to a system f which produces three outputs of $y_u = f(u)$,

$y_M = f(M)$, and $y_L = f(L)$. If the three outputs are finite and satisfy $y_M \le y_u \le y_L$, the system is BIBO stable, otherwise, it is BIBO unstable.

Analysis of control systems can use either time or frequency domains (Owayjan, Daou and Moreau, 2015). The control performance indicators for the time domain systems are also represented by time-response indicators (Kim, Keel and Manabe, 2002). *The first peak time* is the time for the response to reach the first peak. *Maximum peak time* is the time to reach the maximum peak. *Rise time* is the required time for the response to rising from 0% to 100% of its final value. *Maximum overshoot* refers to the maximum exceeding output compared with its target, and vice versa. The required time for the output value to reach and remain within a given error band is called *settling time*.

Because the control system designs aim to be used in practice, it is essential to establish realistic control performance indicators. For example, we want to control solar power investment accurately. Concretely, the desired annually installed capacity of 2,000 MW is assumed. We aim to achieve the control specifications of a rise time of fewer than one year, a settling time of fewer than three years, and a maximum overshoot of less than 20% all the time. Figure 4.3 shows that the output responses satisfy the requirements of the rise time and the settling time. However, the actually annually installed capacity reaches more than 120% of the desired volume. In other words, the control system design does not satisfy the required peak overshoot.

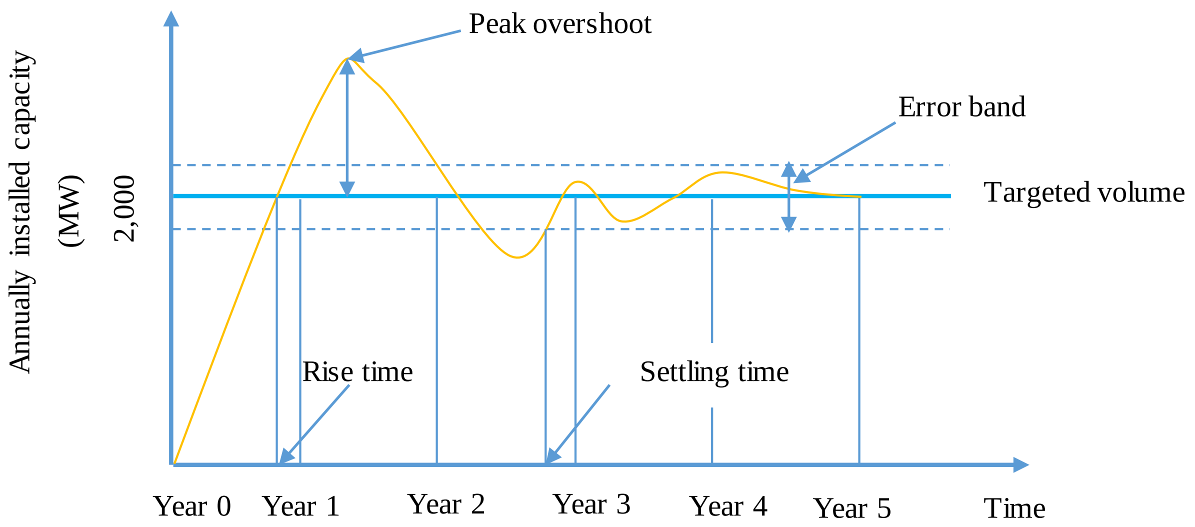



Figure 4.3. Control specifications of a control system design for solar power investment

#### *4.2.4. System models*

Three alternative mathematical forms of the system used in control system designs are differential equations, transfer functions, and state-space functions (Ogata, 2005; Moura, 2018).

*A differential equation* describes dynamic behavior using a time-domain model obtained by applying physical or electrical laws. For example, according to Kirchhoff's voltage law (also known as Kirchhoff's second law), the voltages' directed sum around any closed loop is zero. In other words, the sum of all the voltage drops is equal to the supplied voltage (Wanders, 2010).

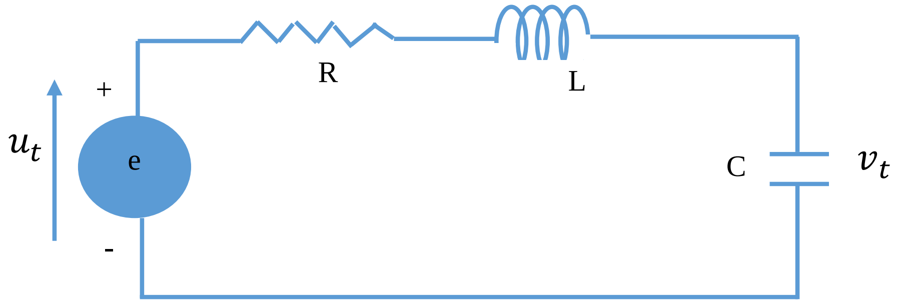



Figure 4.4. Components and principles of an RLC circuit

For an electrical circuit with three components (a resistor R, an inductor L, and a capacitor C), as illustrated in Figure 4.4, the law results in the following equation:

$$v_t^R + v_t^L + v_t^C = u_t \tag{4.1}$$

$$Ri + Li' + v_t = u_t \tag{4.2}$$

Substituting the current passing the capacitor $i = Cv_t'$ to (4.2), we obtain:

$$RCv_t' + LCv_t'' + v_t = u_t \tag{4.3}$$

$$v_t'' + \frac{R}{L}v_t' + \frac{1}{LC}v_t = \frac{1}{LC}u_t \tag{4.4}$$

$u_t$: the input voltage applied to the circuit at time t.

$v_t^R, v_t^L, v_t^C$: the voltages across the resistor, the inductor, and the capacitor at time t.

$v_t^C = v_t$: the voltage across the capacitor or the output voltage of the circuit at time t.

$i$: the current passing the circuit.

Transfer functions are algebraic polynomial equations, which are easier to study and manipulate than differential equations. *A transfer function* is a frequency domain model achieved by calculating the Laplace transform of output and input, with all the initial conditions assumed to be zero.

Applying the Laplace transform on both sides of (4.4), we obtain:

$$s^2V_s + \frac{sR}{L}V_s + \frac{1}{LC}V_s = \frac{1}{LC}U_s \tag{4.5}$$

$U_s$: Laplace transform of the input voltage.

$V_s$: Laplace transform of the output voltage.

Taking the ratio of output to input results in the following equation:

$$\frac{V_s}{U_s} = \frac{\frac{1}{LC}}{s^2 + \frac{sR}{L} + \frac{1}{LC}} \tag{4.6}$$

Equation (4.6) is a transfer function of the electrical circuit.

For high-order differential equations, decomposing them into multiple first-order equations using the state variables is recommended. The *state variables* describe values from inside the system. For example, in the electrical circuits, the node voltages and the mesh currents are state variables.

Assuming that the system has input $u$, output $y$, and state variable $x$, a state-space system includes two equations as follows:

$$\begin{cases} x'_t = g(t_0, t, x_t, x_0, u_t) & \text{[State equation]} \\ y_t = h(t, x_t, u_t) & \text{[Output equation]} \end{cases} \tag{4.7}$$

The state equation determines the system state ($x'_t$), which depends on the time (t), the previous state ($x_t$), the initial state ($x_0$), and the system input ($u_t$). The output equation defines the system output, which varies according to the current state and input.

If the system is time-variant, the state-space system (4.7) is rewritten:

$$\begin{cases} x'_t = A_t x_t + B_t u_t \\ y_t = C_t x_t + D_t u_t \end{cases} \tag{4.8}$$

$A_t, B_t, C_t, D_t$: time-variant state matrix, input matrix, output matrix, and feedthrough matrix.

If the system is time-invariant, the state-space system simplifies in the following form:

$$\begin{cases} x'_t = A x_t + B u_t \\ y_t = C x_t + D u_t \end{cases} \tag{4.9}$$

$A, B, C, D$: time-invariant state matrix, input matrix, output matrix, and feedthrough matrix.

From the second-order differential equation of the electrical circuit (4.4), the state variables are created in the following manner:

Set $x_1 = v_t$,

$x_2 = x_1' = v_t'$,

Then $x_2' = v_t'' = -\frac{R}{L} v_t' - \frac{1}{LC} v_t + \frac{1}{LC} u_t$.

With that, the state-space equations of the system are as follows:

$$\begin{cases} \begin{bmatrix} x_1' \\ x_2' \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{1}{LC} & -\frac{R}{L} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{LC} \end{bmatrix} u_t \\ y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \end{cases} \tag{4.10}$$

Equations in (4.10) represent a state-space system of the electrical circuit.

## 4.3. Feedback control and economic policy

### *4.3.1. Feedback control approaches*

Along with the advancement o control theory, numerous feedback control approaches have been studied and adopted to analyze economic policy problems (Neck, 2009; Derakhshan, 2015). Typical methodological approaches, techniques, and corresponding representatives are summarized in Table 4.1.

Table 4.1. The advancement of feedback control approaches to economic policy

| **Approach** | **Aims** | **Techniques and representatives** |
|---|---|---|
| Stability of control systems | To check if a system produces a bounded output for a given bounded input | Transfer functions in macroeconomic were introduced by Tustin (1953) and developed by Phillips (1957). |
| Deterministic optimal control | To deal with optimizing particular cost indexes | Dynamic programming was developed by Bellman (1954).<br>Pontryagin's maximum principle was formulated by Pontryagin (1956).<br>Control of linear systems with quadratic criteria was studied by Athans and Kendrik (1974).<br>Nonlinearities econometric models were developed by Chow (1976).<br>Economic model predictive control was applied by Heidarinejad, Liu, and Christofdes (2011). |

| **Approach** | **Aims** | **Techniques and representatives** |
|---|---|---|
| Stochastic control | To deal with control design with uncertainty (random noise and disturbances) | The optimization of linear econometric models with parameters as random variables was studied by Chow (1975).<br>The optimization of nonlinear stochastic control models was developed by Chow (1981). |
| Robust control | To cope with bounded system uncertainty | Robust monetary policy under model uncertainty was developed by Onatski and Stock (2002), Zhang and Semmler (2003). |

Although feedback control theory was applied to economic policy quite early, only relatively few works were done, and the achievements are limited. The unfruitful result of the feedback control theory applications to economic policies is for a variety of reasons. According to the review by Neck (2009), one reason comes from system structure conditions. Economists cannot modify the internal relations of economic systems as engineers can do with the engineering systems to achieve the required specifications. Moreover, economic systems are complex, and economic issues include non-linear adaptive human behavior and uncertainty. Finally, models of economic systems are inadequate for prediction. Therefore, the feedback control approaches applied to these models fail for economic policy design.

Despite the unfavorable conditions, scientists consider that some feedback approaches may work well in practice. Taylor and Williams (2010) point out that simple monetary policy rules can effectively guide interest rate decisions.

### *4.3.2. Application to economic policy*

The first typical application of feedback control to economic policy problems must-mentioned is Taylor's rule. Accordingly to Taylor (1993), the Fed Funds rate is adjusted corresponding to the error between the desired macroeconomic performances and the actual ones. The macroeconomic performances are represented by the inflation rate and gross domestic product (GDP). In his review paper (Taylor and Williams, 2010), the simple monetary policy rules are pointed out to work well in the real world. Realizing the model uncertainty of monetary policy, Onatski and Stock (2002) and Zhang and Semmler (2003) suggest robust control techniques to construct robust monetary policies. Hawkins, Speakes and Hamilton (2015) and Shepherd, Torres and Saridakis (2018) prove that most central banks' monetary policy rules follow robust

PI control – a subset of PID control. These studies emphasize that the PID controller is still valuable for economic policy design despite the unknown dynamic system model.

Approaching from the optimal perspective, Alexeenko (2017) applies a Linear-Quadratic-Regulator (LQR) to monetary policies. The principle is choosing the interest rate to minimize the central bank's loss function. The method offers a way to achieve lowered inflation, at the same time, keeps low-interest rates. However, this approach requires a higher interest rate than the ordinary monetary policy to achieve the same performance.

In order to achieve macroeconomic performances by manipulating fiscal instruments, Neck and Karbuz (1997) suggest applying a stochastic control algorithm to Austria's budgetary policy. Five macroeconomic performance variables, including unemployment rate, inflation rate, GDP growth rate, current account, and budget deficit, are considered. By simulating the experiment using the collected data from 1995 to 2000, the findings indicate the high sensitivity of the optimal budgetary policies to model parameters' covariation. Kostarakos and Kotsios (2017) employ the model matching technique to design government spending to achieve targeted inflation rate and GDP. Government spending is divided into general government expenditures (including spendings on employees' compensation and social benefits) and government investments (including spendings on infrastructure). The study emphasizes that immediate responses require relatively small policy adjustment than slower actions.

The feedback method has appeared in designing regulatory systems to achieve the targeted carbon emission. Chu *et al.* (2012) apply the economic model predictive control (EMPC) to the regional dynamic integrated model of climate and economy (RICE model). The findings suggest saving rates and global tax for greenhouse gas emissions. Chu *et al.* (2013) continue applying this approach to the UK 4see model. Accordingly, various policy trajectories are carried out to achieve the targeted carbon emission.

All in all, various control techniques have been applied to analyze economic policy. Among them, the PID control shows its advantages to achieve targeted performances despite uncertainty. Moreover, this control method has been well-known, accounting for almost 95% of feedback controls in technical system control (Astrom, 2002). Therefore, application of the PID control to design price mechanisms for renewable power investment.

## 4.4. PID controller

### *4.4.1. Components and principles*

A PID controller is a feedback controller that compares the desired value with the controlled value and minimizes the error value by applying proportional, integral, and derivative terms (Araki, 2017). Figure 4.5 illustrates the components and principles of a PID controller.

The mathematical formulation of a PID controller is as follows:

$$u_t = K_P e_t + K_I \int_i^t e_\tau d\tau + K_D \frac{de_t}{dt} \tag{4.10}$$

$$u_t = K_P (e_t + \frac{1}{T_i} \int_i^t e_\tau d\tau + T_d \frac{de_t}{dt}) \tag{4.11}$$

$u_t$: manipulated variable at time t.

$K_P$, $K_I$, $K_D$: proportional gain, integral gain, and derivative gain (also known as controller parameters). $K_I = K_P \frac{1}{T_i}$, $K_D = K_P T_d$.

$T_i$, $T_d$: integration time, derivative time.

$e_t$: an error between the desired value and the controlled output at time t.

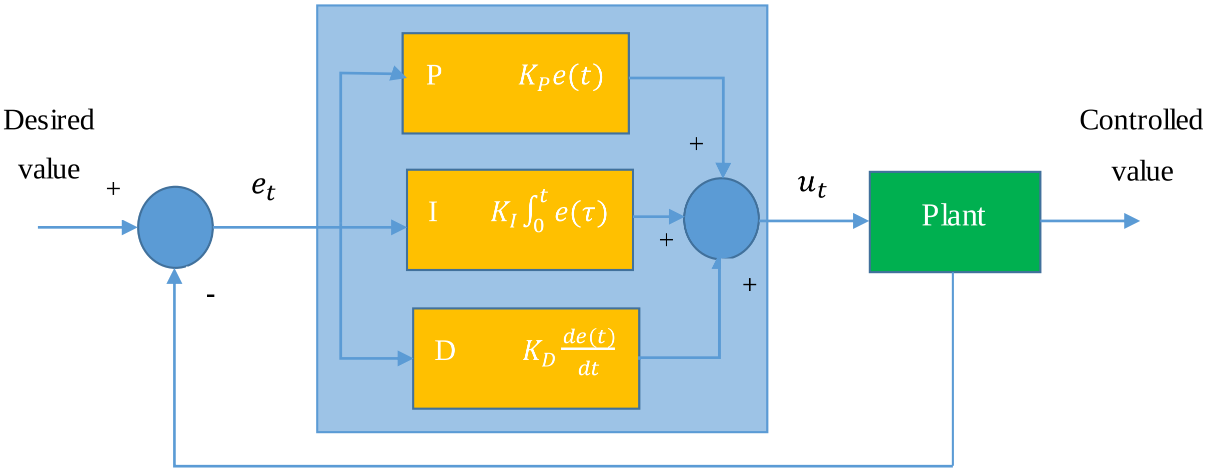



Figure 4.5. Block diagram of a PID controller

The proportional term gives an output that is proportional to the current error value. With a given proportional gain, the larger the error, the larger the controller output, and vice versa. If the error is zero, there is no corrective response. This term maintains a steady-state error (or offset error) because it requires an error to generate the proportional response (Bequette, 2003). The integral term integrates the error over a past period until the error value reaches zero. It eliminates the steady-state error of the proportional term. The integral controller decreases its output when the error is negative. However, it limits the response speed and affects the system's stability. The higher the integral gain, the slower the response. Finally, the derivative controller can predict future behavior by estimating the future error rate based on the current change rate.

Instead of using three controller terms, some applications need only one or two terms. For example, the proportional controller (P controller) is reasonable and straightforward to use if the steady-state error is acceptable. In contrast, the proportional-integral controller (PI controller) helps to reach the targeted value. Moreover, the P controller is fit for integrating processes, while the PI controller is suitable for non-integrating (or self-regulating) processes (Kuphaldt, 2018). Depending on the control aim and process characteristics, the controller designer selects a suitable controller type.

Besides the advantages, the PID control method also has limitations. Firstly, it does not ensure optimal control or stability. Secondly, the PID controller does not react to changing process behavior because of the constant controller parameters. However, the controller's performance can be improved by changing controller parameters by gaining scheduling in different use cases (Leith and Leithead, 1998) or adapting based on performance.

### *4.4.2. Parameter optimization*

Various methods can be used for engineering systems to choose the controller parameters: Ziegler-Nichols' tuning, relay feedback, or software tools (Astrom and Murray, 2009). These methods require implementing experiments on the controlled system. Manual tuning is another option, but it may take time. Finding suitable parameters requires controller designers to understand the effect of parameter adjustments on controller performance intensively (Table 4.2).

Table 4.2. Effects of an increase in parameters of the PID controller on control performance (Ang, Chong and Li, 2005)

| **Control parameter** | **Rise time** | **Overshoot** | **Settling time** | **Steady-state error** | **Stability** |
|---|---|---|---|---|---|
| $K_P$ | Decrease | Increase | Small change | Decrease | Degrade |
| $K_I$ | Decrease | Increase | Increase | Eliminate | Degrade |
| $K_D$ | Small change | Decrease | Decrease | No change | Improve if $K_D$ small |

Principally, an increase in the proportional gain leads to a proportional increase in the control signal for the same error. As a result, the system reacts more quickly but also overshoots more significantly. The increase in the proportional gain reduces the steady-state error but does not eliminate it. With the presence of the integral term, the steady-state error is eliminated. However, this term may cause the system to show more oscillatory behavior when the error signal changes sign. The derivative term predicts the error's future change; therefore, an adjusted signal can be included in the system before the error goes too large. As a result, the derivative term decreases overshoot. In terms of stability, the higher the proportional gain or integral gain, the less stable the control system.

Figure 4.6 illustrates an example of the output responding to step changes of controller gains of PID controller's subsets. When the purely P control is applied, the steady-state error remains at 0.5, 0.33, and 0.17, corresponding with the proportional gains of 1, 2, and 5. With the non-zero integral gains ($K_I = 0.2, 0.5, or\ 1$), the steady-state is eliminated. However, the higher proportional gain or integral gain causes more oscillatory behavior in the system and higher overshoot. With the presence of the derivative gain, the higher derivative gain decreases the oscillatory behavior and overshoot.

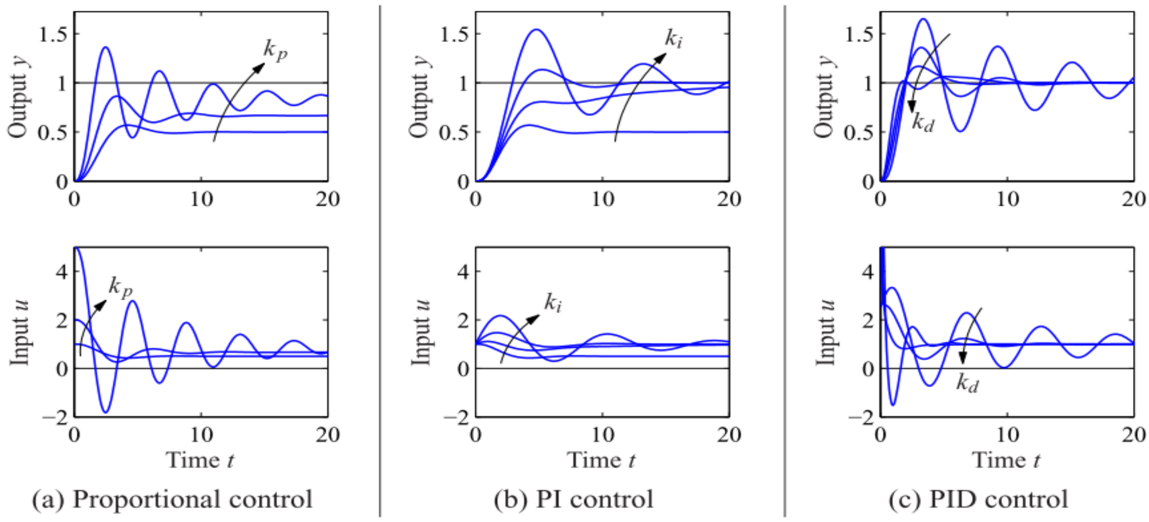



Figure 4.6. Output responses to step changes in the command signal for (a) P controller, $K_P = 1,2, and\ 5$, (b) PI controller $K_P = 1$, $K_I = 0, 0.2, 0.5, and\ 1$ (c) PID controller, $K_P = 2.5$, $K_I = 1.5$, $K_D = 0, 1, 2, and\ 4$ (Astrom and Murray, 2009)

For economic systems, it is a fact that we cannot do experiments on economic systems to find out the suitable controller parameters. Instead, the controller parameters can only be determined through historical analysis or macroeconomic simulations. A *historical analysis* chooses a historical period during which a government conducts an economic policy properly, then fits the control rule to the historical time series data. A *macroeconomic simulation* embeds the economic policy rule within a macroeconomic model and then varies parameters to optimize macroeconomic performance. For example, Taylor (1999) tunes the controller parameters by conducting a historical analysis of monetary policy in the United States. Several years later, Taylor and Wieland (2012) apply macroeconomic simulation, which minimizes the inflation, output, and interest rate variation across three United States economy monetary models to obtain the average parameters. The findings from the two above studies show certain similarities in the controller parameter values.

### 4.5. Chapter conclusion

Although the feedback control method has been studied and applied to the design of economic policies quite early, mainly to analyze macroeconomic policies, the achievements are limited. Despite the unfavorable conditions to apply the feedback control theory to economic policy, scientists consider that some feedback control approaches may work well.

By reviewing the literature, we find that research on using the feedback approach for price mechanism design for renewable power investment is unavailable. Moreover, Chapter 3 has indicated that the accurate dynamic model of investor behavior in renewable power investment markets is unknown. The constructed models show limitations in prediction. If the feedback control approach is applied to these models, the control performance is not achieved. The work of PID control relies on the response of the measured process variable, not on knowledge or a model of the underlying process. Therefore, this technique can control any process with a measurable output, including renewable power investment.

# Chapter 5. Development of PID Controller for Price Mechanism Design

## 5.1. Introduction

Despite the intensive study and careful design of energy policies by policymakers, we are still not sure that, indeed, the intended effects of these energy policies will be achieved. This consideration results from the fact that we cannot predict investor behavior accurately.

Most energy policies, here concretely price mechanisms, have been designed purely based on predicted values. History indicates that Germany switched from a prediction-based FIT mechanism to a hybrid FIT mechanism. Table 5.1 distinguishes and compares these two approaches.

Table 5.1. Current pricing approaches

| | **Prediction-based price mechanism** | **Hybrid price mechanism** |
|---|---|---|
| Principles | Based on predicted values<br>Based on future information<br>Manual control. | Based on both predicted and actual values<br>Based on future, current and historical information<br>Semi-automatic control. |
| Advantages | Easy to implement. | Less sensitive to unpredictable factors<br>Less robust oscillation in investment volume |
| Disadvantages | Sensitive to unpredictable factors<br>More robust oscillation in investment volume. | Be complicated to implement. |

The total or partial sensitivity of the two above approaches to unpredictable factors often results in an unexpected outcome. This chapter develops a feedback approach for price mechanism design to overcome that limitation. Section 5.2 describes the configuration of a feedback control system of price mechanisms for renewable power investment. In section 5.3, the mathematical forms of the PID-based price mechanism are formulated. In order to test and parametrize different control mechanisms which can hardly be performed on the “living” object of a national economy, the historical example of renewable policy making in Germany is used. Section 5.4 discusses two critical aspects of price mechanism design. Chapter conclusions are drawn in the last section.

## 5.2. Configuration of feedback control system

Figure 5.1 illustrates the elements and principles of a feedback control system of price mechanisms for renewable power investment. The investment market is viewed as a controlled system where the capacity of installed solar or wind power is controlled. The PID controller represents the regulator, which compares the desired installed capacity with the actual volume and minimizes the error value by applying proportional, integral, and derivative terms (see Section 5.3).

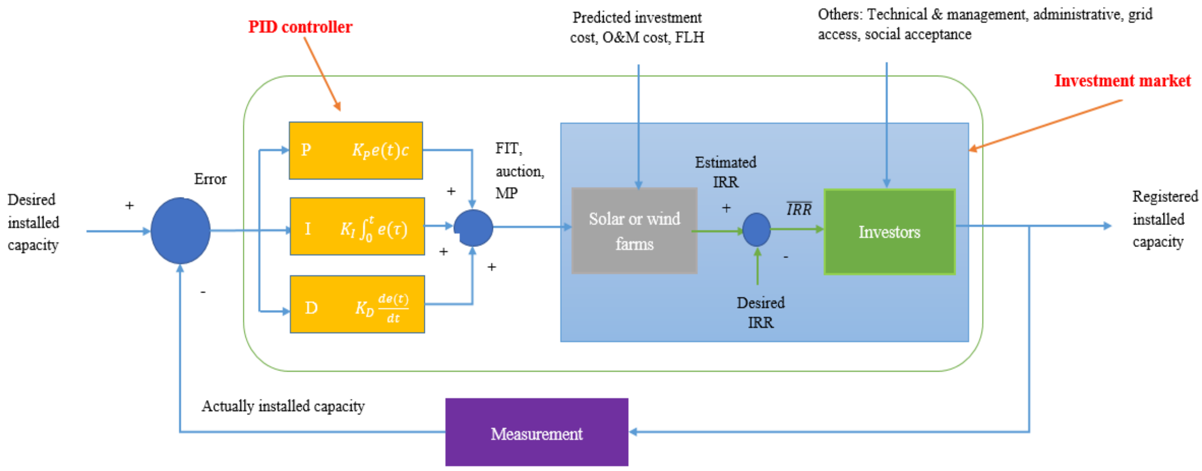



Figure 5.1. PID controller in a feedback control system of price mechanisms for renewable power investment

The measurement monitors the registered or committed installed capacity and the actual volume. Registered or committed projects may be delayed or canceled. This situation results in a lower actual investment than expected. The ratio of the actually installed capacity to the committed one is called the *realization rate*. According to the German Federal Network Agency (2019), the realization rate of solar power in Germany reached 96%, 90%, and 90% at the first, second, and third auction rounds. For simplicity, this research assumes a realization rate of 1.

The desired installed capacity is the development corridor imposed by the government. Usually, the government sets an annually or five-year installed capacity volume. This desired volume is translated to the external signal and applied to a different point of the control system to cause the controller to produce a specific price level.

The electricity price for renewables under the FIT, auction, or MP mechanisms is a manipulated variable (also known as a control variable). Profitability is a manipulated response and directly affects investment decisions. We define investment cost, operation and maintenance cost, and full-load hours as disturbances due to their uncontrollable nature.

Technical and management factors, administrative, grid access, and social acceptance affect investment decisions in practice. However, this study assumes that the effects of these factors on investor behavior insignificantly and that the investment decisions are mainly influenced by profitability.

## 5.3. Development of PID-based price mechanisms

### *5.3.1. Mathematical models*

Along with the maturity of the investment markets, price mechanisms are renewed or replaced to adapt to the changing context. Whatever price mechanism is applied, there is more or less control by the government. This section constructs mathematical shapes of the government's decision-making on the price of renewable power. Using the feedback approach, the government regularly adjusts the electricity price for renewables in response to the deviation between the desired investment and the actual volume. As a straightforward implementation, the government may establish the following proportional rule:

$$P_t = P_{t-1} + K_P e_t \tag{5.1}$$

$P_t, P_{t-1}$: the electricity price at time t, t-1.

$K_P$: proportional gain ($K_p > 0$).

$e_t = v_t^d - v_t^r$: the current deviation between the desired installed capacity and the actual volume. If the deviation is positive, the price is increased. If it is negative, it is decreased, and if zero remained unchanged.

Equation (5.1) is a formula of a proportional-based price mechanism.

A step beyond this simple scheme would be to consider history. If so, the rule can be mathematically expressed as follows:

$$P_t = P_{t-1} + K_P e_t + K_I \int_{\tau=0}^{t} e_\tau \, d\tau \tag{5.2}$$

$K_I$: integral gain.

$\tau = 0 \rightarrow t$: historical time.

Equation (5.2) is a formula of a proportional-integral-based price mechanism.

If the government also considers expectations of the deviation, the proportional-integral-derivative controller has the following formula:

$$P_t = P_{t-1} + K_P e_t + K_I \int_{\tau=0}^{t} e_\tau \, d\tau + K_D \frac{de_t}{dt} \tag{5.3}$$

It is a fact that the additionally installed capacity is measured periodically (e.g., monthly, quarterly, every six months, or annually). Therefore, the price mechanisms are adjusted based on the gap size measurements at discrete points in time. Discretizing the integral and derivative terms in (5.3) at a small sampling interval $\Delta t$, we have:

$$\int_{\tau=0}^{t_k} e_\tau \, d\tau = \sum_{i=1}^{k} e_{t_i} \Delta t \,, t = k * \Delta t \tag{5.4}$$

$$\frac{de_{t_k}}{dt} \approx \frac{e_{t_k} - e_{t-1_{k-1}}}{\Delta t} \tag{5.5}$$

Substituting the continuous integral and derivative terms in (5.3) by discrete terms (5.4) and (5.5), the discrete model of a PID-based price mechanism is obtained:

$$P_t = P_{t-1} + K_P e_t + K_I \sum_{i=1}^{k} e_{t_i} \Delta t + K_D \frac{e_{t_k} - e_{t-1_{k-1}}}{\Delta t} \tag{5.6}$$

According to (5.6), the deviation values must be stored at all the time instants. Applying the velocity algorithm proposed by Astrom (2002) to this equation, the number of stored deviation values is reduced. The velocity algorithm is as follows:

Setting $\Delta t = 1$, and taking the difference between $P_t$ and $P_{t-1}$, the econometric model of a PID-based price mechanism is obtained:

$$P_t = 2P_{t-1} - P_{t-2} + (K_P + K_I + K_D)e_t - (K_P + 2K_D)e_{t-1} + K_D e_{t-2} \tag{5.7}$$

Setting $\alpha = 2P_{t-1} - P_{t-2}$, $\beta_0 = K_P + K_I + K_D$, $\beta_1 = -K_P - 2K_D$, $\beta_2 = K_D$. Equation (5.7) is rewritten:

$$P_t = \alpha + \beta_0 e_t + \beta_1 e_{t-1} + \beta_2 e_{t-2} \tag{5.8}$$

The econometric model of a PI-based price mechanism would look like this:

$$P_t = \alpha + \beta_0 e_t + \beta_1 e_{t-1} \tag{5.9}$$

Dynamic econometric models (5.8) and (5.9) depict that the current electricity price depends on the current deviation and the lagged deviations. Components of the subset of a PID-based price mechanism are summarized in Table 5.2.

Table 5.2. Components of the subset of a PID-based price mechanism

| **Rule** | $P_{t-1}$ | $P_{t-2}$ | $e_t$ | $e_{t-1}$ | $e_{t-2}$ |
|---|---|---|---|---|---|
| P-based price mechanism | Yes | No | Yes | No | No |
| PI-based price mechanism | Yes | Yes | Yes | Yes | No |
| PID-based price mechanism | Yes | Yes | Yes | Yes | Yes |

Thus, if the P controller is applied, the government adjusts the price mechanism based on only the current deviation of the installed capacity. In contrast, the PI controller requires storing one lagged deviation value, and the PID controller requires storing two lagged values of deviation.

### *5.3.2. Controller parameter estimation*

This section estimates the controller parameters using the historical example of renewable policy making in Germany.

#### *5.3.2.1. Mechanism analysis*

Since 2009, the FIT adjustment for solar power in Germany has depended on both predicted and feedback values (German Federal Parliament, 2009, 2010, 2012, 2014, 2017). Table 5.3 shows that an annual FIT adjustment was applied for the period from January 2009 to March 2012. Then, this country introduced a monthly FIT adjustment with quarterly feedback of installed capacity.

Table 5.3. Changes in the FIT adjustment rule for solar power in Germany

| **Applied Period** | **Frequency of FIT adjustment** | **Frequency of installed capacity feedback** | **Frequency of targeted installed capacity** |
|---|---|---|---|
| 2009 – 03/2012 | Annually | Annually | Annually |
| 04/2012 – now | Monthly | Quarterly | Annually |

According to the German Federal Parliament (2010), the annual FIT adjustment in 2011 was chosen with a high prediction-based degression rate of (-9%) and a low feedback-based degression rate of (-3%) to 3%. Figure 5.2 depicts the degression rate corresponding to the deviation between the targeted installed capacity and the actual volume for solar power in Germany in 2011. If the deviation had been zero, the total degression rate would have been 9%. Otherwise, the total degression rate would have been lower or higher levels.

The hybrid FIT mechanism in 2011 can be expressed in a mathematical formula as follows:

$FIT_{2011} = FIT_{2010}(1 + TDR_{2011})$

$TDR_{2011} = PDR_{2011} + FDR_{2011}$: Total degression rate (TDR) in 2011 is the sum of the prediction-based degression rate (PDR) in 2011 and the feedback-based degression rate (FDR) in 2011.

$FDR_{2011} = \mathrm{f}(e_{2010})$: The feedback-based degression rate in 2011 depends on the installed capacity deviation in 2010.

Because of the actually installed capacity in 2010 of 7,440 MW, which equals a deviation of (-3,940) MW, the FIT in 2011 was decreased by 12%.

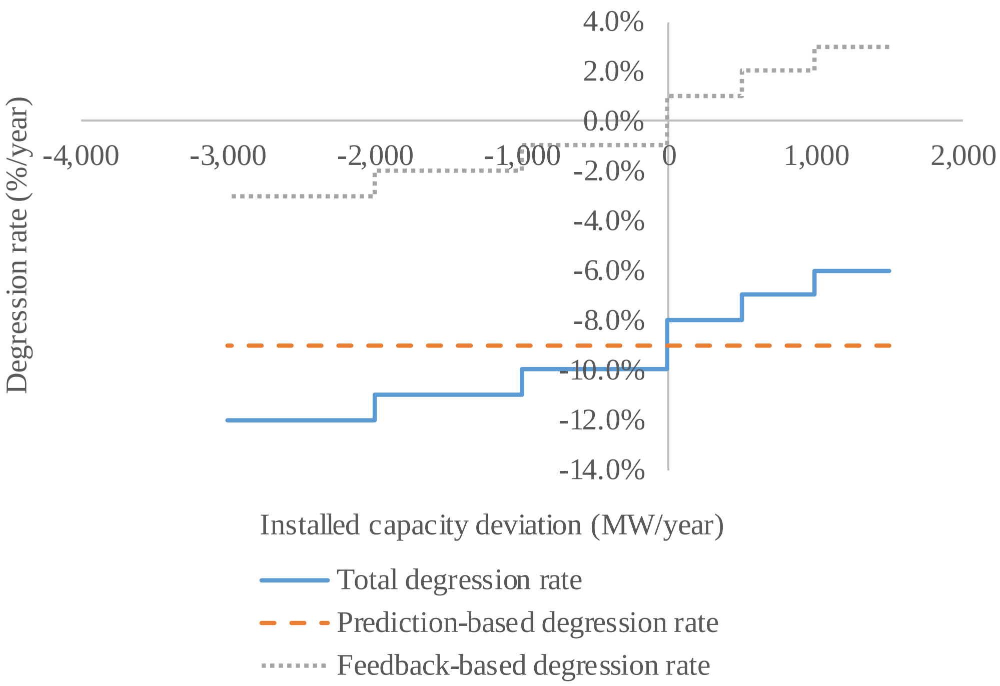



Figure 5.2. Possibly annual FIT degression rate for solar power in Germany in 2011

Since April 2012, a monthly FIT adjustment depending on the actual investment rather than the predicted values has been regulated. According to the German Federal Parliament (2014), a prediction-based degression rate of (-0.5%) and a feedback-based one of (-2.3% to 2.3%) was chosen. Accordingly, if the deviation between the targeted installed capacity and the cumulatively installed capacity of the previous twelve months had been zero, a degression rate of (-0.5%/month) would have been applied. Otherwise, the total degression rate would have been lower or high levels (Figure 5.3).

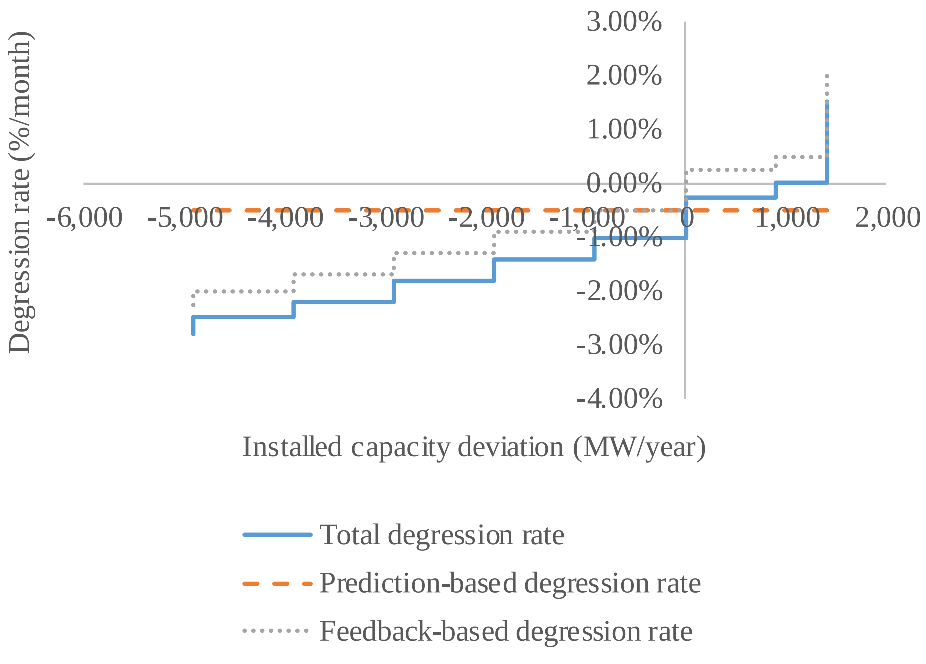



Figure 5.3. Possibly monthly FIT degression rate for solar power in Germany in October 2014

The mathematical shape of the FIT mechanism in October 2014 is as follows:

$$FIT_{Oct,2014} = FIT_{Sep,2014}(1 + TDR_{Oct,2014})$$

$TDR_{Oct,2014} = PDR_{Oct,2014} + FDR_{Oct,2014}$: The total degression rate in October 2014 is the sum of the prediction-based degression rate in October 2014 and the feedback-based degression rate in October 2014.

$FDR_{Oct,2014} = \mathrm{f}(e_{Aug,2014})$: The feedback-based degression rate in October 2014 depends on the annually installed capacity deviation by August 2014.

$e_{Aug,2014} = v^d_{Aug,2014} - v^r_{Aug,2014}$: Deviation between the desired annual investment and the cumulatively installed capacity of the previous twelve months.

*5.3.2.2. Fitting the rules*

We identify that the feedback-based FIT adjustment for solar power in Germany has followed the proportional controller rule. The proportional gain is determined by decomposing the hybrid FIT mechanism into the fixed, prediction-based, and feedback-based components.

The model of the FIT determination in 2011 can be rewritten as follows:

$$FIT_{2011} = \underbrace{FIT_{2010}}_{\substack{\text{Fixed}\\ \text{component}}} + \underbrace{FIT_{2010} * PDR_{2011}}_{\substack{\text{Prediction-based}\\ \text{component}}} + \underbrace{FIT_{2010} * FDR_{2011}}_{\substack{\text{Feedback-based}\\ \text{component}}}$$

$FIT_{2010}$ is known, $PDR_{2011}$ is given. The FIT level in 2011 varies following $FDR_{2011}$. Moreover, we have $FIT_{2010} * FDR_{2011} = K_P * e_{2010}$. With the $FIT_{2010}$ of 34.73 Euro cents/kWh, the $PDR_{2011}$ of (-9%), and the FIT adjustment as shown in Table 5.4, the proportional gain of the FIT adjustment for small-scale solar power projects in 2011 is estimated using the regression analysis.

Table 5.4. Regulation on the monthly FIT adjustment for solar power in Germany in 2011 (German Federal Parliament, 2010)

| **Actual installation (GW/year)** | **Installation deviation (GW/year)** | **Total degression rate (/year)** | **Prediction-based degression rate (/year)** | **Feedback-based degression rate (/year)** | **Feedback-based FIT adjustment (Euro cents/kWh)** |
|---|---|---|---|---|---|
| 1.00 | 1.50 | -6.0% | -9% | 3.00% | 1.04 |
| 1.50 | 1.00 | -6.0% | -9% | 3.00% | 1.04 |
| 1.50 | 1.00 | -7.0% | -9% | 2.00% | 0.69 |
| 2.00 | 0.50 | -7.0% | -9% | 2.00% | 0.69 |
| 2.00 | 0.50 | -8.0% | -9% | 1.00% | 0.35 |
| 2.50 | 0.00 | -8.0% | -9% | 1.00% | 0.35 |
| 2.50 | 0.00 | -9.0% | -9% | 0.00% | 0.00 |
| 3.50 | 0.00 | -9.0% | -9% | 0.00% | 0.00 |
| 3.50 | 0.00 | -10.0% | -9% | -1.00% | -0.35 |
| 4.50 | -1.00 | -10.0% | -9% | -1.00% | -0.35 |
| 4.50 | -1.00 | -11.0% | -9% | -2.00% | -0.69 |
| 5.50 | -2.00 | -11.0% | -9% | -2.00% | -0.69 |
| 5.50 | -2.00 | -12.0% | -9% | -3.00% | -1.04 |
| 6.50 | -3.00 | -12.0% | -9% | -3.00% | -1.04 |

Similarly, with the $FIT_{Sep,2014}$ of 12.69 Euro cents/kWh, the $PDR_{Oct,2014}$ of (-0.5%) and the FIT regulation, as shown in Table 5.5, the proportional gain of the FIT adjustment for small-scale solar power projects in October 2014 is estimated using the regression analysis.

Table 5.5. Regulation on the monthly FIT adjustment for solar power in Germany in October 2014 (German Federal Parliament, 2014)

| **Additionally installation in the reference period extrapolated to one year (GW/year)** | **Installation deviation (GW/year)** | **Total degression rate (/month)** | **Prediction-based degression rate (/month)** | **Feedback-based degression rate (/month)** | **Feedback-based FIT adjustment (Euro cents/kWh)** |
|---|---|---|---|---|---|
| 1.00 | 1.40 | 1.50% | -0.5% | 2.00% | 0.25 |
| 1.00 | 1.40 | 0.00% | -0.5% | 0.50% | 0.06 |
| 1.50 | 0.90 | 0.00% | -0.5% | 0.50% | 0.06 |
| 1.50 | 0.90 | -0.25% | -0.5% | 0.25% | 0.03 |
| 2.40 | 0.00 | -0.25% | -0.5% | 0.25% | 0.03 |
| 2.40 | 0.00 | -0.50% | -0.5% | 0.00% | 0.00 |
| 2.60 | 0.00 | -0.50% | -0.5% | 0.00% | 0.00 |
| 2.60 | 0.00 | -1% | -0.5% | -0.50% | -0.06 |
| 3.50 | -0.90 | -1.00% | -0.5% | -0.50% | -0.06 |
| 3.50 | -0.90 | -1.40% | -0.5% | -0.90% | -0.11 |
| 4.50 | -1.90 | -1.40% | -0.5% | -0.90% | -0.11 |
| 4.50 | -1.90 | -1.80% | -0.5% | -1.30% | -0.16 |
| 5.50 | -2.90 | -1.80% | -0.5% | -1.30% | -0.16 |
| 5.50 | -2.90 | -2.20% | -0.5% | -1.70% | -0.22 |
| 6.50 | -3.90 | -2.20% | -0.5% | -1.70% | -0.22 |
| 6.50 | -3.90 | -2.50% | -0.5% | -2.00% | -0.25 |
| 7.50 | -4.90 | -2.50% | -0.5% | -2.00% | -0.25 |
| 7.50 | -4.90 | -2.80% | -0.5% | -2.30% | -0.29 |

The estimated proportional gains are shown in Table 5.6.

Table 5.6. Estimated proportional gains of the FIT adjustment for solar power in Germany

| **Applied time** | $K_P \left[\frac{Euro\ cents/_{kWh}}{GW/year}\right]$ | **P-value** | $R^2$ |
|---|---|---|---|
| 2011 | 0.483 | $3.56*10^{-6}$ | 81.88% |
| October 2014 | 0.062 | $4.17*10^{-10}$ | 90.48% |

The R-squared values of 81.88% and 90.48% indicate that the feedback-based FIT adjustment fits the proportional controller rule well. In addition, the positive proportional gain means that the higher the deviation between the desired investment and the actual volume, the higher the feedback-based degression rate, and vice versa. Specifically, a proportional gain of 0.483 $\frac{Euro\ cents/_{kWh}}{GW/year}$ indicates that an increase of 1 GW/year in the installation deviation leads to an increase of 0.483 Euro cents/kWh in the feedback-based FIT degression in 2011. In October 2014, an increase of 1 GW/year in the installation deviation requires an increase of 0.062 Euro cents/kWh in the feedback-based FIT degression.

### *5.3.3. Control performance*

The actual installation in 2011 reached 7,910 MW despite the expectation of 2,500 to 3,500 MW. This response indicates that the proportional gain of 0.483 $\frac{Euro\ cents/_{kWh}}{GW/year}$ is too low. The overinvestment in solar power between 2009 and 2012 (Figure 5.4) entailed a considerable increase in the solar energy surcharge from only 0.67 to 2.03 Euro cents/kWh (Figure 5.5).

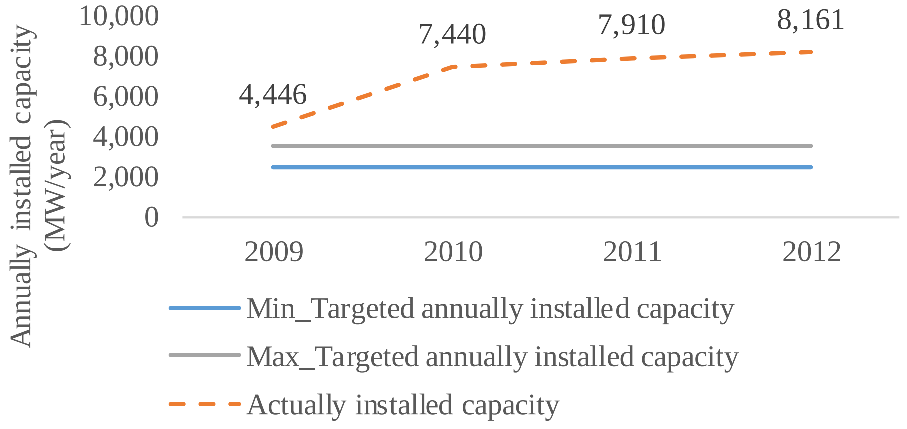



Figure 5.4. Annually installed capacity of solar power in Germany between 2009 and 2012

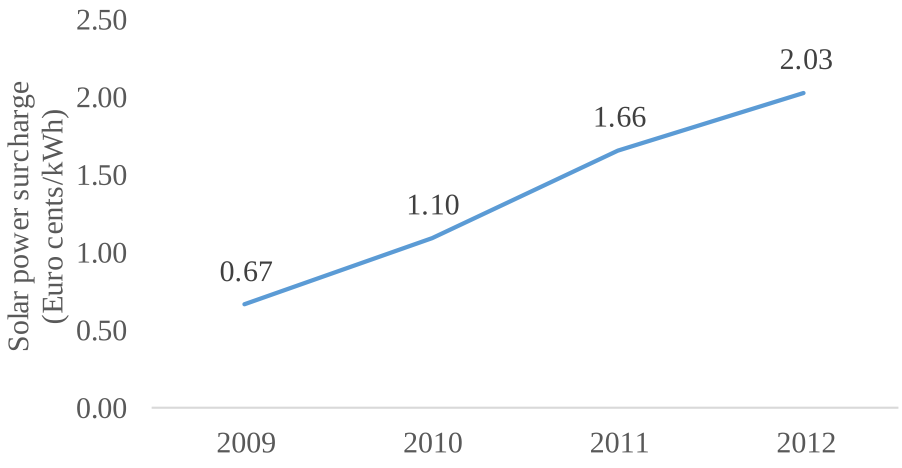



Figure 5.5. Solar power surcharge in Germany between 2009 and 2012

The actually installed capacity in October 2014 closed to the desired value (Figure 5.6) indicates that the proportional gian of 0.062 $\frac{Euro\,cents/_{kWh}}{GW/year}$ is suitable for FIT adjustment.

Due to the lower actually installed capacity than the targeted volume (2,500 MW/year), the monthly FIT remained unchanged or slightly reduced between October 2014 and July 2018. In contrast, since August 2018, the deviation between the targeted installed capacity and the actual volume has been positive (Figure 5.6). Therefore, the FIT levels were decreased significantly (Figure 5.7).

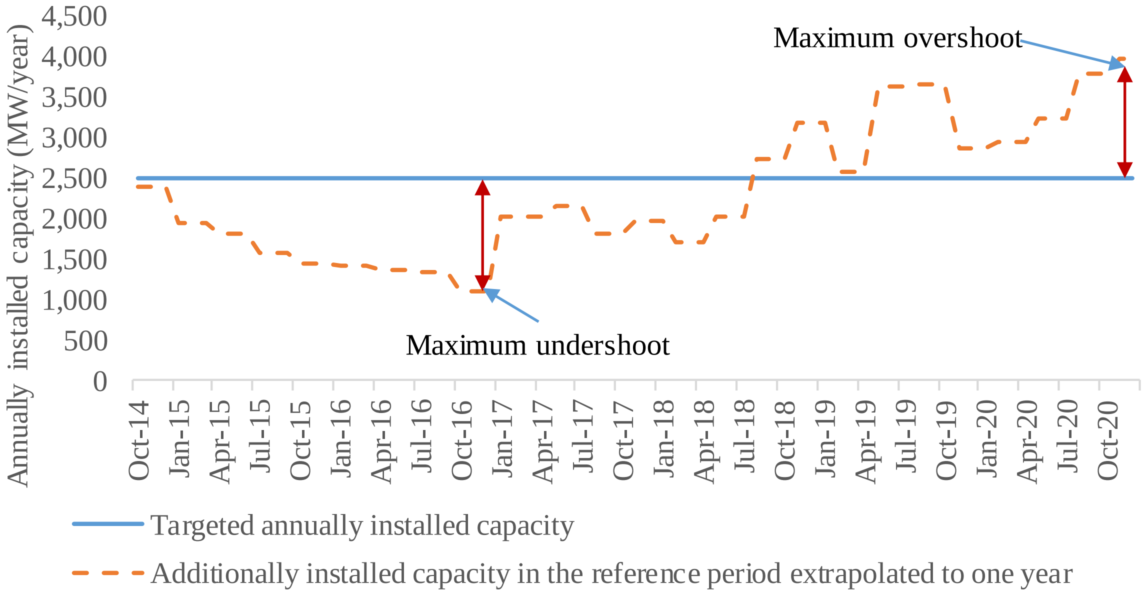



Figure 5.6. Annually installed capacity of solar power in Germany between October 2014 and December 2020

(Source: Data from Federal Network Agency, 2021a)

Despite a more regularly FIT adjustment (monthly adjustment), Germany has not ensured the annually installed capacity in terms of tracking and asymptotic. The underinvestment in solar power remained for an extended period until August 2018, with the maximum undershoot of 44%, the actually cumulative investment reached only 70% of the targeted volume. In contrast, since November 2018, the overinvestment occurred with the maximum overshoot of 60%, the actually cumulative investment reached more than 130% of the targeted volume (Figure 5.6).

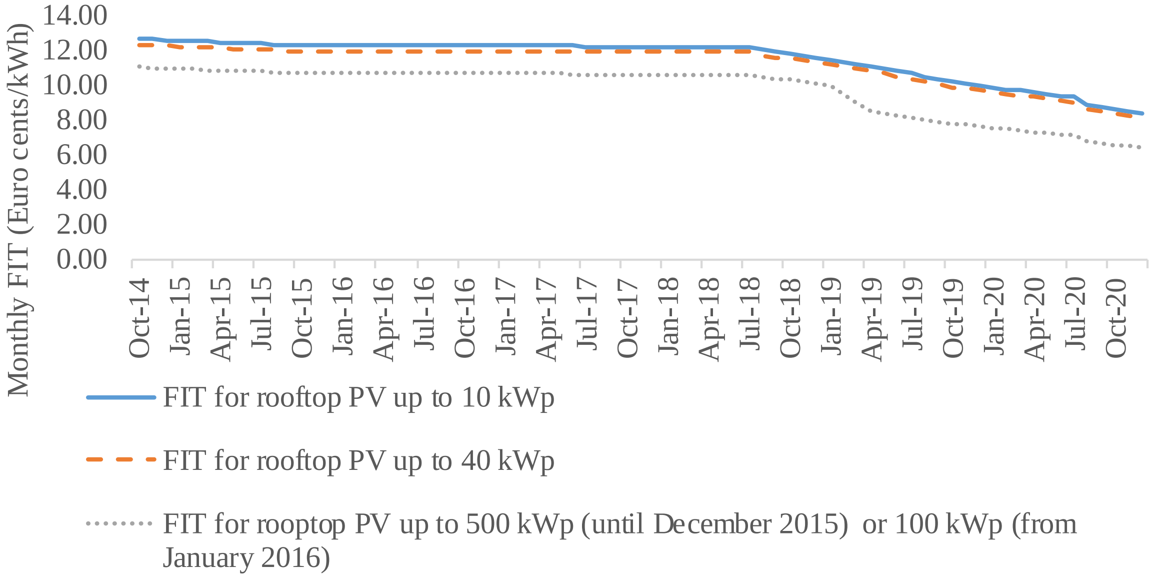



Figure 5.7. Monthly FIT for solar power in Germany between October 2014 and December 2020

(Source: Data from the Federal Network Agency, 2021a)

It should be noted that a significant share of the solar power installed capacity in Germany came from small-scale solar power projects (up to 10 kWp), which takes only 5 to 10 weeks to implement small-scale solar power projects. The PV system price decreased continuously and significantly in Germany between January 2009 and March 2012. The FIT scheme's significant deficiency of being updated only annually at the low degression rate were the opportunities for investors attaining high-profit margins in the last months. In contrast, there is a strong correlation between the PV system price and the FIT since October 2014 (Figure 5.8).

As a result, an unprecedented amount of capacity was added to the power supply system in the last months of 2009, 2010, and 2011 while the monthly investment since October 2014 has been more stable (Figure 5.9). Accordingly, the monthly installed capacity curves' shape differs completely from the annual FIT adjustment versus the monthly one. Between April 2012 and December 2018, the monthly installation of solar PV systems was stable, with an average volume of 34,715 kWp/month and a deviation of 1,743 kWp/month. In contrast, the monthly installed capacity fluctuated considerably between January 2009 and March 2012, with an average of 188,104 kWp/month and a deviation of 24,133 kWp/month (Figure 5.9).

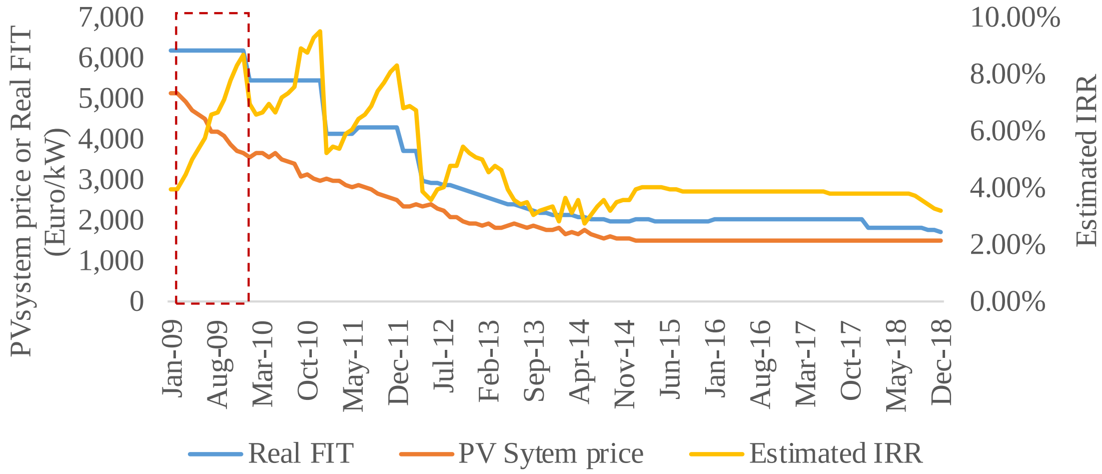



Figure 5.8. Real FIT, PV system price, estimated IRR of small-scale solar power projects in Germany between January 2009 and December 2018

(Source: Data for PV system price retrieved from Ziegler (2011), real FIT and estimated IRR from our calculation)

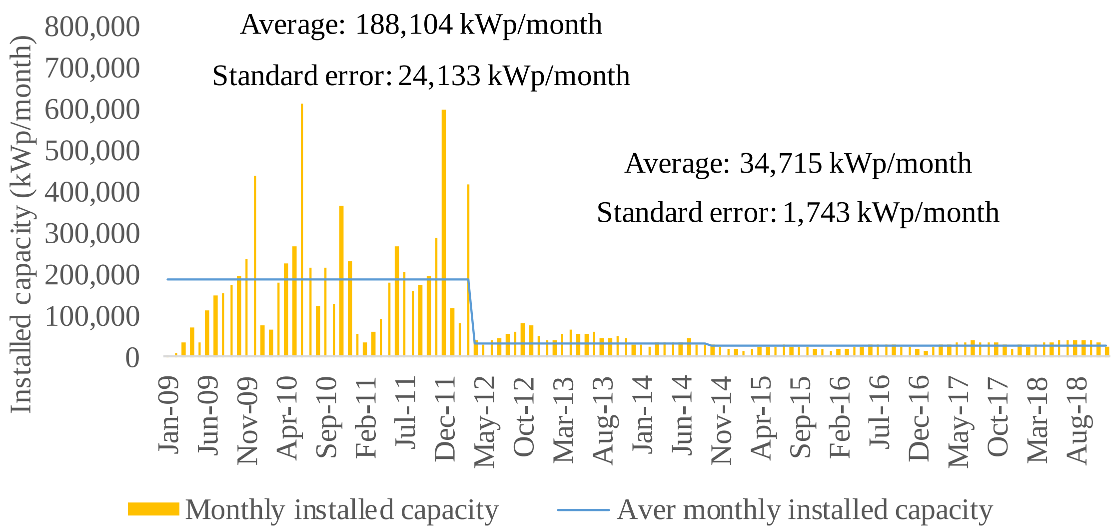



Figure 5.9. Monthly small-scale solar power installed capacity in Germany between January 2009 and December 2018

(Source: Data from Federal Network Agency, 2021a)

All in all, the hybrid FIT mechanism does not achieve sustainable solar power investment growth. However, the findings indicate that the performance of the monthly FIT adjustment is higher than that of the annual one. In other words, the more regular the price adjustment and the more the feedback-based degression rate exceeds the prediction-based value, the smoother the investment rate.

From these results, we consider that if the adjustment frequency and the proportional gain are chosen suitably, the purely feedback-based can help achieve sustainable solar power investment growth.

### 5.4. Aspects of price adjustments

The above analysis indicates two critical aspects of a feedback control system design of price mechanisms, including adjustment frequency and adjustment level. This section discusses the factors affecting the selection of the two aspects.

#### *5.4.1. Adjustment frequency*

The frequency is predetermined and independent of the controller model. The selection of adjustment frequency depends on project implementation duration and investment cost reduction rate. The project implementation duration is the time from the pre-construction (project agreements - financial, contractual, and interconnection) to commissioning (testing and verification, interconnection verification, permission to operate) (Agut *et al.*, 2016). A shorter duration requires a more regular price adjustment. Table 5.7 indicates that the larger the solar power project, the longer the project implementation duration.

Table 5.7. Project implementation duration of solar power projects in Germany and Vietnam

| | | **Small-scale rooftop PV systems** | **Medium-scale rooftop PV systems** | **Large-scale rooftop PV, ground-mounted PV systems** |
|---|---|---|---|---|
| Germany (Grau, 2014) | Project scale | Up to 30 kW | 30 – 750 kW | 750 kW – 10 MW |
| | Project implementation duration | 5 – 10 weeks (average of 1.5 months) | 5 – 15 weeks (average of 2 months) | 24 – 53 weeks (average of 9 months) |
| Vietnam (interviewed experts) | Project scale | Up to 100 kW | 100 kW – 1 MW | 1 MW – 450 MW |
| | Project implementation duration | 2 – 10 weeks (average of 1.5 months) | 5 – 15 weeks (average of 2.5 months | 3 - 9 months (average of 6 months) |

The investment cost of solar power includes the costs for PV modules, inverters, EPC (engineering, procurement, and construction). According to the IRENA (2020), the global average investment cost of solar power projects commissioned in 2019 was 79% lower than in 2010 and 18% lower than in 2018.

Taking the project implementation duration and the investment cost reduction rate into account, we suggest the options of the FIT adjustment frequency for solar power projects, as illustrated in Table 5.8.

Table 5.8. Proposed FIT adjustment frequency for solar power projects

| **Option** | **Adjustment frequency** | **Application** |
|---|---|---|
| 1.1 | Monthly | Small-scale projects |
| 1.2 | Quarterly | |
| 2.1 | Quarterly | Medium-scale projects |
| 2.2 | Every six months | |
| 3.1 | Every six months | Utility-scale projects |
| 3.2 | Annually | |

With the auction mechanism, a ceiling price is regulated to biddings. Ceiling price adjustment should be considered at each bidding round. The selection of the auction frequency depends on the market scale, represented by the auction volume: the more significant the targeted auction volume, the more regular the auction frequency. For example, if the annual targeted volume is 500 MW, every half-year auctions may be sufficient. However, to achieve the annual target of 1,000 MW, quarterly auctions may be required. Table 5.9 presents auction frequency for solar and wind power in several countries. Although being born later than other countries, Germany's auction mechanism has been quite active, with 3 to 7 auction rounds per year for solar and onshore wind power, an annual auction for offshore wind.

Table 5.9. Auction frequency for solar and wind power in several countries

| **Country** | **Year of introduction** | **Auction frequency** | | |
|---|---|---|---|---|
| | | **Solar power** | **Onshore wind power** | **Offshore wind power** |
| Germany | 2015 | 3 – 7 rounds/year | 3 – 7 rounds/year | Annually |
| France | 2011 | 1 – 3 rounds/year | - | - |
| Brazil | 2009 | 1– 2 rounds/year | 1 – 2 rounds/year | |

| Country | Year of introduction | Auction frequency | | |
|---|---|---|---|---|
| | | Solar power | Onshore wind power | Offshore wind power |
| Denmark | 2004 | - | - | less than once per year |
| China | 2003 | - | 1 round/year | - |

### *5.4.2. Adjustment level*

The price adjustment level depends on the value of controller parameters. The controller parameters can be realized through the historical analysis as analyzed in Section 5.3.2 if the historical data is available. If the historical data is unavailable, the controller parameters can be selected through learning.

The controller parameter values define how active or aggressive the price is adjusted in response to investment deviation. Particularly, a significant gain leads to an extensive price modification or fast response for a given error with the proportional controller application, creating instability in the system and cause high risks to investors' revenue. Most investors are reluctant to participate in high volatile or risky markets. Besides, a substantial FIT adjustment may require a high budget, increasing electricity, a burden on consumers, and vice versa.

With the auction mechanism, an appropriate setting of the ceiling price is challenging. If the ceiling price is too high, the competition among biddings is low. Consequently, the bidders will submit the biddings towards the ceiling price rather than their actual costs. In contrast, if the ceiling price is too low, the auction is not attractive to players. As a result, the targeted volume may not be achieved.

## 5.5. Chapter conclusion

This chapter has shaped mathematical models of feedback-based price mechanisms which support policy decision-making. The feedback approach is novel regarding two aspects. On the one hand, it removes the prediction-based component, thus avoiding faulty decision-making because of the unpredictable behavior. On the other hand, the regular price adjustment based on the deviation between the desired investment volume and the actual one narrows the deviation over time.

The main contributions and findings of this chapter are as follows:

Firstly, elements and principles of a feedback control system of price mechanisms for renewable power investment are defined where the PID controller is selected for price mechanism design.

Secondly, the discrete econometric models of the subsets of a PID-based price mechanism to control renewable power investment are formulated. P-based price adjustment is based on the current deviation of the installed capacity. PI-based price adjustment requires storing one lagged value of the installed capacity, while the PID-based one requires two lagged values.

Thirdly, by decomposing the hybrid FIT mechanism into the fixed, prediction-based, feedback-based components and applying the regression analysis to the historical data, we point out the consistency of the feedback-based FIT adjustment for solar power in Germany with the proportional control rule. We conclude that the feedback-based price mechanism can help achieve sustainable solar power investment growth if the adjustment frequency and the suitable proportional gain are chosen.

Finally, this chapter has proposed a monthly or quarterly FIT adjustment for small solar power projects, a quarterly or semi-annually FIT adjustment for medium ones, a semi-annually or annually FIT adjustment for utility-scale ones. Also, we suggest that if the accurate econometric historical data is unavailable, the controller parameters can be selected through learning.

# Chapter 6. Application of PID-Based Price Mechanisms to Germany

## 6.1. Introduction

The term "*Energiewende"* (German for "energy transition") first appeared in 1980 in Germany's plan for the energy transition to low carbon and nuclear-free economy (Krause, Bossel and Mueller-Reissmann, 1980). Up to now, this term has told more stories apart from phasing out nuclear power and expanding renewables in the power sector. Solar and wind energy have also been used for heating and cooling systems in buildings and electric mobility of transport (Wietschel *et al.*, 2018).

Germany has employed various energy policies to become one of the leading countries in the energy transition. Price mechanisms have been the main drivers for the achievements. However, the unsuitable support mechanisms have entailed numerous negative consequences (Gawel, Korte and Tews, 2015). The innovation from a prediction to a hybrid FIT mechanism has helped achieve smoother solar power investment. However, it does not guarantee sustainable investment growth.

Apart from the FIT mechanism, the competitive auctions have been applied for around 80% of new solar or wind power installations since 2017 (German Federal Parliament, 2017). Also, Germany is a member of the European Union emissions trading system (EU ETS). This carbon price mechanism is expected to force investment in low carbon power plants in European countries.

This chapter proposes applying the feedback approach to the auction mechanism and the carbon price mechanism in Germany. Section 6.2 presents an overview of the solar and wind power investment markets in Germany. In section 6.3, we analyze the effects of price mechanisms on solar and wind power investment markets. Section 6.4 devotes the PID controller design of the auction mechanism and carbon price mechanism. Finally, Section 6.5 highlights the main chapter conclusions.

## 6.2. Solar and wind power investment markets in Germany

### *6.2.1. The dominance of solar and wind power*

Germany's power generation sector has undergone a remarkable change over the past two decades. It is being restructured towards the dominance of renewable resources instead of the traditional ones. As of 2020, renewables reached approximately 62% (132 GW) of the total installed capacity (211 GW), with 55% (116 MW) from solar and wind power energy. However, because of weather dependence, electricity generation from solar and wind energy amounted to only 37% (181,565 GWh) of the total electricity supply (488,700 GWh) (Figure 6.1).

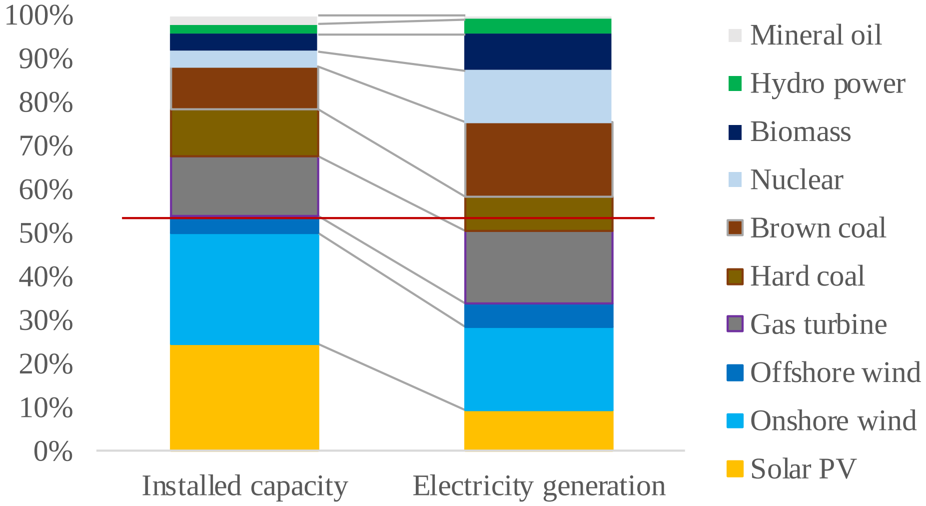



Figure 6.1. Installed capacity and electricity generation structures in Germany in 2020

(Source: Data from Burger, 2021)

Figure 6.2 shows that in 2000, there was 6.097 GW onshore wind, no offshore wind power, and only 0.114 GW solar power. Eighteen years later, the cumulatively installed capacity reached 52.565 GW of onshore wind, 6.417 GW of offshore wind, and 45.277 GW of solar power. Moreover, there is a preference for onshore wind power in Germany in the first decade. However, between 2009 and 2012, solar power increased massively. Recent years have seen a gradual increase in offshore wind power investment.

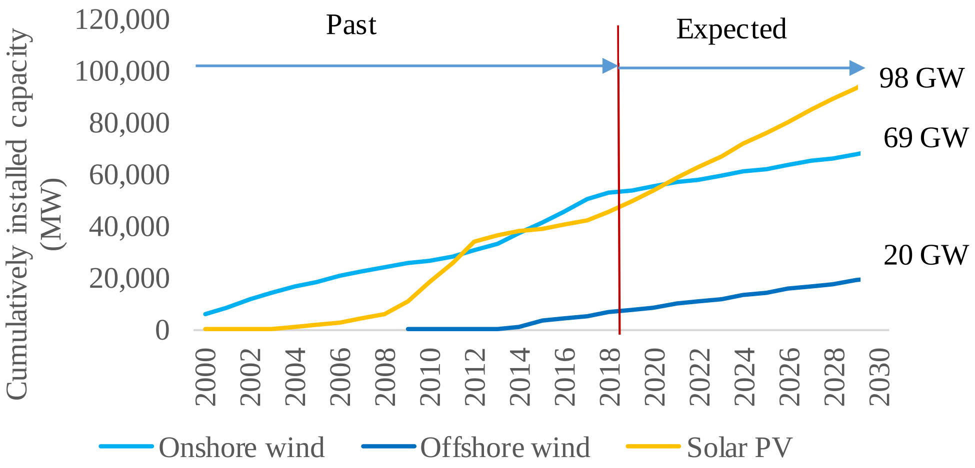



Figure 6.2. Past and expected cumulatively installed capacity of solar and wind power in Germany between 2000 and 2030

(Source: Historical data from the BMWi and AGEE-Stat, 2021, future data from our calculation)

According to the Federal Government of Germany (2019), Germany aims to achieve a renewable energy share of 65% in the total electricity consumption in 2030. The cumulatively installed capacity of solar PV, onshore wind, and offshore wind power are set at 98 GW, 65-71 GW (an average of 69 GW), and 20 GW, respectively. In other words, an average of the annually installed capacity is expected at 4,415 MW of solar power, 1,458 MW of onshore wind, and 1,225 MW of offshore wind power between 2021 and 2030. This plan shows the priority in developing solar power over wind power in the next decade.

### *6.2.2. Investors and project scales*

Investors are interested in solar and wind power investment in Germany to a different extent. Figure 6.3 shows the opposite pattern of the ownership structures of solar and wind power installed capacity in Germany.

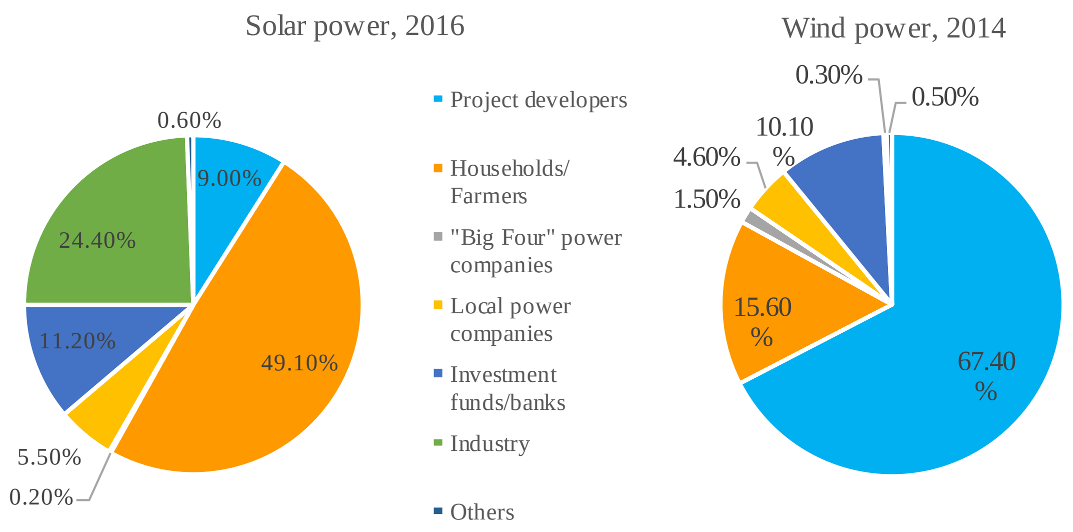



Figure 6.3. Ownership structures of solar power installed capacity in 2016, wind power installed capacity in 2014 in Germany

(Source: Data from Morris, 2018b)

By 2016, 73% of solar power installed capacity was owned by end-users such as households, farmers, and industrial consumers. In contrast, by 2014, project developers were leading players in the wind power investment market, accounting for 67% of installations, followed by local power companies with 15.60%.

Moreover, there is an increase in solar power project scales during the last 20 years. In 2000, small and medium-scale power projects of no more than 100 kW contributed 90% of the total solar power installed capacity. In contrast, recent years have seen more than 50% of solar power installed capacity from projects of more than 500 kWp (Figure 6.4). We consider that the development towards larger projects is due to the decrease in the investment cost, the change in the price mechanism, and the potential investors.

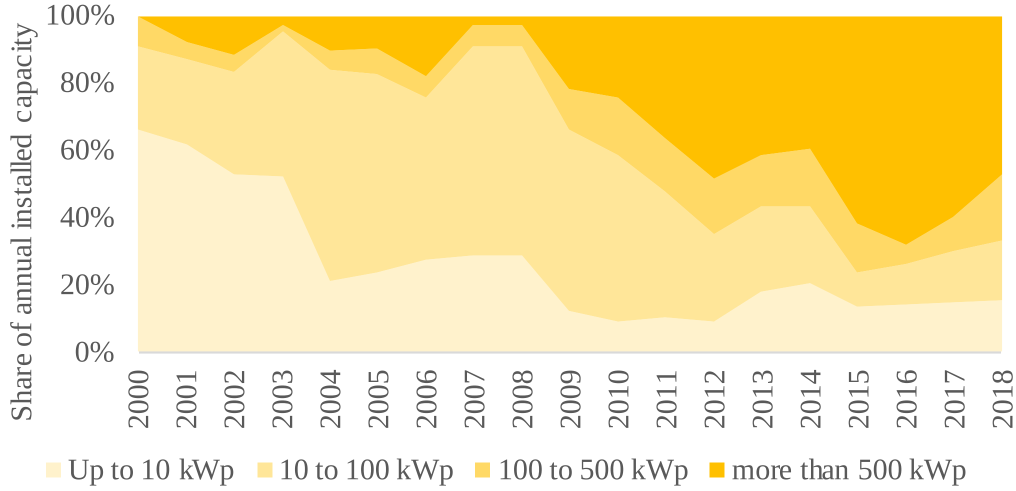



Figure 6.4. Annual project scale structure of solar power in Germany between 2000 and 2018

(Source: Data from the ISE, 2020)

## 6.3. Price mechanisms and their effects on solar and wind power investment in Germany

### *6.3.1. Renewable Energy Sources Act*

The introduction of the Renewable Energy Sources Act (EEG) in 2000 and its later amendments accelerated the renewable power deployment in Germany (German Federal Parliament, 2000, 2004, 2009, 2012, 2014, 2017). The amendments entailed the shifts in investment market responses (Figure 6.5, Figure 6.6).

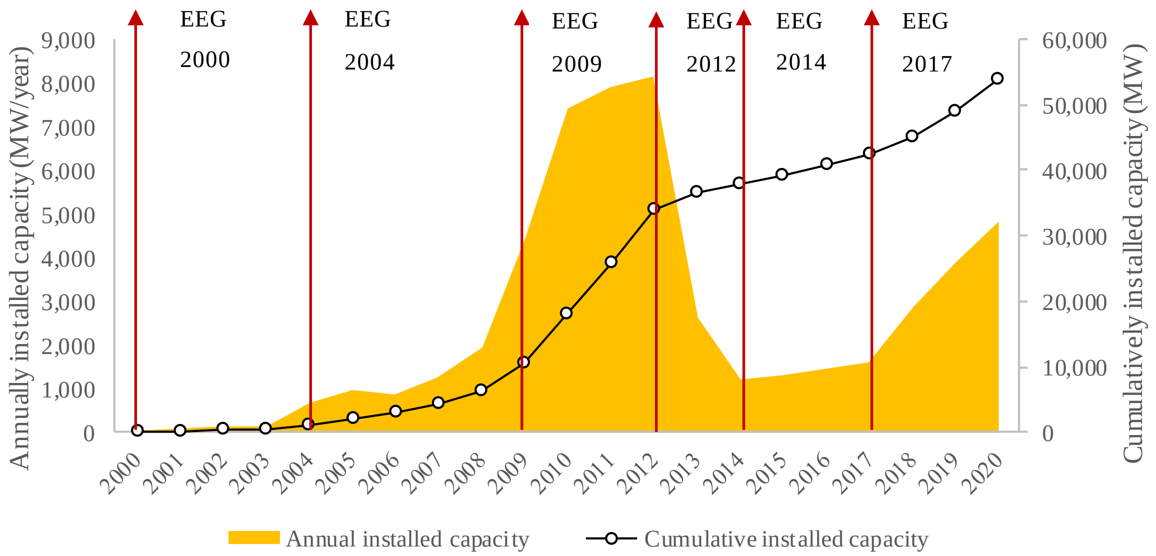



Figure 6.5. Solar power installed capacity and EEGs in Germany between 2000 and 2020

(Source: Data from BMWi and AGEE-Stat, 2020)

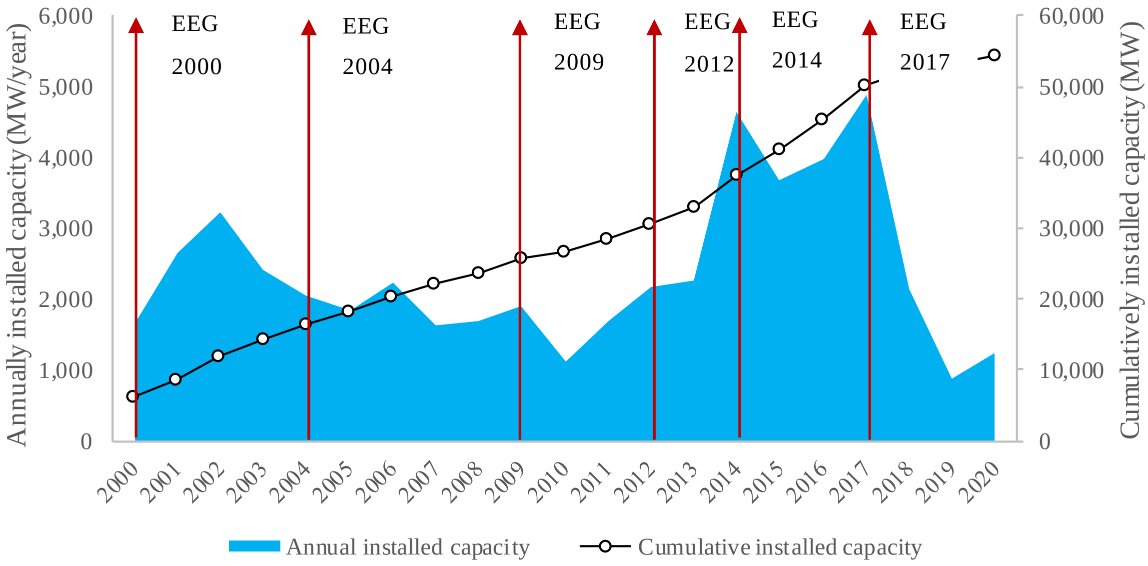



Figure 6.6. Onshore wind installed capacity and EEGs in Germany between 2000 and 2020

(Source: Data from BMWi and AGEE-Stat, 2020)

Price mechanisms are the core of the Act. Over the last two decades, Germany has renewed or replaced price mechanisms from the fixed FIT, auction, to market premium. Currently, three mechanisms are applied depending on technology and project scale (German Federal Parliament, 2017) (Table 6.1).

Table 6.1. Current price mechanisms for solar and wind power in Germany

| **Project scale** | **Applied price mechanism** |
|---|---|
| <=100 kW | Fixed FIT |
| 100 – 750 kW | FIT-based MP (a combination of the fixed FIT mechanism and the spot electricity market) |
| 750 kW – 10 MW | Auction-based MP (a combination of the auction mechanism and the spot electricity market) |

The support mechanisms aim to achieve annual deployment corridors of 2,500 MW of solar power, 2,800-2,900 MW of onshore wind power. For offshore wind power, the target is 6,500 MW by 2020 and 15,000 MW by 2030.

### *6.3.2. Feed-in tariff mechanism*

#### *6.3.2.1. Regulation*

The FIT levels for solar power in Germany differed according to technology and project scale. Currently, only projects of less than 100 kW enjoy this support policy (Table 6.2).

Table 6.2. Solar power project scales in Germany

| **Period** | **Small PV rooftop** | **Medium PV rooftop** | **Large PV rooftop** | **Largest PV rooftop** | **Ground-mounted** |
|---|---|---|---|---|---|
| 2000 - 31.03.2012 | ≤ 30 kW | 30-100 kW | 100 kW – 1 MW | > 1 MW | Every project scale |
| 01.04.2012 - 30.07.2014 | ≤ 10 kW | 10-40 kW | 40 kW – 1 MW | 1-10 MW | ≤ 10 MW |
| 01.08.2014 - 30.12.2015 | ≤ 10 kW | 10-40 kW | 40-500 kW | NA | ≤ 500 kW, NA from 01.09.2015 |
| 01.01.2016 - now | ≤ 10 kW | 10-40 kW | 40-100 kW | NA | NA |

*NA: the FIT mechanism is not applied.*

The FIT trend is reflected through the real FIT, which is defined as follows:

$$\overline{FIT} = \frac{FIT * FLH}{\sum_{t=1}^{n}(1+r)^t} \tag{6.1}$$

$\overline{FIT}$: real FIT (Euro/kW).

FIT: nominal FIT (Euro cents/kWh).

$FLH$: full load hours (hours).

r: interest rate (%).

n: power plant life cycle (years).

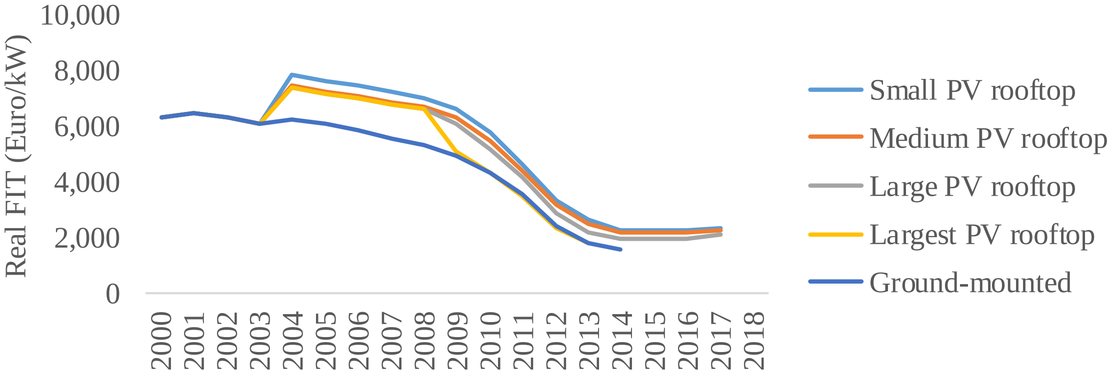



Figure 6.7. Real FIT for new solar power projects in Germany between 2000 and 2018

(Source: Data from our calculation)

Figure 6.7 illustrates the decreasing trend in the real FIT levels for solar power. Moreover, due to economies of scale, the higher FIT level was applied to the smaller-scale projects and vice versa.

The FIT mechanism for wind power did not differentiate project scales but distinguished between onshore and offshore wind power projects. Since 2017, new wind power plants have no longer be eligible for the FIT mechanism.

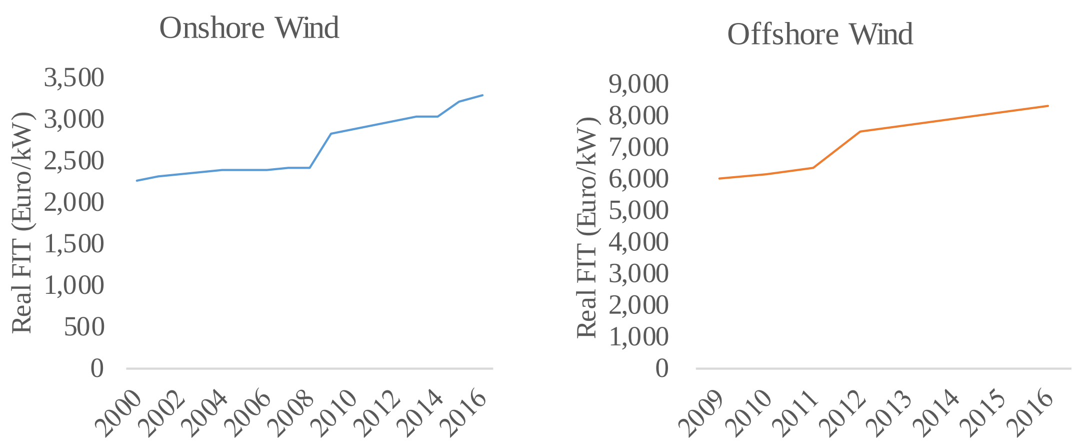



Figure 6.8. Real FIT for new wind power projects in Germany between 2000 and 2016

(Source: Data from our calculation)

Although the nominal FIT for wind power remained unchanged or only slightly increased, the real FIT increased significantly over time due to the decrease in the interest rate (Figure 6.8).

*6.3.2.2. Impacts of the FIT mechanism on solar power investment*

Between 2000 and 2008, Germany applied the prediction-based FIT mechanism, with an annual degression rate of 5 to 6% (German Federal Parliament, 2000, 2004) (Figure 6.9). However, Figure 6.10 indicates a low correlation coefficient of 14.08% between the investment cost and the FIT.

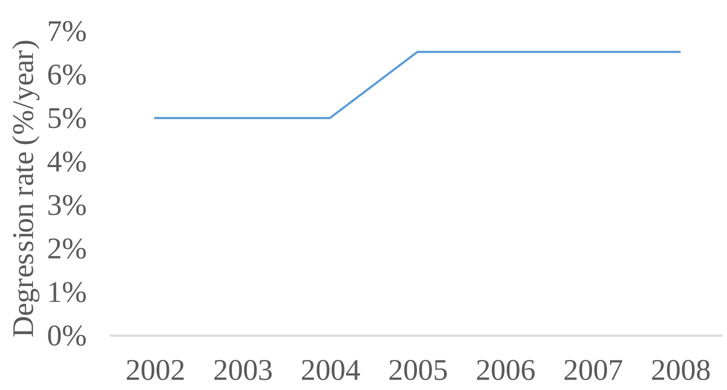



Figure 6.9. Annual FIT degression rate for solar power in Germany between 2000 and 2008

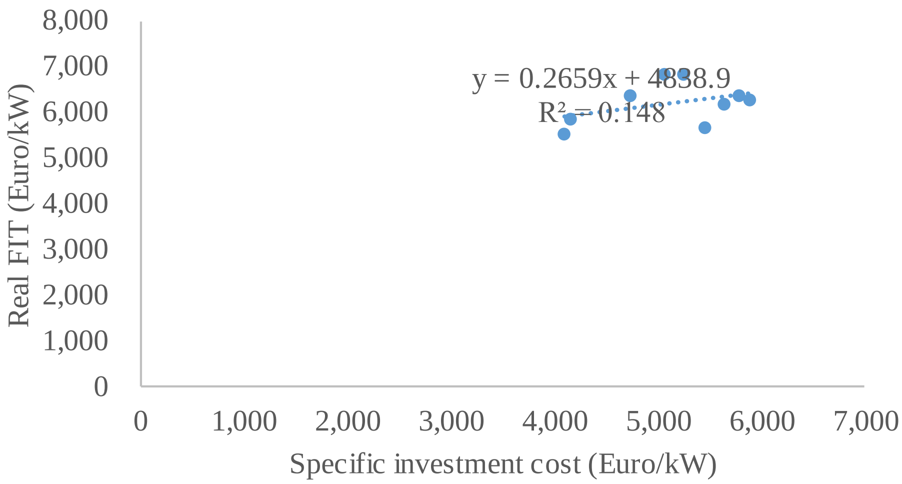



Figure 6.10. Correlation between specific investment cost and real FIT for solar power in Germany between 2000 and 2008

(Source: Data from our calculation)

To tackle the unsuitable prediction-based FIT design, since 2009, Germany has employed the hybrid FIT mechanism. After several amendments, this pricing approach results in a stable investment volume. However, it does not ensure sustainable solar power investment growth (see Chapter 5, Section 5.3.2).

### *6.3.3. Auction mechanism*

#### *6.3.3.1. Regulation*

The first pilot auction round for PV ground-mounted projects from 100 kW to 10 MW took place in April 2015. In February 2017, competitive auctions were introduced for the other renewable power technologies, including onshore wind, offshore wind, and biomass. Since then, projects exceeding 750 kW are obliged to participate in the auctions (German Federal Parliament, 2017). Table 6.3 presents the frequency and targeted volume of solar and wind power auctions in Germany.

Table 6.3. The auction frequency and auction volume of solar and wind power in Germany

| | | **Solar power** | **Onshore wind** | **Offshore wind** |
|---|---|---|---|---|
| Auction frequency | 2017 | Every four months | Every four months | Annually |
| | 2018 | Every four months | Every three months | Annually |
| | 2019 | Basic: Every four months<br>Special: Two rounds | Basic: Every three months | |

| | | Solar power | Onshore wind | Offshore wind |
|---|---|---|---|---|
| | | | Special: Two rounds | |
| | 2020 | Basic: Every four months<br>Special: Four rounds | Basic: Every four months<br>Special: Four rounds | |
| Targeted volume (MW/round) | 2017 | Basic: 200 | Basic: 900 | |
| | 2018 | Basic: 200 | Basic: 900 | |
| | 2019 | Basic: 150-175<br>Special: 500 | Basic: 900<br>Special: 900 | |
| | 2020 | Basic: 100-150<br>Special: 300-400 | Basic: 900<br>Special: 300-400 | |

Apart from the basic auctions regulated by the German Federal Parliament (2017), the German Federal Parliament (2018) issues special auctions with the total targeted solar and wind power capacity of 4 GW between 2019 and 2021 to achieve Germany's 2020 climate targets.

*6.3.3.2. Impacts of the auction mechanism on solar power investment*

Solar power auctions have attractive to investors. The received volume was two to five times higher than the targeted volume. For example, the received volume reached 493 MW despite the target of only 100 MW in the auction round in February 2020 (Figure 6.11).

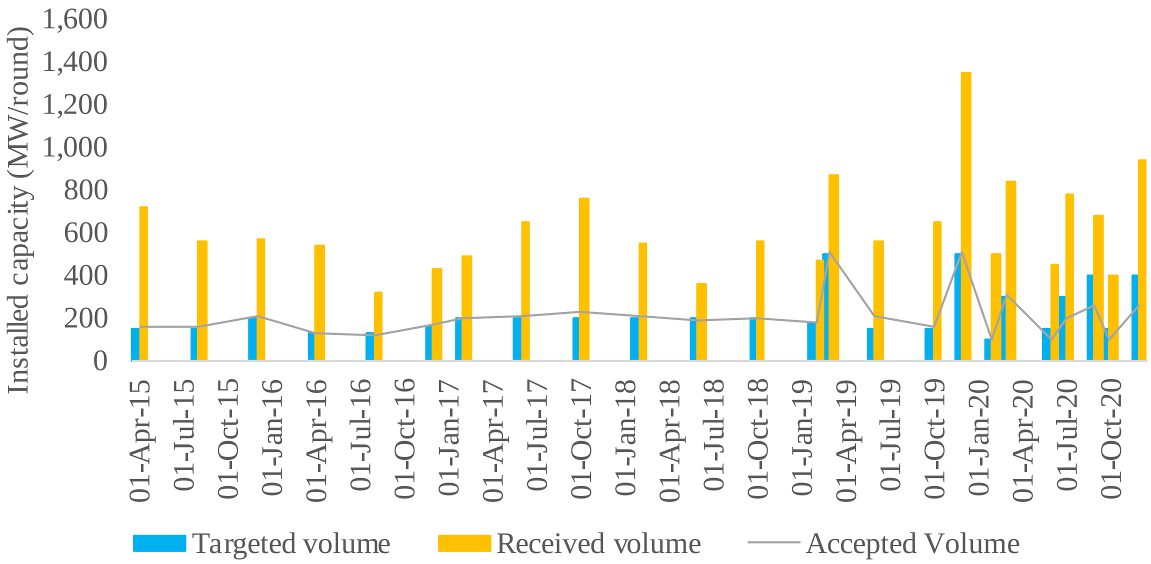



Figure 6.11. Auction volumes of solar power in Germany between April 2015 and December 2020

(Source: Data retrieved from Federal Network Agency, 2021b)

The intense competition in the solar power auctions achieved cost-effectiveness because only low-price biddings were accepted for installation. The average bid price decreased consecutively through the auction rounds and hit the bottom in January 2018 with 4.64 Euro cents/kWh. It increased in the following rounds and remained stable in the recent rounds. Moreover, the average bid prices were significantly lower than the ceiling price (Figure 6.12). According to the German Federal Parliament (2017), the ceiling price for the first solar power auction in 2017 was set to 8.91 Euro cents/kWh. The hybrid approach was applied for ceiling price adjustment.

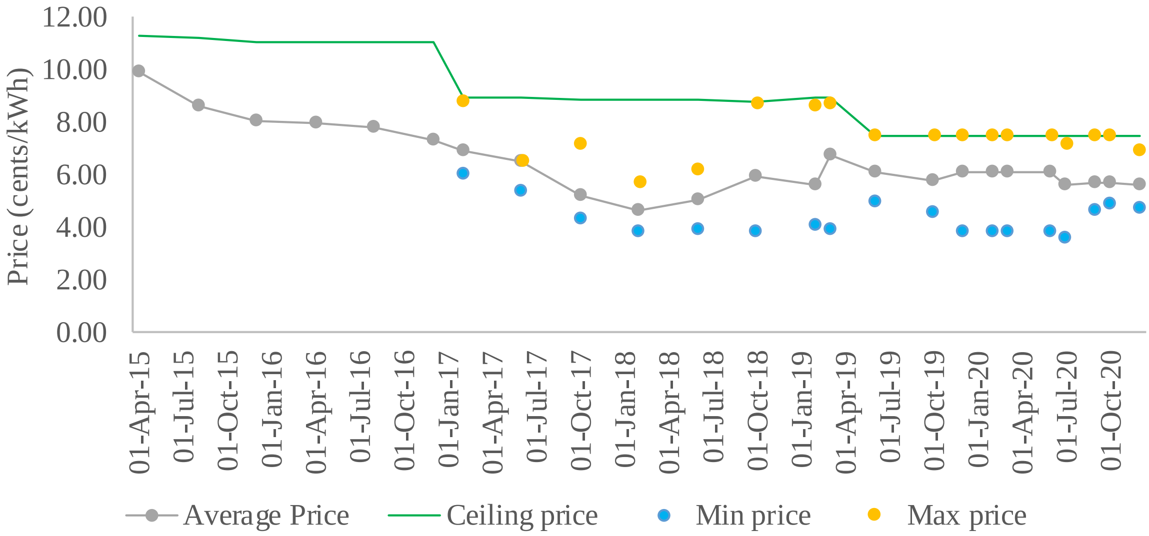



Figure 6.12. Auction prices of solar power in Germany between April 2015 and December 2020

(Source: Data retrieved from Federal Network Agency, 2021b)

*6.3.3.3. Impacts of the auction mechanism on onshore wind power investment*

Since 2017, new onshore wind power projects have participated in competitive auctions (German Federal Parliament, 2017). The first onshore wind power auction rounds were intensely competitive. The received volume was two to three times higher than the targeted one. However, the interest in onshore wind power has decreased considerably since the second auction round in 2018. The accepted volume was even three times lower than the expected one (Figure 6.13).

The average bid price decreased consecutively through the first three auction rounds and hit bottom in the round in November 2017 with 4.02 Euro cents/kWh. It increased in the following rounds and remained stable in the recent rounds. Moreover, the average price was significantly lower than the ceiling price in the first auctions because of the intense competition. However, the average price approached or even reached the ceiling price (Figure 6.14).

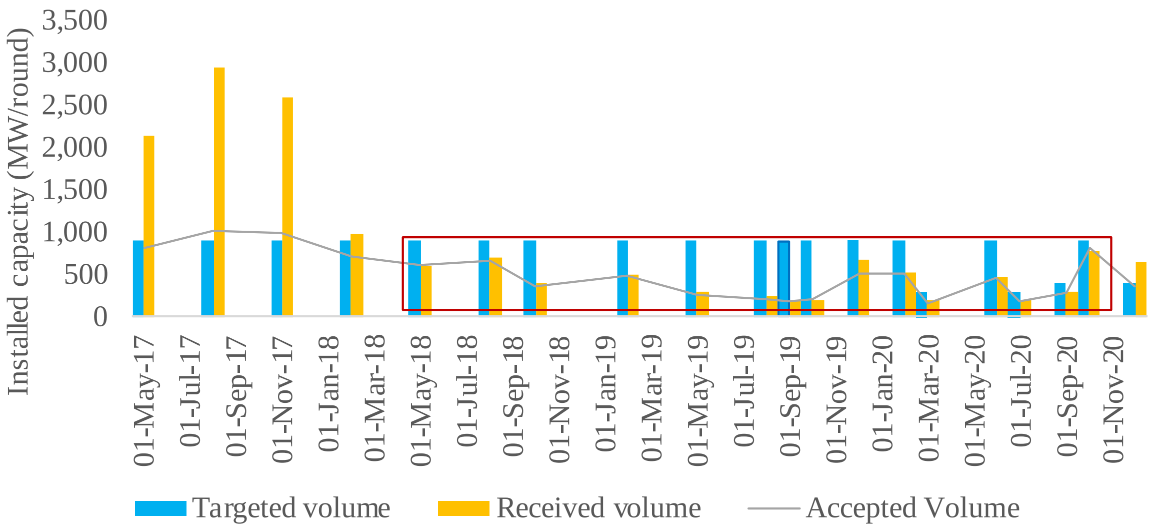



Figure 6.13. Auction volumes of onshore wind power in Germany between May 2017 and December 2020

(Source: Data retrieved from Federal Network Agency, 2021a)

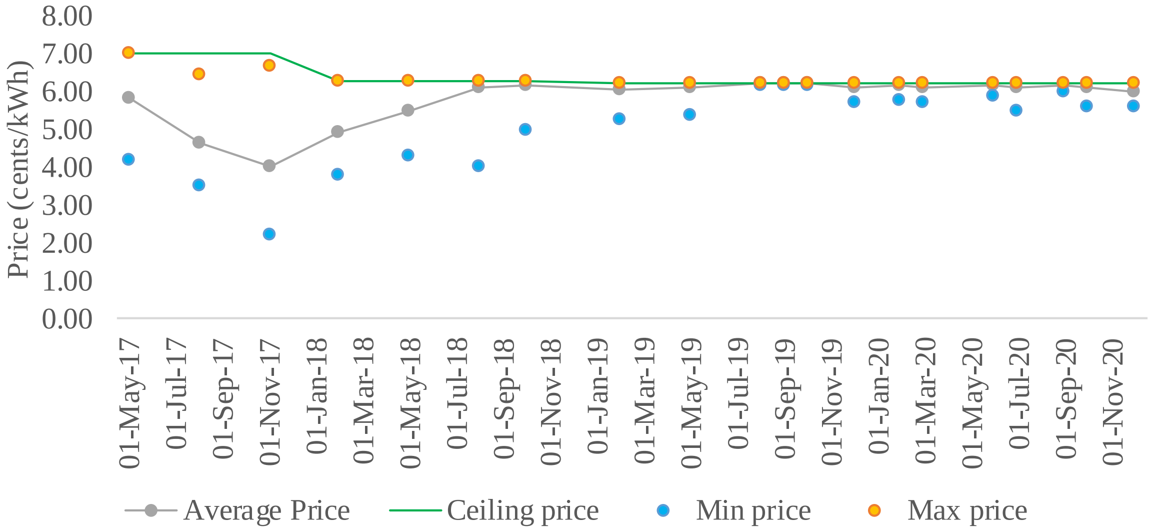



Figure 6.14. Auction prices of onshore wind power in Germany between May 2017 and December 2020

(Source: Data from Federal Network Agency, 2021a)

The lack of competition over consecutive auction rounds of onshore wind power reveals the government's slow reaction. According to the German Federal Parliament (2017), the ceiling price for onshore wind auctions is adjusted annually. The price was set to the average of the highest awarded price of the previous three bidding rounds and increased by 8%. In practice, the initial ceiling price was set at 7 Euro cents/kWh for the auctions in 2017, decreased to 6.3

Euro cents/kWh in 2018, and 6.2 Euro cents/kWh in 2019 and 2020. The prediction-based ceiling price adjustment is one reason for the ineffectiveness of the wind power auction.

### *6.3.4. Carbon price mechanism*

The introduction of the EU ETS in 2005 aims to cap carbon emissions while promoting green energy investments in European countries. This mechanism covers 40% of the total carbon emissions in Europe (*EU Emissions Trading System (EU ETS)*, no date). With 805 million tons of carbon dioxide emitted in 2019, Germany accounted for almost one-quarter of all EU ETS emissions. The energy sector is the most significant contributor to emissions, accounting for 32% of the emissions in 2019 (Federal Ministry for the Environment Nature Conversion and Nuclear Safety (BMU), 2020).

Electricity generation is one of the main targeted sectors of the EU ETS. With the presence of a carbon price, the marginal cost of electricity generation increases. The carbon price varies according to power generation technology. With the carbon emission factor of 0.74 to 0.91 kg$CO_2$/kWh (World Nuclear Association, 2011), coal-fired power plants pay the highest carbon price.

Since 2013, emission allowances have been allocated in the electricity generation sector through the carbon auction mechanism (European Commission, 2015). The auction is formatted with a sealed bid and uniform price. In each auction round, a volume of allowances is pre-determined. The carbon price is determined by balancing the allowance supply and the demand. The biddings with higher prices than the clearing price will receive the allowances.

By doing a survey on three hypotheses on firm's investment decisions under a carbon constraint: firm's price perception of the EU ETS, compliance strategies, and carbon leakage, using the data of 268 installations received emission allowances in Belgium in 2011, Brohé and Burniaux (2016) point out that the carbon price has not been high enough to incentivize the low green energy investment. Martin, Muûls and Wagner (2011), Neuhoff (2011) also support the conclusion that the EU ETS has captured investors' attention, but the investment effects have been statistically insignificant.

Figure 6.15 depicts carbon price variability over the second phase (2008– 2012) and the third phase (2013 – 2020) of the EU ETS. The carbon price was low during the second half of the second phase and the first half of the third phase. The EU ETS reform in 2018 with low allowances resulted in a rise of the carbon price to 30 Euro/t$CO_2$. Still, Flachsland *et al.* (2018) argue that the allowance limitation is only a short-term solution for improving the carbon price.


Figure 6.15. The carbon price in the EU ETS between 07 April 2008 and 14 September 2020

(Source: Data from *Daily EU ETS carbon market price*, 2021)

Clearly, only sufficiently high carbon prices will sustain investments into low emitting technology. A measure to keep the carbon price higher than a specific value is the introduction of a carbon price floor (CPF). Three basic CPF approaches may be distinguished: an *auction reserve price*, a *top-up carbon price*, and a system of *permit buybacks* (Newbery, Reiner and Ritz, 2018). The top-up carbon price is the difference between the CPF level and the ETS allowance price. This CPF approach has been preferred and significantly affected the electricity generation structure. In Great Britain, the share of coal power generation declined from 41% to less than 8% between 2013 and 2017 (Newbery, Reiner and Ritz, 2018). France and Netherland have also introduced national CPFs (Flachsland *et al.*, 2018). In Germany, although the CPF was firstly considered in 2017 (Egli and Lecuyer, 2017), this price mechanism has so far not been applied to the electricity generation sector. Despite the applied national CPFs, Newbery, Reiner and Ritz (2018) criticize that not a national CPF but the EU one with suitable CPF levels will force Europe in general and members to achieve the targeted carbon emissions. An EU CPF design using the top-up approach with the price from 25 to 30 Euro/t$CO_2$, an annual rise of 3 – 5% above inflation is suggested. We should note that the top-up-based CPF comprises two components: the EU ETS allowance price and the carbon price support (CPS). The EU ETS allowance price is determined through the auction mechanism, while the CPS is the top-up of the EU ETS allowance prices projected by the government to achieve the CPF. Mathematically, the CPS of fuel i in year t is defined using the following formula:

$$CPS_t^i = (CPF_t - PETS_t) * ef^i \tag{6.2}$$

$CPS_t^i$: carbon price support of fuel i in year t (Euro/t$CO_2$).

$CPF_t$: targeted carbon price floor in year t (Euro/t$CO_2$).

$PETS_t$: average EU ETS allowance price in year t (Euro/t$CO_2$).

$ef^i$: the emission factor of fuel i (t$CO_2/kWh$).

The CPS is a type of tax. In Great Britain, it is called Climate Change Levy (Hirst, 2018). In summary, the CPF combines the quantity-based (the EU ETS mechanism) and the price-based (the CPS mechanism) carbon price mechanisms.

## 6.4. Proposed PID-based price mechanisms for Germany

### *6.4.1. PID-based ceiling price*

The ceiling price is a crucial signal for investors in competitive auctions. The auction mechanism with the application of a ceiling price itself can help avoid overinvestment. However, it cannot avoid underinvestment if the ceiling price is too low. The analysis in Section 6.3.3.3 indicates the ineffectiveness of onshore wind auctions due to the unsuitable prediction-based ceiling price adjustment. This section formulates the models of the feedback-based ceiling price and applies the models to determine the ceiling price for onshore wind power auctions.

The feedback-based ceiling price is adjusted every auction round based on the deviation between the targeted auction volume and the accepted one. As a straightforward implementation, the government only takes the capacity deviation of the previous auction for the ceiling price adjustment. The proportional controller model is formulated as follows:

$$CP_r = CP_{r-1} + K_P e_{r-1} \tag{6.3}$$

$CP_r, CP_{r-1}$: ceiling price at rounds r and r-1.

$K_P$: proportional gain.

$e_{r-1}$: the latest deviation between the targeted auction volume and the accepted one. If under-subscription occurs, the ceiling price is increased. If over-subscription occurs, the ceiling price is decreased. If zero remained unchanged.

If the PI controller rule is applied, the new ceiling price is defined as follows:

$$CP_r = \alpha + \beta_1 e_{r-1} + \beta_1 e_{r-2} \tag{6.4}$$

If the PID controller rule is chosen, the new ceiling price is determined as follows:

$$CP_r = \alpha + \beta_1 e_{r-1} + \beta_2 e_{r-2} + \beta_3 e_{r-3} \quad (6.5)$$

Where $\alpha = 2CP_{r-1} - CP_{r-2}, \beta_1 = K_P + K_I + K_D, \beta_2 = -K_P - 2K_D, \beta_3 = K_D$.

It should be noted that the further auction information, the lower its influence on the instant decision.

Applying the models of the subset of the PID controller to the input data in Table 6.4, we obtain possible ceiling price scenarios for the onshore wind power in February 2021, as illustrated in Figure 6.16.

Table 6.4. Input data for a ceiling price adjustment for onshore wind power auction in February 2021 in Germany (Federal Network Agency, 2021a)

| **Auction time** | **Targeted volume (GW)** | **Accepted volume (GW)** | **Deviation (GW)** | **Ceiling price (Euro cents/kWh)** |
|---|---|---|---|---|
| 01-Sep-20 | 0.367 | 0.285 | 0.082 | 6.2 |
| 01-Oct-20 | 0.826 | 0.659 | 0.167 | 6.2 |
| 01-Dec-20 | 0.367 | 0.400 | -0.033 | 6.2 |

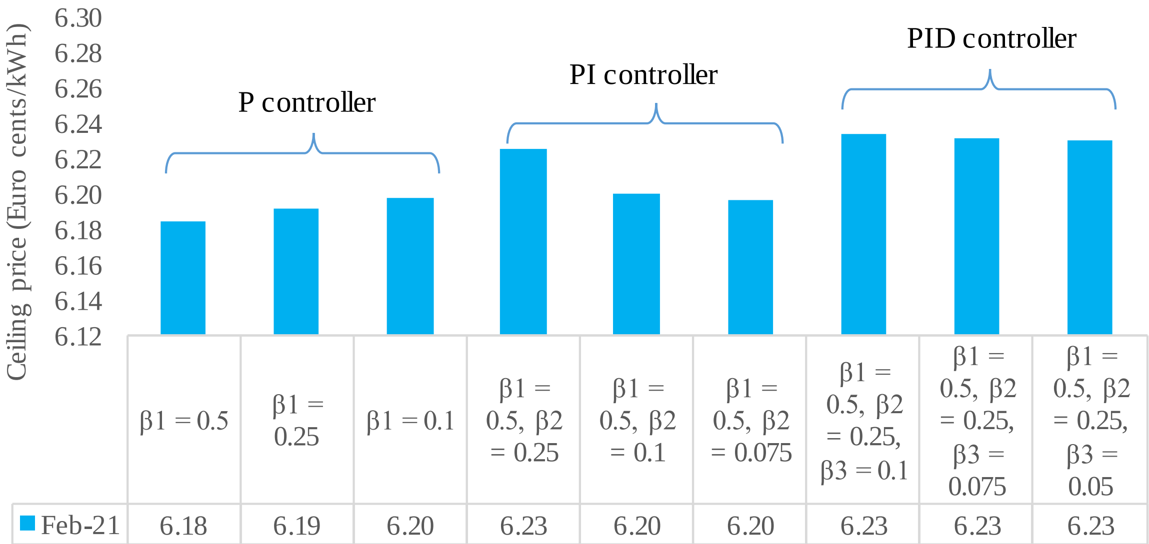



Figure 6.16. Scenarios of the ceiling price for the onshore wind power auction in February 2021

Table 6.4 shows the high under-subscription in the auction rounds in September and October 2021. However, the over-subscription occurred in the auction round in December 2020. Figure 6.16 suggests scenarios of aggressive or robust ceiling price adjustment.

### *6.4.2. PID-based carbon price floor*

Despite doubts about the carbon price floor's effectiveness, this work supports the idea of the EU CPF application for the electricity generation sector based on the top-up approach as implemented in Great Britain. Newbery, Reiner, and Ritz (2018) suggest an annual price increase of 3-5% above inflation to achieve the desired carbon emission reduction.

The CPF determination is challenging. If the CFP level is too high, the low profitability due to the high carbon price may cause power investors to switch to other investment areas. Consequently, a lack of power supply may occur. Moreover, the sold emission allowance volume may be lower than the issued one. In contrast, if the CPF level is too low, it does not force the investment transition in the power sector.

For the first attempt to use feedback approach to design CPF, a proportional-based CPF adjustment is proposed:

$$CPF_t = CPF_{t-1} - K_P e_t \tag{6.6}$$

$CPF_{t,}CPF_{t-1}$: carbon price floor at time t, t-1.

$K_P$: proportional gain ($K_p > 0$).

$e_{t-1} = EUA_t^d - EUA_t^r$: the latest transaction deviation between the issued European Union Allowance and the actual sold one. If the allowance gap is positive, the CPF should be decreased.

## 6.5. Chapter conclusion

This chapter describes the dominance of solar and wind power in the power supply system in Germany. We highlight the opposite pattern of the ownership structures of solar and wind power installed capacity in Germany. The majority of solar power installed capacity was owned by end-users, while project developers were leading players in the wind power investment market. Besides, there is an increase in solar power project scales during the last 20 years. Investors tend to invest in large-scale solar power projects, over 500 kWp instead of small or medium-scale projects as before.

The impacts of price mechanisms on solar and wind power investment in Germany are analyzed. Historical analysis indicates a low correlation between the investment cost and the FIT. As a result, the prediction-based price mechanisms entail the overinvestment in solar power and under-subscription in onshore wind power auctions.

Finally, we propose applying a PID controller for ceiling price design for onshore wind power in Germany. Also, the proportional-based carbon price floor application is recommended to limit the deviation between the targeted EU allowance volume and the sold volume.

# Chapter 7. Application of PID-Based Price Mechanisms to Vietnam and Energy Policy Improvements

## 7.1. Introduction

Germany and Vietnam have a comparable size of area and population but have otherwise very different characteristics in their geographical placement, their historical, industrial, political and economic development. The renewable power investment markets in Germany achieve a particular maturity, while those in Vietnam are at the early growth phase.

The government of Vietnam has adopted and gradually improved energy policy frameworks in order to achieve a more environmentally friendly power system. The introduction of the FIT mechanism has attracted businesses and individuals to solar and wind power investment markets. However, with the high and short-term FIT, overinvestment in solar power occurred. In contrast, the low FIT and slow adjustment caused the underinvestment in wind power. The mismatch between the desired investment and the actual volume has failed to achieve economic efficiency, at the same time, created challenges for the transmission system operation and investment.

Innovative policy designs are therefore vital and urgent to avoid negative consequences of unsuitable energy polices. This chapter is structured as follows: Section 7.2 compares Vietnam and Germany's energy economic indicators and describes the Vietnamese electric power system. Section 7.3 analyses the impacts of the FIT mechanism on solar and wind power investment markets, classifies investors, and assesses project scales in Vietnam. Section 7.4 discusses scenarios of price mechanism in the next year and proposes applying the proportional-based FIT mechanism for Vietnam. Realizing inconsistencies among several existing energy policies and a lack of essential policies, we propose energy policy improvements in Section 7.5. The last section presents the conclusions for this chapter.

## 7.2. Energy economics of Vietnam

### *7.2.1. Energy indicators*

Table 7.1 presents Vietnam and Germany's macroeconomic and electricity indicators in 2020. Even though Germany and Vietnam have a comparable size of population, the ratio of GDP is off by a factor of 14, and electricity consumption of 2.57 which says that Germany is larger responsible for fighting climate change.

Table 7.1. Macroeconomic and electricity indicators of Vietnam and Germany in 2020 (updated from press releases)

| **Indicator** | **Unit** | **Germany** | **Vietnam** | **Ratio Germany/Vietnam** |
|---|---|---|---|---|
| Area | $km^2$ | 357,022 | 331,212 | 1.08 |
| Population | people | 83,783,942 | 97,338,579 | 0.86 |
| GDP | million USD | 3,806,060 | 271,160 | 14.04 |
| GDP per capita | USD/person | 45,427 | 2,790 | 16.28 |
| Electricity consumption | TWh | 557.50 | 216.8 | 2.57 |
| Electricity intensity | kWh/1,000 USD | 146 | 800 | 0.18 |
| Electricity per capita | kWh/person | 6,654.02 | 2,227.28 | 2.99 |
| Electricity price | US cents/kWh | 37 | 8.20 | 4.51 |
| Electricity payment per capita | USD/person | 2,048 | 122 | 16.79 |
| Share of GDP per capita for electricity | % | 4.51 | 4.39 | 1.03 |
| Carbon emissions | million t$CO_2$ | 604.8 | 305.2 | 1.98 |
| Carbon emissions per GDP | kg$CO_2$/USD | 0.16 | 1.13 | 0.14 |
| Carbon emissions per capita | t$CO_2$/person/year | 7.22 | 3.14 | 2.30 |
| Global share of carbon emissions | % | 1.92 | 0.97 | 1.98 |
| Primary energy supply | KTOE | 83,369 | 306,260 | 0.27 |

Despite the large discrepancy in per capita energy consumption, the energy intensity (energy per GDP) is very unfavorable for Vietnam meaning that energy efficiency, production methods have to be largely improved. Although the electricity price in Germany was 4.51 higher than that in Vietnam, it is surprising that the Germans and the Vietnamese people spent a similar income share of around 4.5% on electricity.

On average, Germany emitted 0.16 kg$CO_2$/USD, which was much lower than Vietnam with 1.13 kg$CO_2$/USD. However, CO2 emissions per capita in Vietnam were relatively low, with 3.14 t$CO_2$/person/year, while that in Germany reached 7.22 t$CO_2$/person/year. These numbers reveal that although the energy consumption in Vietnam was small-scale, it was ineffective.

Because of the large amount of electricity produced and consumed, high gasoline consumption per capita for transport, and natural gas for house heating, Germany was responsible for 1.92% of the global carbon emissions. In contrast, Vietnam contributed only 0.97% to global emissions.

### *7.2.2. Energy balance*

In 2018, the primary energy supply in Vietnam was only 0.27 times that in Germany. High carbon-emitting fuels accounted for more than 70% of the total primary energy supply in both countries. Solar and wind energy made up only 4.71% in Germany and 0.05% in Vietnam (Figure 7.1).

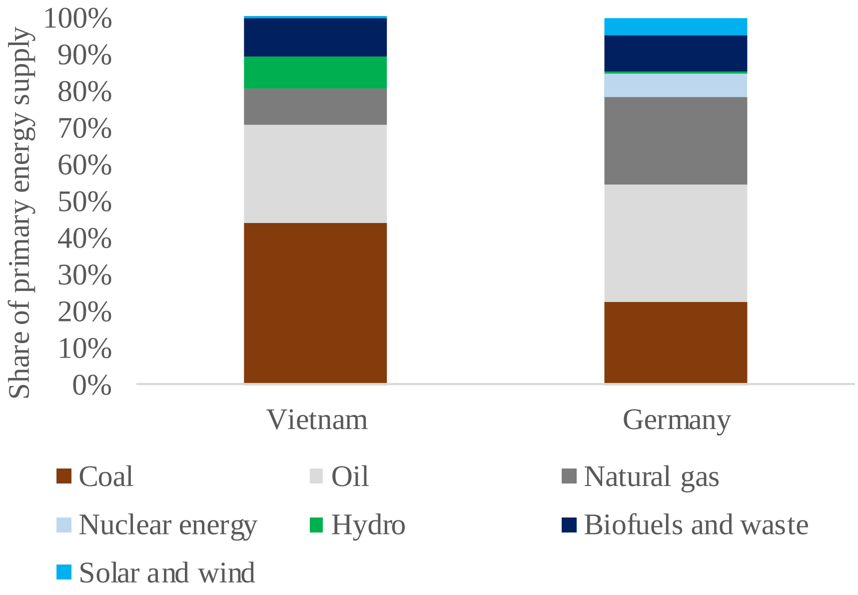



Figure 7.1. Primary energy supply structure in Vietnam and Germany in 2018

(Source: Data from *Total energy supply (TES) by source, Vietnam 1990-2019*, no date; *Total energy supply (TES) by source, Germany 1990-2019*, no date)

Vietnam has increasingly imported coal, oil, and gas because the domestic fossil fuel reserves are running out while the energy demand increases. It is forecasted that the coal demand in Vietnam will be around 121 tons in 2025 and 156 million tons in 2030. More than half of the demand will depend on imported coal sources (Prime Minister of Vietnam, 2016). Similarly, the imported liquefied natural gas (LNG) will increase, from 1 to 4 billion $m^3$/year between

2021 and 2025, from 6 to 10 billion $m^3$/year between 2026 and 2035 (Prime Minister of Vietnam, 2017b).

Vietnam has a vast potential of hydropower of around 26,000 MW. However, as of 2018, the total hydro power installation reached 23,182 MW. In other words, the exploitation of hydropower has almost reached its limits.

The final energy consumption in Vietnam increased significantly from 48,545 KTOE in 2010 to 61,863 KTOE in 2019. Oil accounted for the highest share of the final energy consumption with 34.4%, followed by electricity and coal with 29.1% and 25.2% in 2019 (Figure 7.2).

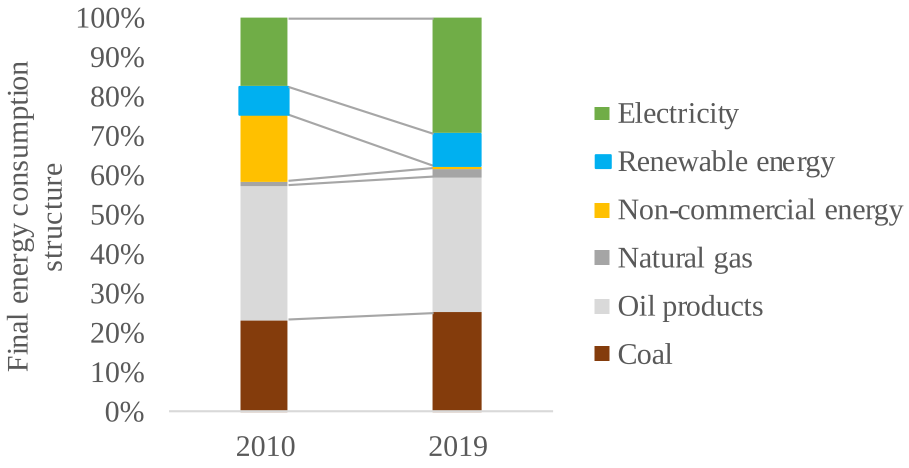



Figure 7.2. Final energy consumption structure according to energy type in Vietnam in 2010 and 2019

(Source: Data from the Ministry of Industry and Trade of Vietnam, 2021)

In 2019, the industrial sector consumed around 51% of the total final energy, followed by the transportation sector with 23% and the residential with 12% (Figure 7.3).

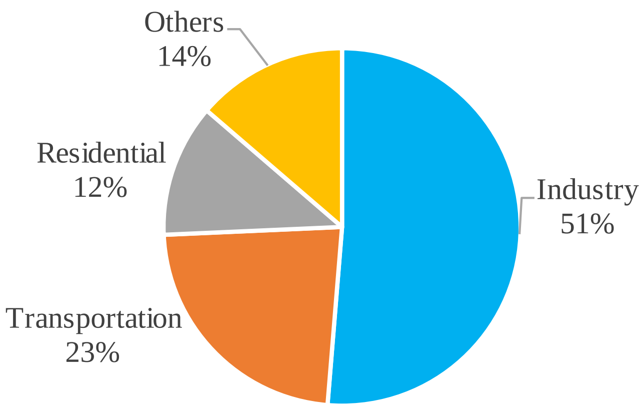



Figure 7.3. Final energy consumption structure according to the sector in Vietnam in 2019

(Source: Data from the Ministry of Industry and Trade of Vietnam, 2021)

Vietnam is a dynamically developing economy with a high GDP growth rate of 6.8% in 2019. The rate is estimated to remain at around 6.5% in the upcoming years (*Vietnam's Economy Expanded by 6.8 Percent in 2019 but Reforms are Needed to Unleash the Potential of Capital Markets*, 2019). An annual energy consumption growth rate of 4 to 5% is forecasted to meet the energy demand for economic development.

Regarding development orientation, Vietnam aims to achieve 175 to 195 MTOE of primary energy supply, 105 to 115 MTOE of final energy consumption by 2030. The power installed capacity is expected at 125 to 130 GW, equivalent to 550 to 600 TWh, doubles 246 TWh in 2020. Renewable energy is targeted to contribute 15 to 20% to the primary energy supply in 2030 (The central executive committee of Vietnam, 2020).

### *7.2.3. Electric power system*

The scale of Vietnam's power system is ranked second highest in Southeast Asia, after Indonesia, and twenty-third worldwide. As of 2020, the total installed capacity reached more than 69,300 MW, equivalent to the electricity generation of 246 TWh. Hydropower, coal-fired power, and natural gas accounted for the majority of the electricity supply. However, there is a decreasing trend of these sources in the installed capacity structure between 2018 and 2020. In contrast, solar power emerged with a proportion of 0.17% in 2018 to 24% in 2020 (Figure 7.4).

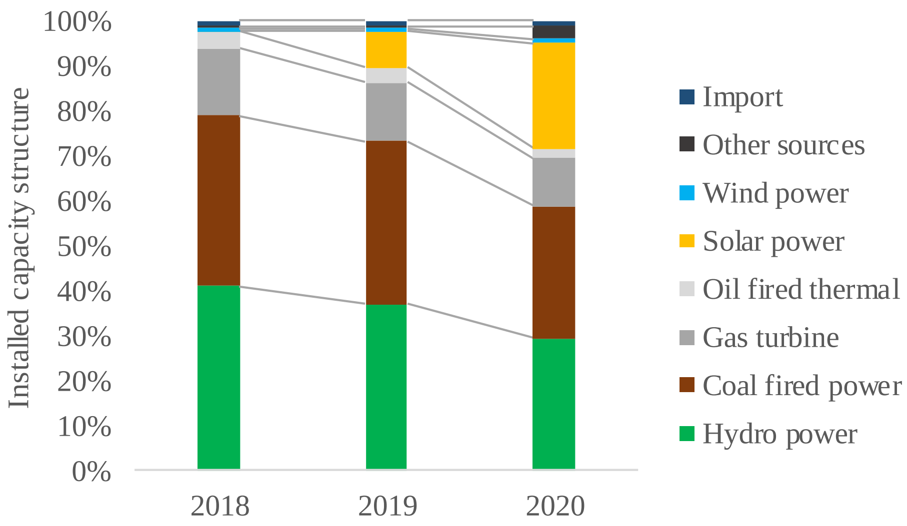



Figure 7.4. Installed capacity structure in Vietnam between 2018 and 2020

(Source: Data from the Ministry of Industry and Trade of Vietnam, 2020)

Most coal-fired power plants are located in the northeast region, mainly in Quang Ninh province, to take advantage of locally available coal. Natural gas and diesel power plants are situated in the south, while most hydropower plants are situated in the northern and central regions. Provinces in the central and southern regions have strived towards Vietnam's renewable power centers thanks to the high solar radiation and wind speed concentration.

Regarding the electricity generation cost, the LCOE of new solar and wind power plants is higher than that of coal-fired power plants. However, we estimate that the LCOE of new solar and onshore wind power plants will be cheaper than coal-fired power ones in 2030 (Figure 7.5) (see input data for our calculation in Appendix 3, Appendix 4, Appendix 5, and Appendix 6).

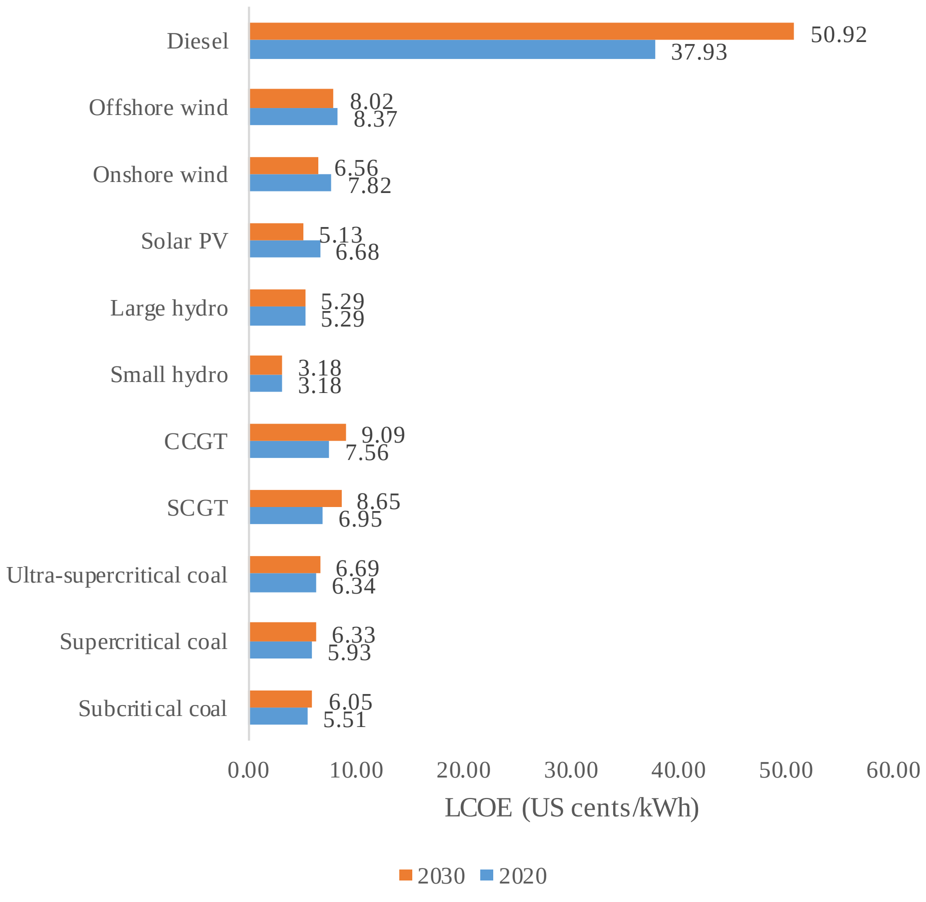



Figure 7.5. Estimated LCOE of new power plants in Vietnam in 2020 and 2030

(Source: Data from our calculation)

Vietnam uses 500 kV, 220 kV, and 110 kV transmission grid systems to transmit electricity from power plants to consumers. The 500 kV transmission line plays a critical role in inter-regional energy transmission throughout three economic zones (North, Central, and South). Meanwhile, the 200 kV and 110 kV transmission lines ensure a safe and uninterrupted power supply for consumers within eight regions (Northwest, Northeast, Red River Delta, North Central Coast, South Central Coast, Central Highlands, Southeast, and Mekong River Delta). The distribution grid systems include 35 kV, 22 kV, 6 kV, and 0.4 kV lines.

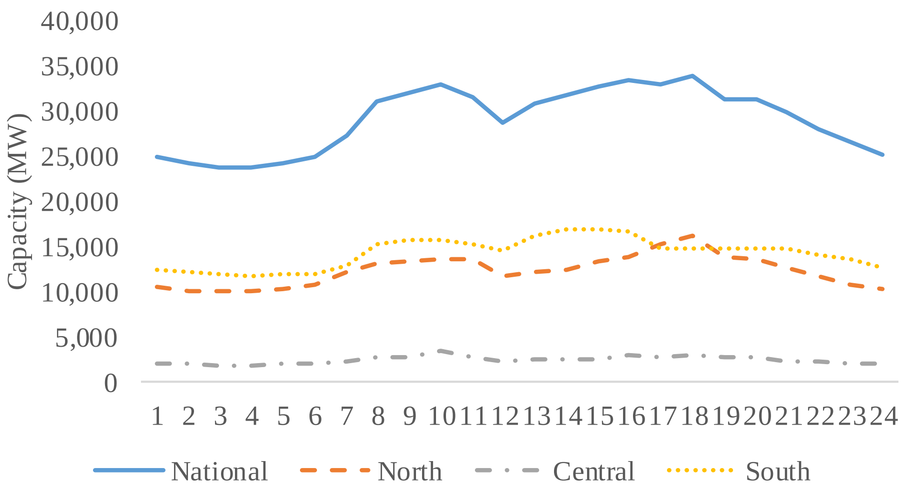



Figure 7.6. A daily load curve according to the region in Vietnam

(source: Data from *Information on Hour-Ahead Market, date 03 March 2020*, no date)

The electricity demand varies considerably according to the region because of the differences in weather conditions, population, and economic scale. The southern region consumes the most considerable electricity, followed by the north and the least in the central region (Figure 7.6).

## 7.3. Solar and wind power investment markets in Vietnam

### *7.3.1. Effects of the FIT mechanism on the solar power investment market*

Vietnam has a substantiated technical potential of solar power of around 339 GW (Togeby, 2017). The potential varies significantly according to the region (see Appendix 7 and Appendix 9).

However, only after 2019, due to the introduction of the FIT mechanism at 9.35 US cents/kWh, the solar power investment started to boom (Prime Minister of Vietnam, 2017a). Because of the high FIT levels and short-term validity, a massive solar power volume of 4,976 MW (equivalent to 86 ground-mounted and floating solar power plants) was added to the power supply system before the deadline by June 2019. Many new plants energized quickly as a record for Vietnamese electricity history (Figure 7.7).

The solar power investment market almost paused in the following months due to no specific support mechanism. After that, the market was recovered due to the issue of the second FIT mechanism. The new tariff distinguished between ground-mounted solar PV (7.09 US cents/kWh), floating solar PV (7.69 US cents/kWh), and rooftop PV installations (8.38 US cents/kWh) (Prime Minister of Vietnam, 2020) (Figure 7.7).

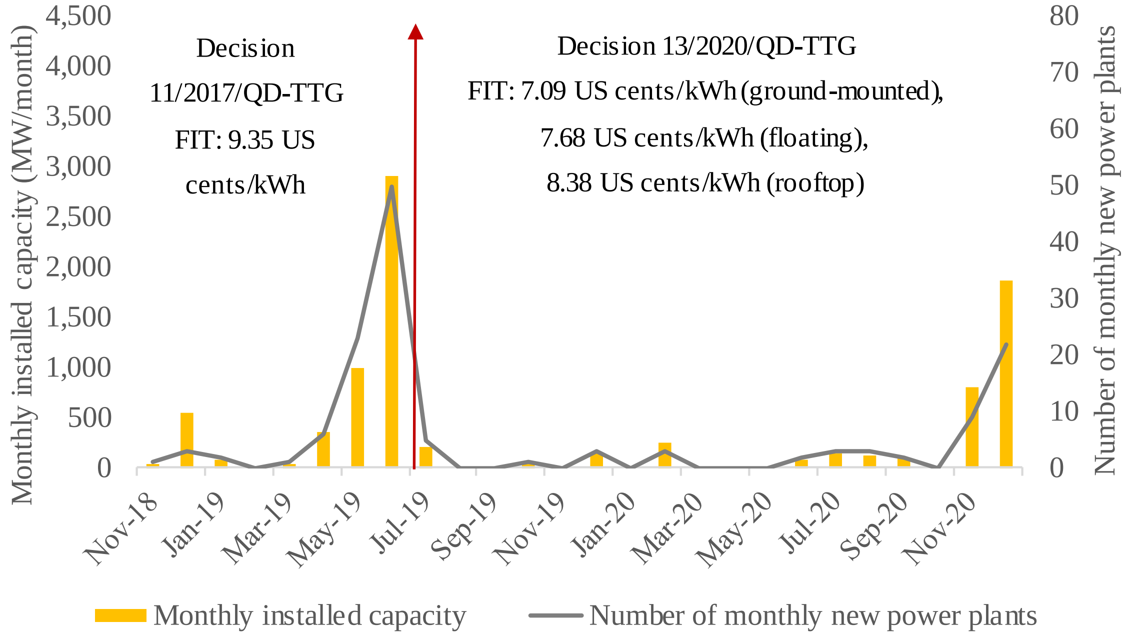



Figure 7.7. Monthly ground-mounted and floating solar power installations in Vietnam between November 2018 and December 2020

(Source: Data from *List of solar projects in Vietnam*, 2021, and press releases)

Moreover, Figure 7.7 reveals a typical characteristic of the solar power investment market with FIT mechanisms. Before the FIT expiration, investors accelerate their project implementation to enjoy the higher FIT levels. This behavior represents the "clearance sale" effect as defined by Grau (2014). Similarly, the rooftop solar power investment increased steadily through 2020 before skyrocketing in December 2020 to end up with a total capacity of 9,584 MWp (Figure 7.8).

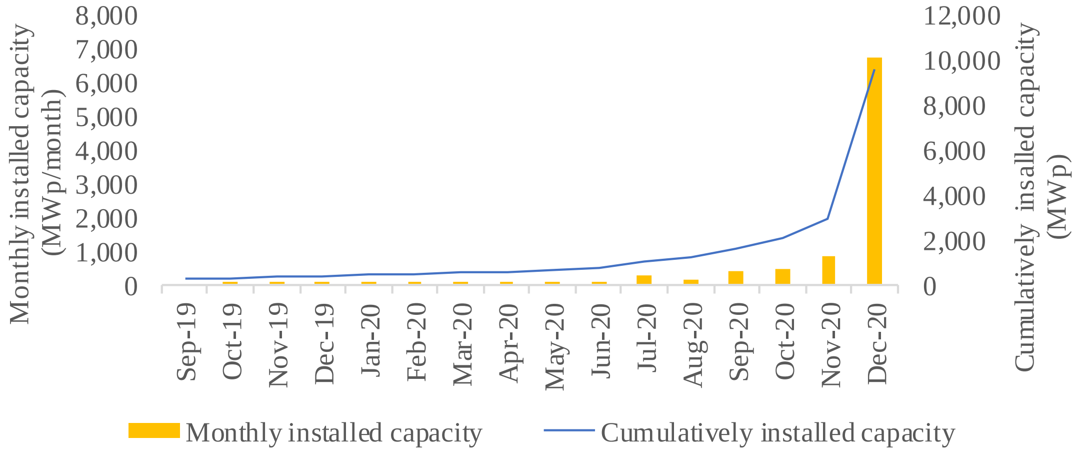



Figure 7.8. Rooftop solar installations in Vietnam between September 2019 and December 2020

(Source: Data from *Rooftop Solar Market Update (Until May 2020)*, no date, and press releases)

Thus, as of 2020, the total solar power installed capacity reached 19,400 MWp (equivalent to 16,500 MW), accounting for 25% of Vietnam's total power capacity. Accordingly, electricity from solar power reached 10.6 TWh, accounting for about 4.3% of the total electricity generation. Moreover, solar power development has contributed increasingly to carbon emission reduction. With the avoidance emission factor of 0.4 kg$CO_2$/kWh (equaling the emission factor of gas power plants), solar power's annual avoided carbon emissions are estimated at more than 4.24 million tons.

### *7.3.2. Effects of the FIT mechanism on the wind power investment market*

The technical onshore wind power potential of Vietnam is estimated at 214 GW (Togeby, 2017). However, the potential varies according to wind speed (see Appendix 8 and Appendix 10).

Despite the relatively early introduction of the FIT mechanism, the wind power investment market has remained far below expectations. After seven years of the first FIT of 7.8 US cents/kWh (Government of Vietnam, 2011), the total installed capacity of wind power was only around 260 MW, with either only one or two, or even no new power plants into operation each year (Figure 7.9).

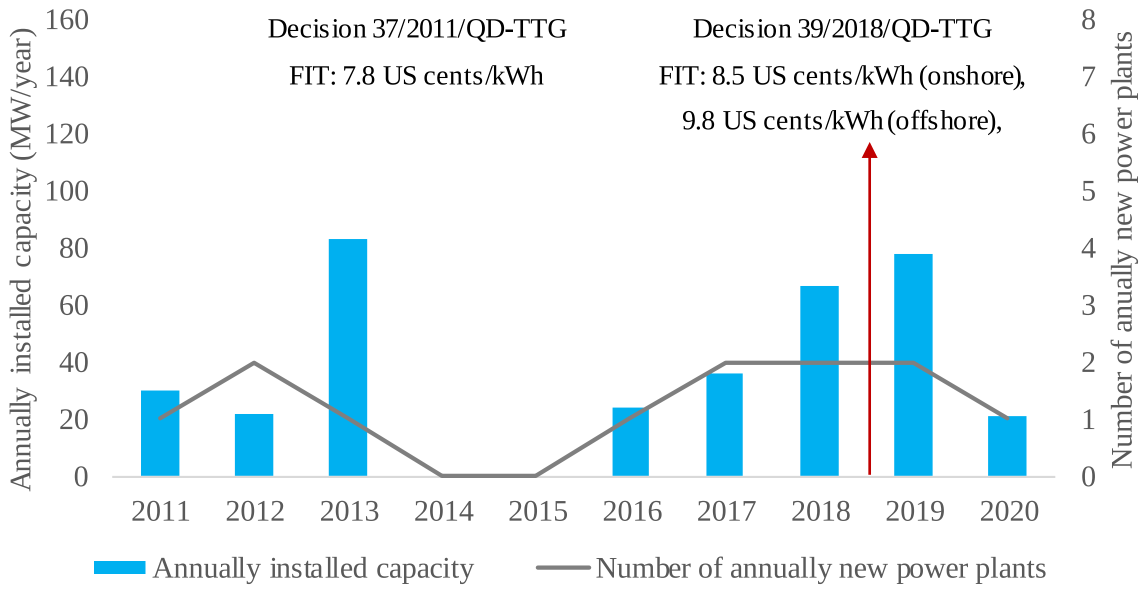



Figure 7.9. Annual wind power installation in Vietnam between 2011 and 2020

(Source: Data from *List of wind projects in Vietnam*, 2021a, and press releases)

The approval of a new FIT scheme of 8.5 US cents/kWh for onshore wind power and 9.8 US cents/kWh for offshore wind power (Government of Vietnam, 2018) was expected to get more investors' attention. However, as of 2020, Vietnam had only 14 wind power plants with a total installed capacity of less than 430.6 MW – only equals 54% of the target of 800 MW (Government of Vietnam, 2016a) and 2% of the total solar power installed capacity.

### *7.3.3. Investors and project scales*

The renewable power investment markets in Vietnam have gotten the attention of various investors. Learning from the classification method based on ownership and primary business activity proposed by Bergek, Mignon, and Sundberg (2013), we divide investors into five groups: utilities, publicly owned non-energy companies, independent power producers, private diversified, and end-users.

In order to determine the structure of investors in Vietnam, information about operating solar and wind power projects collected (see Appendix 11 and Appendix 12). In addition, the ownership and business areas of investors are extracted from the *National Business Registration Portal* (2021).

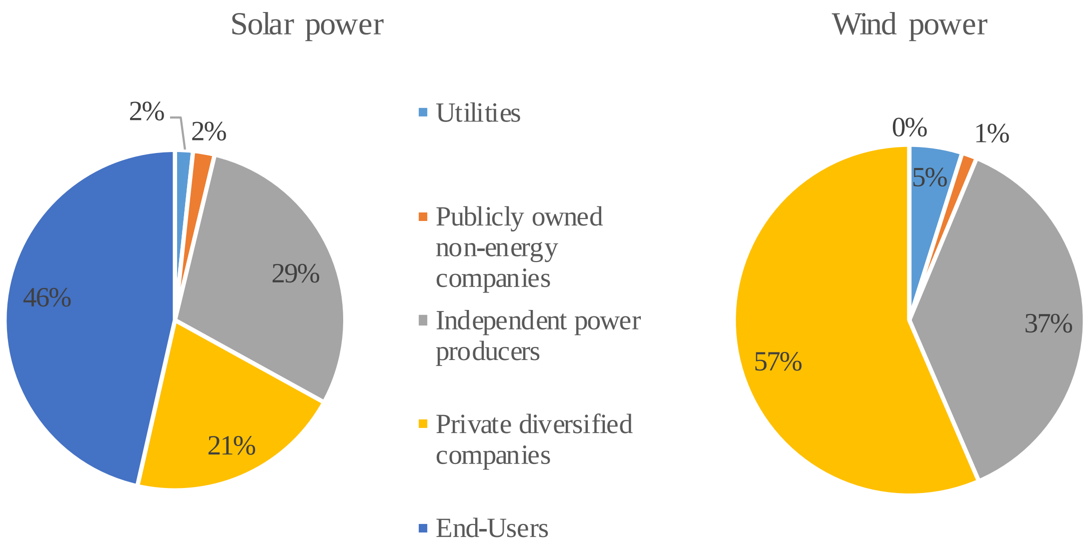



Figure 7.10. The solar and wind power installed capacity structures by ownership in Vietnam by the end of 2020

(Source: Data from our calculation)

After processing the collected data, we find that private investors dominate both the solar and wind power investment markets, accounting for 96% of the total solar power installed capacity and 94% of the total wind power installed capacity. In which diversified companies owned 21% of solar power and 57% of wind power. New IPPs accounted for 29% of solar power and 37% of wind power by the end of 2020. End-users took advantage of roof ownership to contribute around 46% to the total solar power capacity. Surprisingly, although having advantages in the electric power area and accounting for almost 46% of the total installed capacity, the EVN contributed only 2% to the total solar power and 5% to the total wind power. The publicly non-energy companies made up 1-2% of the total capacity (Figure 7.10).

Regarding project scale, 75% of ground-mounted and floating farms have 10 to 50 MW (Figure 7.11). The most massive-scale solar power project reached 450 MW.

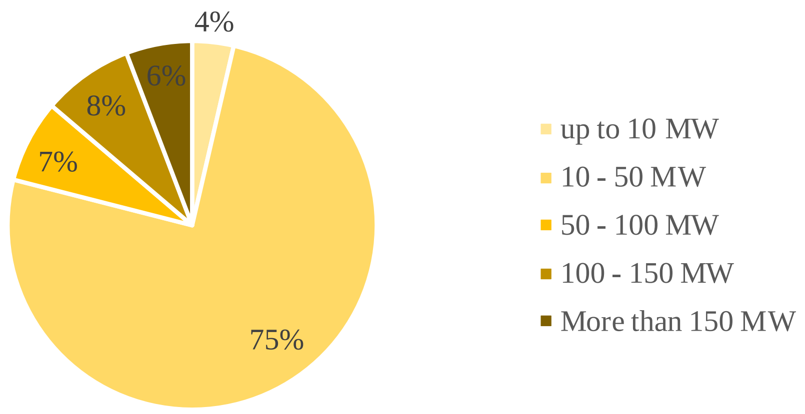



Figure 7.11. Scale structure of solar power projects in Vietnam by the end of 2020

(Source: Data from our calculation)

## 7.4. PID-based price mechanisms for Vietnam

### *7.4.1. Recommendations of price mechanisms*

Renewing the FIT mechanism or introducing a competitive auction mechanism for new solar and wind power investments after the expire of the current FIT mechanism is being considered. Considering the electricity generation cost and the national renewable power target, we propose assessing scenarios of price mechanisms, as shown in Figure 7.12.

*Scenario 1: the FIT mechanism is amended for new solar and wind power projects.*

Vietnam is at the early stage of the renewable power growth phase. The solar power investment market has strongly attracted private investors. However, other investor groups have still limited their investment flow or even not appeared yet. The actual wind power investment has remained far below the targeted volume; therefore, an amendment of the FIT mechanism will attract new players and keep the current ones.

*Scenario 2: an auction mechanism for large-scale rooftop systems, ground-mounted and floating solar power projects is introduced. Small and medium-scale solar power projects, wind power projects enjoy an amended FIT mechanism.*

This proposal is based on the fact that large-scale solar power projects are competitive with conventional power sources in electricity generation costs. An auction mechanism is too complicated and may become an obstacle for small and medium-scale rooftop investors; therefore, an amended FIT mechanism is recommended. Because the wind power investment cost is still higher than that of the other electricity generation technologies and the wind power investment market has not been taken off yet, an amended FIT mechanism for wind power is necessary.

| | |
|---|---|
| Scenario 1 | - 100% FIT mechanism |
| Scenario 2 | - FIT mechanism for small and medium-scale rooftop solar PV systems (≤ 1 MW)<br>- Auction mechanism for large-scale rooftop solar PV (> 1MW), ground-mounted, and floating solar PV farms<br>- FIT for wind power projects |
| Scenario 3 | - FIT mechanism for small and medium-scale rooftop solar PV systems (≤ 1 MW)<br>- Auction mechanism for large-scale rooftop solar PV (> 1MW), ground-mounted, and floating solar PV farms<br>- Auction mechanism for onshore wind power projects<br>- FIT mechanism for offshore wind power projects |
| Scenario 4 | - FIT mechanism for small-scale rooftop solar PV systems (≤ 100 kW)<br>- FIT- based MP mechanism for medium-scale rooftop solar PV systems (>100 kW and ≤ 1 MW)<br>- Auction-based MP mechanism for large scale-rooftop solar PV (> 1MW), ground-mounted, and floating solar PV farms<br>- Auction-based MP mechanism for onshore wind power projects<br>- FIT mechanism for offshore wind power projects |

Figure 7.12. Scenarios of price mechanisms for solar and wind power in 2022 in Vietnam

*Scenario 3: an auction mechanism is proposed for large-scale rooftop systems, ground-mounted and floating solar power projects, and onshore wind power installations. Small and medium-scale solar power projects, offshore wind power projects enjoy an amended FIT mechanism.*

The current FIT mechanism in Vietnam has caused a lack of transparency in investment licensing. A competitive auction mechanism is a solution to improve transparency. Nevertheless, due to the high investment cost, an amendment of the FIT mechanism is suggested to attract investors to offshore wind power projects.

*Scenario 4: an auction-based market premium may be an alternative for large-scale rooftop systems and onshore wind power projects. Small-scale solar power projects, offshore wind power projects enjoy an amended FIT mechanism.*

In January 2019, the Vietnam wholesale electricity market (VWEM) officially came into operation (Ministry of Industry and Trade of Vietnam, 2018). Due to the existence of the wholesale electricity market, a FIT-based market premium may be suitable for medium-scale rooftop systems; an auction-based market premium is a solution for large-scale solar power and onshore wind power projects. These price mechanisms ensure partial revenue while reflecting price fluctuations in the competitive wholesale electricity market.

Policymakers should intensively analyze the possible impacts of price mechanisms on investment decisions before deciding which scenario will be applied. Whatever scenario is chosen, the feedback approach is recommended for price mechanisms to achieve the desired effects.

### *7.4.2. PID-based FIT mechanism*

The unexpected results of the prediction-based FIT mechanism in Vietnam have been analyzed in Section 7.3. Moreover, an amendment of the FIT mechanism for new solar and wind power projects in 2022 is possible. Therefore, this section proposes the proportional controller rule for FIT adjustments to minimize the deviation between the targeted renewable power investment and the actual volume. The following sections suggest setting the control specifications, selecting adjustment frequency, and constructing scenarios of FIT adjustments.

#### *7.4.2.1. Control specifications*

Vietnam's renewable targets are set in terms of overall value rather than differentiated by technology and project size. Therefore, FIT adjustments are recommended based on the deviation between the total installed capacity and the targeted value. According to the draft National Power Development Plant for the period 2021-2030, with a vision to 2045 (known as draft PDP VIII), Vietnam aims to achieve 13,420 MW of solar power, 9,290 MW of wind power by 2025, and 19,330 MW each of them by 2030 (Ministry of Industry and Trade of Vietnam,

2020) (Figure 7.13). This plan equals a five-year development corridor of 6,000 MW solar power and around 10,000 MW wind power between 2021 and 2025.

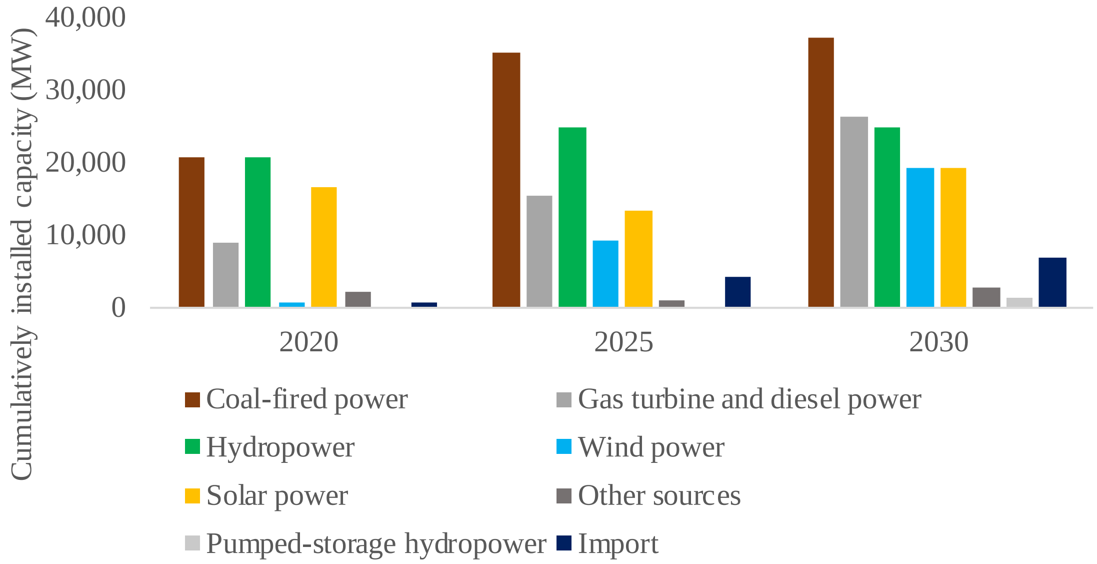



Figure 7.13. Installed capacity structure in Vietnam in 2020, 2025 and 2030 according to the drafted PDP VIII

(Source: Data from the Ministry of Industry and Trade of Vietnam, 2020)

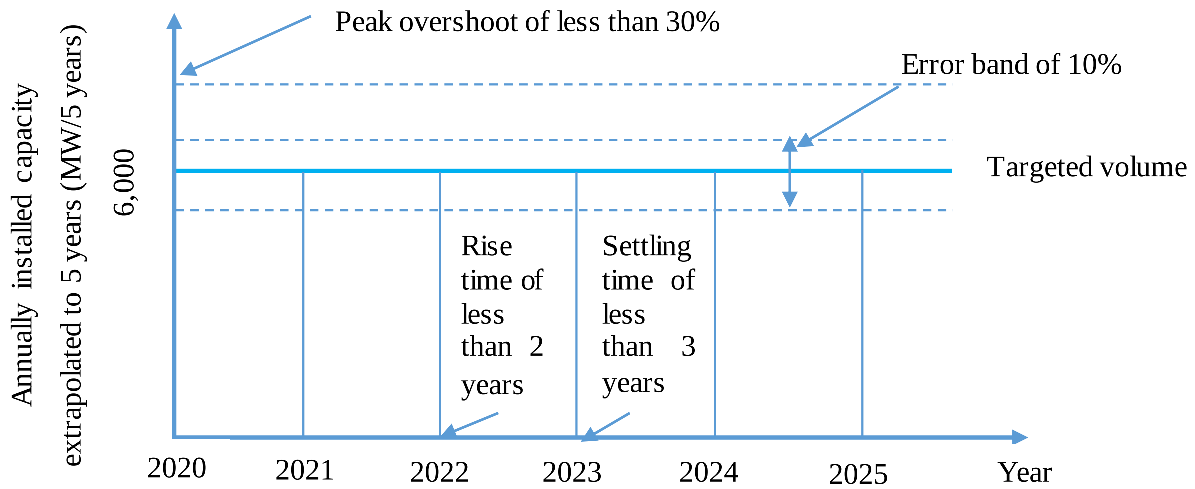



Figure 7.14. Control specifications for solar power investment in Vietnam between 2020 and 2025

The FIT adjustment aims to guarantee sustainable solar power investment growth between 2020 and 2025. We set the required time of less than two years for the annually installed capacity extrapolated to five years to rise from 0 to 6,000 MW of solar power, from 0 to 10,000 MW of wind power. The time to reach and remain within a 10% error band is less than three years. The peak overshoots are less than 30% (equals to 1,800 MW of solar power, and 3,000 MW of wind power) at all the time. Figure 7.14 depicts the required specifications of the control system design for solar power investment in Vietnam until 2025.

*7.4.2.2. Adjustment frequency*

The adjustment frequency depends on the project implementation duration and investment cost reduction rate. It takes an average of 1.5 months to implement a small-scale rooftop power project, 2.5 months for a medium-scale one, and 6 months for large-scale rooftop, ground-mounted, floating solar power projects. 1 to 2 years are the project implementation duration of an onshore wind power project of up to 50 MW (Table 7.2).

Table 7.2. Project implementation duration of solar and wind power projects in Vietnam

| **Technology** | **Small-scale rooftop** | **Medium-scale rooftop** | **Large-scale rooftop, ground-mounted, floating PV** | **Onshore wind** |
|---|---|---|---|---|
| Capacity range | Up to 100 kW | 100 kW – 1 MW | More than 1 MW | Up to 50 MW |
| Project implementation duration | 2 – 10 weeks (aver: 1.5 months) | 5 – 15 weeks (aver: 2.5 months | 3 - 9 months (aver: 6 months) | 1 – 2 years |

We estimate that annual average LCOE reduction rates are at 2.60% for solar power, 1.74% for onshore wind power, and only 0.42% for offshore wind power in the next decade (Figure 7.15) (see the input data for our calculation in Appendix 3, Appendix 4, Appendix 5, and Appendix 6).

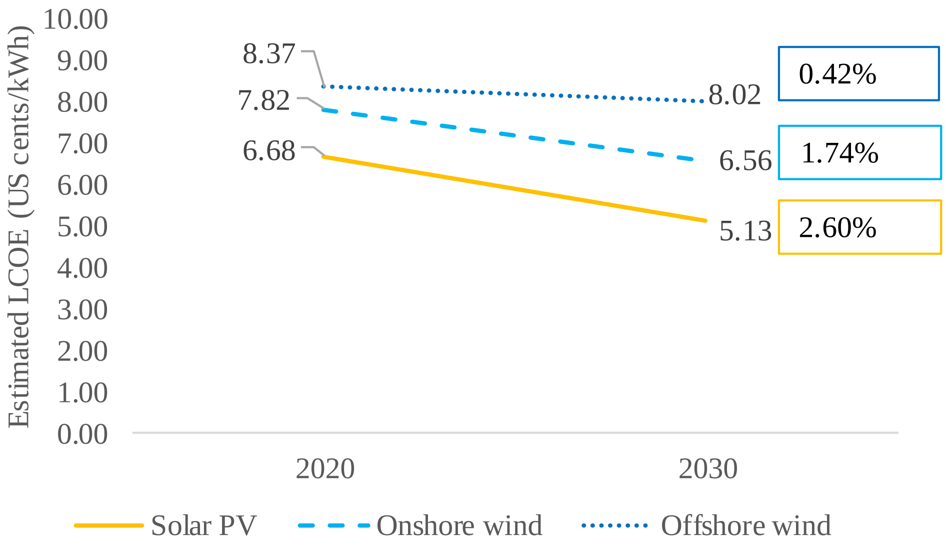



Figure 7.15. Estimated LCOE of new solar and wind power in Vietnam between 2020 and 2030

(Source: Data from our calculation)

Considering the project implementation duration and the investment cost reduction rate, we propose a quarterly FIT adjustment for rooftop solar PV installations, semi-annually for ground-mounted and floating solar power projects, and annually for wind power projects.

*7.4.2.3. Proportional-based FIT mechanism*

The proportional-based quarterly FIT adjustment for rooftop solar PV systems has a mathematical form as follows:

$$FIT_q = FIT_{q-1} + K_P^r e_q$$

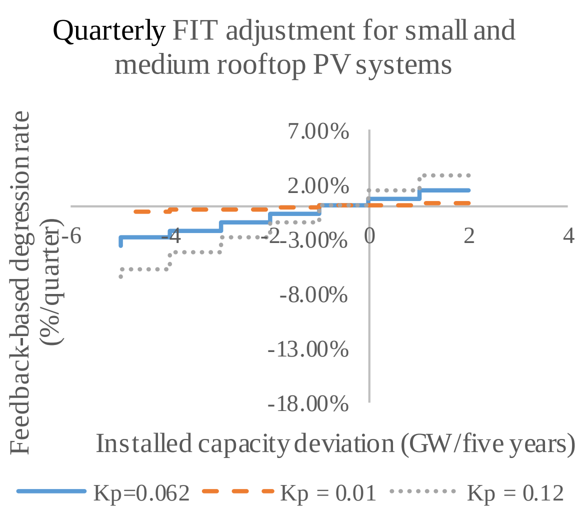
$FIT_q, FIT_{q-1}$: FIT levels at quarter q, q-1.

$K_P^r$: proportional gain.

$e_q = v_q^d - v_q^r$: the current deviation between the desired five-year installed capacity and the projected volume.

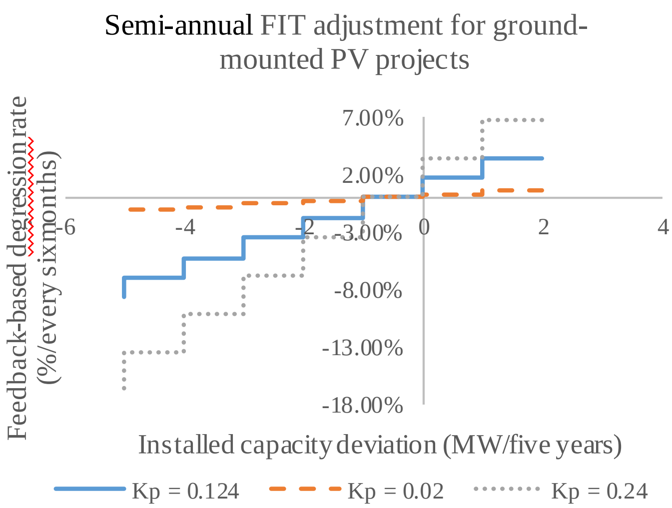
The proportional-based FIT mechanisms models for other technologies are similar.

With the current FIT levels (see Section 7.3.1 and Section 7.3.2), a proportional gain of 0.062 is referenced from the finding in Chapter 5, Section 5.3.2.2, an average scenario of the degression rate for rooftop PV systems for Vietnam is carried out. Due to the semi-annual adjustment, a proportional gain of (0.062*2 = 0.124) is chosen for FIT adjustments for ground-mounted and floating PV systems. The proportional gain of 0.124 is also chosen to determine the average FIT adjustment for wind power. Apart from the average scenario, low and high scenarios are achieved for each technology (Figure 7.16).

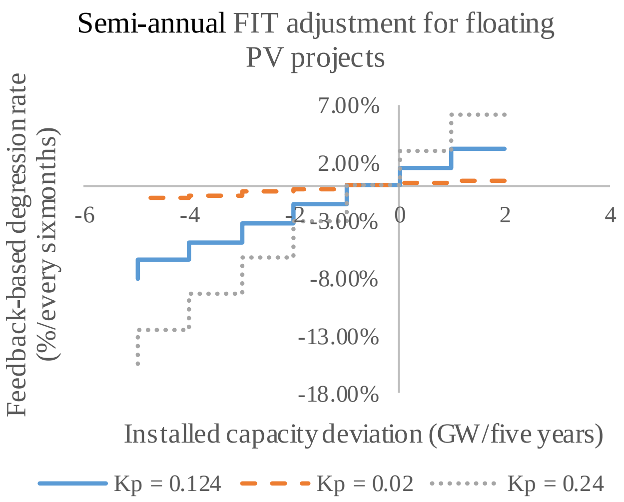



| Deviation (GW/five years) | Average scenario (Kp = 0.062) | Low scenario (Kp = 0.01) | High scenario (Kp = 0.12) |
|---|---|---|---|
| 2 | 1.48% | 0.24% | 2.86% |
| 1 | 1.48% | 0.24% | 2.86% |
| 1 | 0.74% | 0.12% | 1.43% |
| 0 | 0.74% | 0.12% | 1.43% |
| 0 | 0.00% | 0.00% | 0.00% |
| -1 | 0.00% | 0.00% | 0.00% |
| -1 | -0.74% | -0.12% | -1.43% |
| -2 | -0.74% | -0.12% | -1.43% |

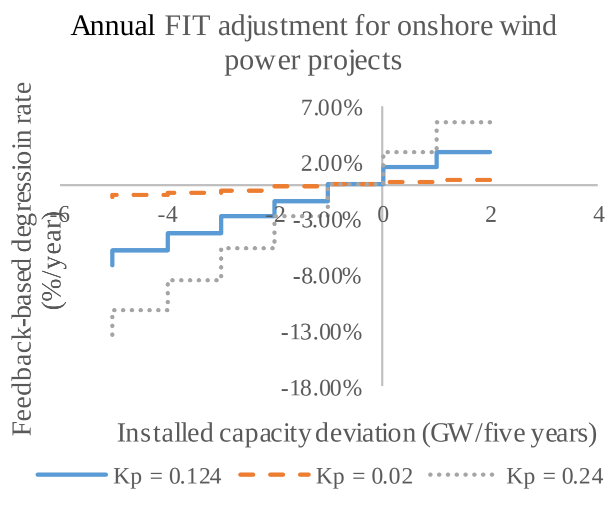
| | | | |
|---|---|---|---|
| -2 | -1.48% | -0.24% | -2.86% |
| -3 | -1.48% | -0.24% | -2.86% |
| -3 | -2.22% | -0.36% | -4.30% |
| -4 | -2.22% | -0.36% | -4.30% |
| -4 | -2.96% | -0.48% | -5.73% |
| -5 | -2.96% | -0.48% | -5.73% |
| -5 | -3.70% | -0.60% | -7.16% |




| **Deviation (GW/five years)** | **Average scenario (Kp = 0.124)** | **Low scenario (Kp = 0.02)** | **High scenario (Kp = 0.24)** |
|---|---|---|---|
| 2 | 3.50% | 0.56% | 6.77% |
| 1 | 3.50% | 0.56% | 6.77% |
| 1 | 1.75% | 0.28% | 3.39% |
| 0 | 1.75% | 0.28% | 3.39% |
| 0 | 0.00% | 0.00% | 0.00% |
| -1 | 0.00% | 0.00% | 0.00% |
| -1 | -1.75% | -0.28% | -3.39% |
| -2 | -1.75% | -0.28% | -3.39% |
| -2 | -3.50% | -0.56% | -6.77% |
| -3 | -3.50% | -0.56% | -6.77% |
| -3 | -5.25% | -0.85% | -10.16% |
| -4 | -5.25% | -0.85% | -10.16% |
| -4 | -7.00% | -1.13% | -13.54% |
| -5 | -7.00% | -1.13% | -13.54% |
| -5 | -8.74% | -1.41% | -16.93% |

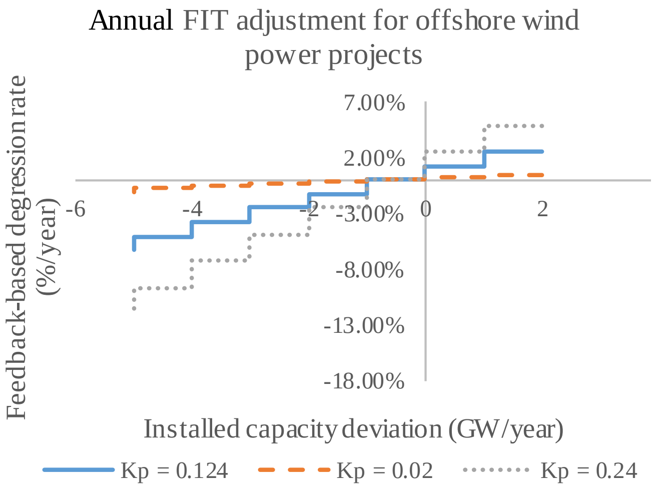



| Deviation (GW/five years) | Average scenario (Kp = 0.124) | Low scenario (Kp = 0.02) | High scenario (Kp = 0.24) |
|---|---|---|---|
| 2 | 3.22% | 0.52% | 6.24% |
| 1 | 3.22% | 0.52% | 6.24% |
| 1 | 1.61% | 0.26% | 3.12% |
| 0 | 1.61% | 0.26% | 3.12% |
| 0 | 0.00% | 0.00% | 0.00% |
| -1 | 0.00% | 0.00% | 0.00% |
| -1 | -1.61% | -0.26% | -3.12% |
| -2 | -1.61% | -0.26% | -3.12% |
| -2 | -3.22% | -0.52% | -6.24% |
| -3 | -3.22% | -0.52% | -6.24% |
| -3 | -4.84% | -0.78% | -9.36% |
| -4 | -4.84% | -0.78% | -9.36% |
| -4 | -6.45% | -1.04% | -12.48% |
| -5 | -6.45% | -1.04% | -12.48% |
| -5 | -8.06% | -1.30% | -15.60% |




| Deviation (GW/five years) | Average scenario (Kp = 0.124) | Low scenario (Kp = 0.02) | High scenario (Kp = 0.24) |
|---|---|---|---|
| 2 | 2.92% | 0.47% | 5.65% |
| 1 | 2.92% | 0.47% | 5.65% |
| 1 | 1.46% | 0.24% | 2.82% |
| 0 | 1.46% | 0.24% | 2.82% |
| 0 | 0.00% | 0.00% | 0.00% |
| -1 | 0.00% | 0.00% | 0.00% |
| -1 | -1.46% | -0.24% | -2.82% |
| -2 | -1.46% | -0.24% | -2.82% |

| | | | |
|---|---|---|---|
| -2 | -2.92% | -0.47% | -5.65% |
| -3 | -2.92% | -0.47% | -5.65% |
| -3 | -4.38% | -0.71% | -8.47% |
| -4 | -4.38% | -0.71% | -8.47% |
| -4 | -5.84% | -0.94% | -11.29% |
| -5 | -5.84% | -0.94% | -11.29% |
| -5 | -7.29% | -1.18% | -14.12% |




| **Deviation (GW/five years)** | **Average scenario (Kp = 0.124)** | **Low scenario (Kp = 0.02)** | **High scenario (Kp = 0.24)** |
|---|---|---|---|
| 2 | 2.53% | 0.41% | 4.90% |
| 1 | 2.53% | 0.41% | 4.90% |
| 1 | 1.27% | 0.20% | 2.45% |
| 0 | 1.27% | 0.20% | 2.45% |
| 0 | 0.00% | 0.00% | 0.00% |
| -1 | 0.00% | 0.00% | 0.00% |
| -1 | -1.27% | -0.20% | -2.45% |
| -2 | -1.27% | -0.20% | -2.45% |
| -2 | -2.53% | -0.41% | -4.90% |
| -3 | -2.53% | -0.41% | -4.90% |
| -3 | -3.80% | -0.61% | -7.35% |
| -4 | -3.80% | -0.61% | -7.35% |
| -4 | -5.06% | -0.82% | -9.80% |
| -5 | -5.06% | -0.82% | -9.80% |
| -5 | -6.33% | -1.02% | -12.24% |

Figure 7.16. Scenarios of proportional-based FIT adjustment for solar and wind power projects for Vietnam

The above scenarios indicate that the lower initial FIT level leads to a higher FIT degression rate with a similar proportional coefficient and installed capacity deviation. For example, with the proportional coefficient of 0.124 and the annual installation deviation of (-1) GW, the FIT adjustment rates are (-1.75%) for ground-mounted systems and (-1.61%) for floating PV systems.

## 7.5. Energy policy improvements for Vietnam

Vietnam has adopted various energy policies to support renewable power development (see Chapter 2, Table 2.4). However, some of them have been inconsistent or intransparent. This section will analyze those limitations and propose approaches for improvements.

### *7.5.1. Power development planning in line with carbon emission reduction targets*

Problem:

Being a member of the Paris Agreement (United Nations Framework Convention on Climate Change, 2016), Vietnam commits to reducing 8% to 25% of greenhouse gases (GHGs) emission compared to the BAU scenario (787 Mt$CO_2$) by 2030 (Vietnam, 2016). With 16% of emissions from the power sector (Ministry of Natural Resources and Environment of Vietnam, 2017), energy transition from a power system dominated by conventional sources to a system characterized by renewables plays a crucial role in greenhouse gas emission reduction.

However, according to the national power development plan for the period from 2011 to 2020, with a vision to 2030 (also known as PDP VII), the Vietnamese government aims to achieve 25,620 MW (42.7%) by 2020, 55,167 MW (42.6%) by 2030 of coal-fired installation (Government of Vietnam, 2016a). In other words, the upcoming years are expected to be "coal years" (Figure 7.17).

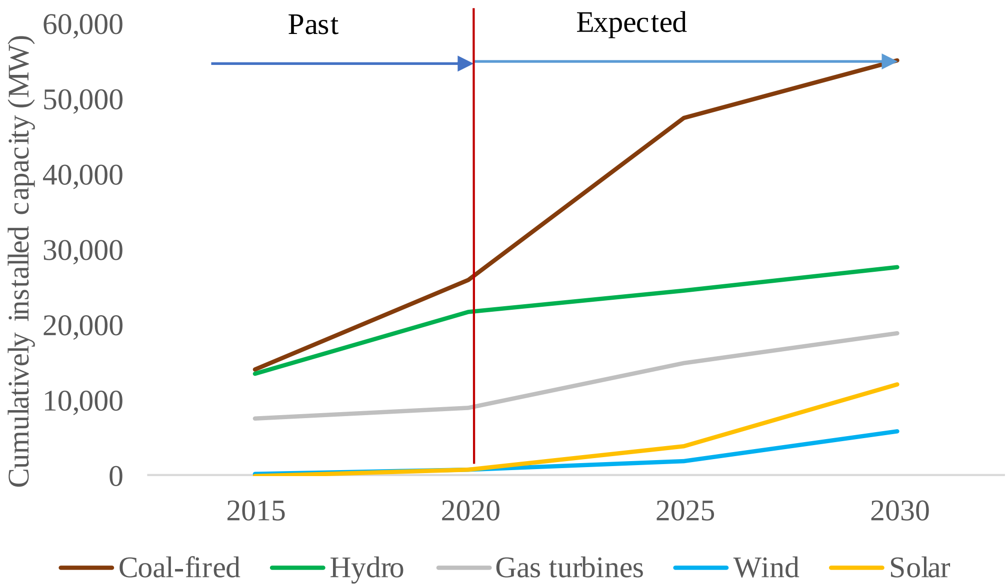



Figure 7.17. Installed capacity structure in Vietnam between 2015 and 2030 according to the PDP VII

(Source: Data from The Vietnamese government, 2016a)

The electricity generation from coal is estimated at around 130 TWh (equivalent to 123 Mt$CO_2$) in 2020, 306 TWh (equivalent to 245 Mt$CO_2$) in 2030 (Bui, 2017). This plan conflicts with the ambitious carbon emission reduction targets mentioned in The Vietnamese government (2016c).

Proposed approach:

The national power development plan is the legal basis that gives the message and orientation for power investment. We propose constructing a power development plan in line with carbon emission reduction targets. Mathematically, an optimal power source planning problem that includes the environmental cost into objective function and considers the constraint of carbon emissions is introduced.

The details of the optimal problem, input data, and results are presented in our published paper "A power development planning for Vietnam under the $CO_2$ emission reduction targets" (Hiep and Hoffmann, 2019a). We suggest three power development scenarios under carbon emission targets for Vietnam from 2018 to 2030. The findings indicate that by 2030, coal-fired power capacity will account for around 29% (scenario of 8% carbon reduction) and 19% (scenario of 25% carbon reduction) instead of 42.6%, as mentioned in the PDP VII. Also, the low emission sources such as hydro, solar, and wind power will be prior for investment in the next decade. Coal-fired power plants should be replaced by natural gas stations.

### *7.5.2. Making electricity price structure transparent*

Problem:

Vietnamese electricity consumers currently do not know how much they are paying for solar and wind power development. According to the Ministry of Industry and Trade (2019), Vietnam's mean retail electricity price is 1.864,44 VND/kWh (around 8 US cents/kWh). The price structure contains the electricity generation price, transmission price, distribution price, and management price. The electricity generation price accounts for 79% of the retail electricity price in Vietnam in 2019 (Figure 7.18).

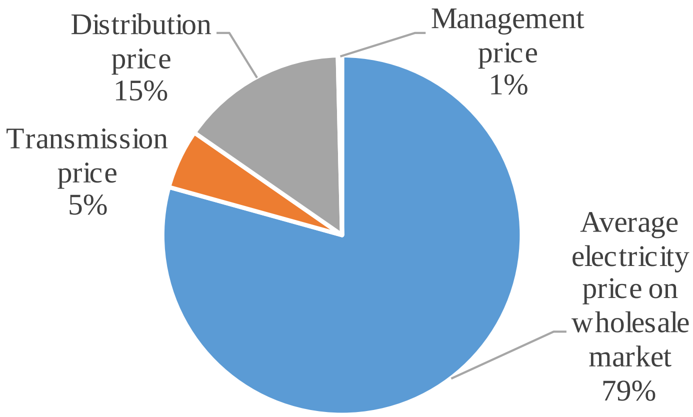



Figure 7.18. Mean retail electricity price structure in Vietnam in 2019

According to The Vietnamese government (2017b), the mathematical formulation of annual mean retail electricity price looks like this:

$$\bar{P} = \frac{C_{gen} + C_{trans} + C_{dis\_re} + C_{smo} + C_{an} + C_{com} + C_{others}}{TE} \quad (7.1)$$

$$C_{gen} = C_{mar} + C_{mul} + C_{BOT} + C_{smal\_hy} + C_{RE\_FIT} + C_{im} \quad (7.2)$$

$$C_{RE\_FIT} = E_{on} * FIT_{on} + E_{off} * FIT_{off} + E_{PV} * FIT_{PV} \quad (7.3)$$

$\bar{P}$: annual mean retail electricity price (VND/kWh).

$TE$: total commercial electricity (kWh).

$C_{gen}$, $C_{mar}$, $C_{mul}$, $C_{BOT}$,$C_{small\_hy}$, $C_{RE\_OTC}$, $C_{im}$: total electricity buying cost from all power plants, power plants participating in the competitive electricity market, multi-purpose hydropower plants, BOT (build – operate – transfer) power plants, small hydropower plants, renewable power plants, and import power, respectively (VND).

$C_{trans}$, $C_{dis\_re}$,$C_{smo}$,$C_{an}$,$C_{com}$, $C_{others}$: total transmission service buying cost, distribution and retail service buying cost, system and market operation service buying cost, ancillary service buying cost, management cost, and other costs (deviation of the exchange rate), respectively (VND).

$C_{RE\_FIT}$: total contract revenue for renewables (based on the FIT levels) (VND).

$E_{on}$, $E_{off}$, $E_{PV}$: total commercial electricity from onshore wind power plants, offshore wind power plants, and solar PV power plants (kWh).

$FIT_{on}$, $FIT_{off}$, $FIT_{PV}$: feed-in tariffs for onshore wind power plants, offshore wind power plants, and solar PV power plants, respectively (VND/kWh).

Proposed approach:

In Vietnam, the public wants to know how much they pay for solar and wind power development. Therefore, the transparency of the electricity price structure will motivate the electricity consumers to contribute to the energy transition. The recommended solution is the introduction of a renewable energy surcharge. Whereby, equations (7.1) and (7.2) can be rewritten as:

$$\bar{P} = \frac{C_{gen\prime} + C_{trans} + C_{dis\_re} + C_{smo} + C_{an} + C_{com} + TS + C_{others}}{TE} \tag{7.4}$$

$$C_{gen\prime} = C_{mar} + C_{mul} + C_{BOT} + C_{smal\_hy} + C_{RE\_mar} + C_{im} \tag{7.5}$$

$TS$: total renewable energy surcharge (VND).

$C_{RE\_mar}$: wholesale electricity market revenues for renewables (VND).

The total renewable energy surcharge is defined:

$$\mathrm{TS} = C_{RE\_\mathrm{FIT}} - C_{RE\_mar} \tag{7.6}$$

The detailed formulation and suggested application of the renewable energy surcharge are presented in our published paper "Estimation of the future electricity price surcharge for the integration of wind and solar power into the Vietnamese electricity system" (Hiep and Hoffmann, 2019b). The findings indicate an increase in renewable energy surcharge from 0.10 US cents/kWh in 2020 to 1.07 US cents/kWh after two decades. Additionally, it is forecasted that the electricity generation cost of solar power and onshore wind will be lower than the average wholesale market price by 2032 and 2034, respectively.

### *7.5.3. Allowing private investment in transmission systems*

Problem:

It takes an average of 6 months to implement a large-scale solar power project, while the construction time of transmission lines (including planning compensation, land clearance, and operation) is 2 – 3 years for 220 kV systems, 3 – 5 years for 500 kV ones. In other words, the transmission grid investment should go *one step ahead* to be available and be capable enough to transmit electricity from both old and new power plants to consumers. Unfortunately, in Vietnam, the transmission line construction has lagged behind new power connections. Figure 7.19 depicts the capacity release ability in several provinces.

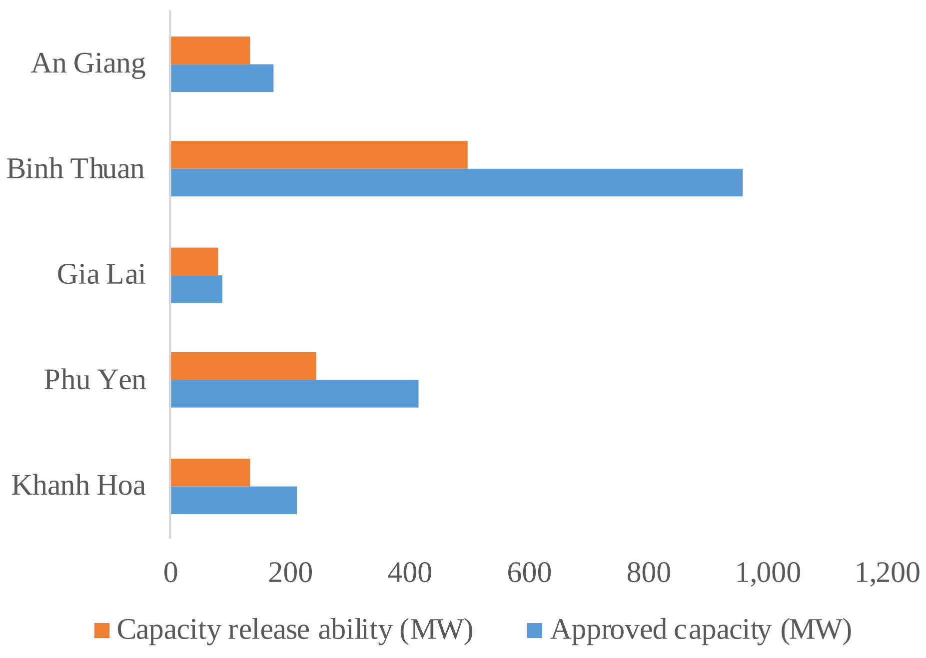



Figure 7.19. Capacity release ability in several provinces in Vietnam up to June 2019

(Source: Data from the NLDC of Vietnam, 2019)

The congested grid has led to partial dispatched electricity. Moreover, the lines and substations continuously operate at a limit level, causing system instability, harming equipment, and more work for the dispatch center. This fact requires reinforcing renewable generation hotspots quickly.

In Vietnam, transmission is a state-owned monopoly that the state undertakes to build, manage, and operate (The Vietnamese national assembly, 2004; Government of Vietnam, 2017b). However, being a state-owned enterprise, the national power transmission corporation (EVNNPT) lacks financial resources.

Proposed approach:

Revision of the electricity law and other applicable laws to attract private finance to transmission grid investment is recommended. Private investors may spend their money on new transmission lines and then transfer them to EVNNPT for operation. In other words, the state-owned enterprise and private companies will cooperate in transmission grid development under long-term contracts such as public-private partnerships (PPP). The private sector's participation in the transmission grid investment proactively helps release the capacity and will be essential for power expansion in the upcoming years. Also, private sector involvement creates competition, such that the transmission price will ultimately correctly reflect the cost.

In order to effectively achieve private finance, business models of private investment in transmission must be studied and constructed. World Bank Group (2017) points out four primary business models: indefinite privatization, whole-of-grid concession, independent power transmissions (IPTs), and merchant investment. Indefinite privatizations provide the opportunity for indefinite private ownership of the transmission grid through a trade sale or a public flotation. Then, the private owner has the right to develop the transmission network in the purchased area. Whole-of-grid concessions provide the opportunity for definite private ownership of the transmission grid through a competitive tender of the concession. IPTs provide the opportunity for private ownership of a single transmission line or a package of a few lines through a long-term contract. Finally, merchant investors build and operate a single transmission line to move power from low-price to high-price areas and benefit from the price deviation. The international experiences have proven that IPTs provide the rights and obligations concerning a single transmission line or a package of a few lines. Therefore, they positively attract private finance in developing countries. Being a lower-middle-income country with new renewable power investment markets, the IPTs can be an option for Vietnam. However, for application, Vietnam needs to study the conditions and capabilities to apply models carefully.

#### *7.5.4. Regulating curtailment as an ancillary service*

<u>Problem:</u>

Renewable energy curtailment reduces the electricity generation of a solar or wind power plant below its potential. Consequently, it decreases profit and becomes a risk to renewable power investors.

| |
|---|
| Examples of curtailment:<br>Before the first FIT mechanism for solar PV, only two wind power projects (Phu Lac 1 (24 MW) and Tuy Phong (30 MW)) were connected to the grid. The 110kV transmission line Phan Ri – Ninh Phuoc has a capacity of more than 100 MW. However, within only a few months, more than ten solar power farms were connected to this grid line with a total installed capacity of 400 MW, by far exceeding the line's capacity. Consequently, all connected power plants to this line were forced to cut down the electricity generation. As a result, the curtailment rate reached 38 to 65%. |

The 110kV transmission line Eco Seido – Phan Ri connected eight power plants (with a total capacity of 228.43 MW) despite the line's capacity of only 98.4 MW. This situation caused a curtailment rate of up to 61%.

The 110kV transmission line Ninh Thuan 1 – Thap Cham can only load 137.6 MW. However, the total installed capacity of power farms connected to this line is 387.6 MW.

Renewable curtailment can occur due to line overloading, a geographic mismatch between renewable resources and load, systemwide oversupply (O'Schaughnessy E, Cruce JR and Xu.K, 2020), or the higher bidding price than the market-clearing price (Bird, Cochran and Wang, 2014).

In Vietnam, it is regulated that the renewable power curtailment rate has been similar for projects on the same grid line. It is a fact that the unpaid curtailment reduces the motivation for new investments.

Proposed approach:

It is a fact that curtailment guarantees power system security. Therefore, we recommend regulating the curtailment as an ancillary service. In other words, renewable power plants should be paid for reducing power output. Bird, Cochran, and Wang (2014) and Windeurope (2016) suggest setting the price for this service via both the day-ahead market price and the lost incentive value. The payment for curtailment is a compensation scheme to reduce market risks for new players, thereby propelling renewable power. Vietnam can learn from other countries' experiences to make curtailment regulations more suitable.

### 7.6. Chapter conclusion

Being a later adopter of renewables, Vietnam can learn from Germany's successes and, at the same time, avoid mistakes made in Germany to develop the solar and wind power investment markets sustainably. However, this chapter indicates that the prediction-based FIT mechanism has caused a significant deviation between the targeted renewable power investment and the actual volume.

Because of the unknown price mechanisms in 2020, four scenarios of price mechanisms for Vietnam after the current FIT mechanism are proposed to be assessed. Moreover, the proportional-based FIT adjustments are recommended to avoid unsustainable renewable power investment in the future. Accordingly, scenarios of future FITs have been carried out for solar and wind power technologies at different project scales.

Last but not least, realizing the inconsistency of the current energy policies and a lack of necessary policies, this chapter proposes several urgent energy policy improvements to contribute to the sustainable energy transition in the power sector in Vietnam. Firstly, an optimization problem of power development planning with carbon emissions constraints will drive new investments towards low carbon technologies. Secondly, the introduction of the renewable energy surcharge is expected to render the electricity price structure more transparent. Accordingly, the path of green electricity power development is supported by society. Thirdly, regarding transmission grid development, public-private partnership models are suggested to attract private investment. Finally, market regulations on curtailment are necessary to reduce the revenue risk, therefore, stimulate renewable power investment.

# Chapter 8. Conclusion

This chapter summarizes the main findings of the dissertation and formulates perspectives for future works.

## 8.1. Summary

This dissertation has combined an insight in the macroeconomic, energy economy, and energy market policies of renewable power development with control theory. A novel approach to feedback control has been studied and proposed for price mechanism design to guarantee sustainable solar and wind power investment growth. The main scientific contributions of the dissertation are as follows:

**Contribution 1: Emphasis on the understanding of stages of technology diffusion**

In contrast to techno-physical systems, the application of system identification to a collective of human agents, i.e. investors, requires courage. Yet based on a thorough background study of technology diffusion, investment motivations, investors' internal resources and the effect of micro and macro factors on investor behavior, relevant structures of the investor market dynamics as a whole have been extracted statistically. Important is the emphasis of understanding of the different stages of technology diffusion comprising the inception phase, growth phase and saturation phase which all require different approaches of incentive schemes and transitions between them. Apart from the investment market, there is the electricity market itself and the interaction between them have to be considered as well. It is clear that the crucial coupling between them takes place when the investment market enters the saturation phase.

**Contribution 2: Identification of possible scenarios of renewable power development**

In order to structure the energy system transformation on a global scale, a differentiation of scenarios of renewable power development which provides a helpful tool to characterize the status in different countries is offered. Principally, a completion date for the targeted renewable power installation is set to fight climate change effectively. However, suppose the installation rate is initially too low. In that case, there will be an increasing market overshooting above the desired smooth S-curve behavior (see the four scenarios of renewable power diffusion in Figure 2.3). It is questionable whether such high implementation speeds can be achieved at all, given the availability, particularly of the skilled labor force. However, even if it could, it would lead to an overheated industry where the then-built capacities would later have to be reduced again - with all the dire consequences this would have on this new industry sector. If a country acts too late, the targeted climate political goals will be getting harder and harder to achieve as raw materials costs are constantly increasing. Moreover, the delay will force the energy economy to accept investment "detours," resulting in stranded investments.

**Contribution 3: Emphasis on the crucial role of rational price mechanism design**

Chapter 5, Chapter 6, and Chapter 7 have highlighted the dramatic effects of unsuitable pricing approaches on the development of renewable investment markets by analyzing the cases in Germany and Vietnam. We conclude that the main reason for the unsustainable solar and wind power development is the unsuitable FIT or auction mechanisms. Accurately, in Germany, the hybrid FIT mechanism from 2009 to 2012 caused unprecedented solar power investment because of the high predetermined degression rate. The later introduction of the monthly FIT adjustment has then demonstrated a smoother investment; however, the over or under-investment with high overshoot or undershoot has still occurred. On the other hand, the prediction-based FIT mechanism has caused massive solar power investment in Vietnam while wind power investment volume remained much lower than expectations. The unsustainable renewable power development entails consequences. Solar power overinvestment has failed to achieve social equality between electricity suppliers and consumers. Also, it has created challenges for the transmission system operation and investment. In contrast, wind power underinvestment has caused a lack of power supply, and in the long term, it would fail to meet climate change targets.

**Contribution 4: Construction of four different variants of models of investor behavior**

A major scientific result is the mathematical formulation of four different variants of models of investor behavior, termed a) threshold regression model, b) adaptive model, c) distributed lag model, d) first-order auto regressive model. The applicability of these models is tested against the historical data of the German investment market. The comparison shows the highest rate of predictability for the adaptive model. However, the predictive power of these models still needs further improvement to be used in practice.

**Contribution 5: Development of mathematical models of feedback-based price mechanisms**

The most forward-looking and valuable contribution of this dissertation is the development of mathematical shapes of feedback-based price mechanisms. This work is the first attempt to systematically analyze and apply feedback control theory to economic price mechanisms. The feedback approach is novel to modeling and thinking about price mechanisms with regard to two aspects: on the one hand, it removes the predetermined component, thus avoiding faulty decision-making because of unpredictable behavior. On the other hand, the regular price adjustment based on the deviation between the desired investment volume and the actual one narrows the deviation over time.

The approach to the PID controller – which compares the desired value and the system output and then minimizes the error by applying proportional, integral, and derivative terms – is developed to adjust prices for electricity from renewables to achieve the targeted development corridors. Chapter 5 has presented the efforts in formulating the discrete econometric PID-based price mechanisms. If the P controller is applied, the electricity price is adjusted based on the current investment gap. The PI controller requires storing one lagged investment deviation, while the PID controller requires two lagged investment deviations.

Applying regression analysis to historical data of FIT levels and solar power investment in Germany, we point out the consistency between feedback-based FIT adjustment for solar power in Germany and the proportional control rule. We conclude that if the steady-state error is acceptable, the proportional controller is reasonable and straightforward to use for price mechanism designs.

**Contribution 6: Suggestion of the application of the PID-based price mechanisms to specific renewable power investment markets**

Chapter 6 and Chapter 7 have suggested the application of the PID-based price mechanisms in Germany and Vietnam. These mechanisms are expected to avoid unnecessary mistakes while achieving more sustainable solar and wind power investment growth.

Besides the FIT mechanisms, Germany has applied the auction mechanism for renewables. In Chapter 6, we have suggested applying the feedback approach to determine the ceiling price under the auction mechanism. Similarly, Germany has also participated in the EU ETS; therefore, the proportional-based carbon price floor is recommended.

The current FIT mechanisms in Vietnam will be renewed or replaced with the auction mechanism or market premium mechanism. Chapter 7 has outlined possible scenarios of price mechanisms for Vietnam after the current FIT mechanism. We emphasize that whatever price mechanism will be employed, the feedback-based price mechanisms are necessary to guarantee sustainable renewable power investment growth. Moreover, scenarios of proportional-based FIT mechanisms for different technologies and scales have been carried out.

The formulation of simple rules, which attracted as they can be promoted as a transparent and effective policy, play an essential role in economic policy design in general, particularly energy policy design. It is a fact that most policymakers do not know and do not need to know the models of investor behavior. Because of simple rules and uncomplicated formulations, PID-based price mechanisms are easy to design, understand and preferable for policymakers. With suitable control parameters, the mechanisms can help achieve sustainable renewable power investment growth.

**In conclusion**, the market response is always the most accurate measure of any policy. Although the results of this study still leave room for further development, they already provide a good reference for policymakers and researchers in different nations and markets for designing energy policies and conducting relevant studies.

## 8.2. Limitations and further works

This dissertation has made an effort to achieve the research aims and answer the research questions in Chapter 1. However, due to the limited availability of accurate econometric data, the developed methodology has not yet been extensively and widely tested. This section suggests future research directions to reinforce the methodological foundations. Besides, some potential research expansions are also pointed out.

Firstly, Chapter 2 has illustrated regulatory policy patterns for technology diffusion, focusing on the incentive schemes for renewable power development. Such regulatory policy patterns are applicable for the energy transition in other sectors. For example, most of the energy used for space heating, cooling, and water heating in buildings is provided by fossil fuels. According to the REN21 (2020), renewables contributed only 10.1% to the global heating and cooling demand in 2018. Similarly, oil and petroleum products accounted for 96.7% of energy demand in the transport sector, while electricity from renewables contributed only 0.3%. Therefore, further and more detailed **studying of regulatory policies following the three-phase approach of research programs, funding incentives, auction incentives to entirely competitive markets for the diffusions of energy systems in buildings and the transport sector is suggested.**

Secondly, in Chapter 3, aggregate mathematical models of investor behavior have been constructed and tested. However, it is a fact that investors naturally behave differently, and they also respond significantly differently to changes in the market. Consequently, the prediction using the aggregate models has errors. In order to predict investor behavior more accurately, we suggest **constructing and studying individual-based models of investor behavior**.

Thirdly, due to data limitations and the impossibility of doing experiments, the performance and robustness of the feedback approach have not yet been simulated. Therefore, we suggest **evaluating the performance and robustness of the PID-based price mechanisms when more data is available**.

Fourthly, although the mathematical formulations of feedback-based price mechanisms are uncomplicated, choosing suitable controller parameter values in practical application is not easy. There are a few reasons for this. On the one hand, the historical data for the controller parameter estimation over different investment markets is unavailable. Consequently, we do not have reference values of the controller parameters. On the other hand, the controller parameters are time-variant because of investor behavior and investment environment variability. Therefore, using time-invariant parameters may lead to unsuitable price mechanism adjustments. Thus, a suggestion for future work is to **study the PID controller parameters with the consideration of country and time**.

Fifthly, in this research, the performance of the models of investor behavior and feedback-based price mechanisms have been evaluated for solar power investment only. Therefore, **a test on wind power investment markets** is necessary to reinforce the applicability of the developed approaches.

Finally, the feedback control approach is not limited to policy design for renewable power investment markets. It is applicable for any investment markets driven by regulatory policies to achieve the targeted investment volume by the government. For example, **the feedback approach can equally help policy design to guarantee sustainable heating and cooling system investment growth and mobility investment growth.**

## References


Abdelzaher, T. *et al.* (2008) 'Introduction to Control Theory And Its Application to Computing Systems', *Performance Modeling and Engineering*, pp. 185–215. doi: 10.1007/978-0-387-79361-0_7.

Agut, A. *et al.* (2016) *Wind Power Investment Guidelines for Vietnam. Volume 1: Project Development*.

Alexeenko, P. (2017) 'State Feedback Control in Macroeconomic Policy', pp. 1–24.

Ang, K. ., Chong, G. C. . and Li, Y. (2005) 'PID control system analysis, design, and technology', *IEEE Transaction on Control Systems Technology*, 13(November), pp. 559–576. doi: 10.1016/b978-85-352-7263-5.50018-7.

Anh Tu, C., Sarker, T. and Rasoulinezhad, E. (2020) 'Factors Influencing the Green Bond Market Expansion: Evidence from a Multi-Dimensional Analysis', *Journal of Risk and Financial Management*, 13(6), p. 126. doi: 10.3390/jrfm13060126.

Araki, M. (2017) 'PID Control', *Control Systems, Robotics, and Automation*, II, pp. 694–696. doi: 10.1109/icit.2017.7915443.

Astrom, K. J. (2002) 'PID control', in *Control System Design*, pp. 91-1-91–9. doi: 10.1201/b15474.

Astrom, K. J. and Murray, R. M. (2009) *Feedback Systems: An Introduction for Scientists and Engineers, Princeton University Press*. Princeton University Press.

Athans, M. and Kendrik, D. (1974) 'Control Theory and Economics: A Survey, Forecast, and Speculations', *IEEE Transactions on Automatic Control*, (October).

Azhgaliyeva, D., Kapsalyamova, Z. and Low, L. (2019) *Implications of Fiscal and Financial Policies on Unlocking Green Finance and Green Investment, Handbook of Green Finance*. doi: 10.1007/978-981-13-0227-5_32.

Bakhtyar, B. *et al.* (2017) 'Review of CO2 price in Europe using feed-in tariff rates', *Renewable and Sustainable Energy Reviews*. Elsevier, 69(October 2015), pp. 685–691. doi: 10.1016/j.rser.2016.11.146.

Baltagi, B. H. (2008) *Econometrics*. Fourth, *Springer*. Fourth. doi: 10.1007/978-3-540-76516-5.

Barbosa, J. C. (2003) 'What is Mathematical Modelling?', in *Mathematical Modelling: A Way* *of Life*, pp. 227–234. doi: 10.1533/9780857099549.5.227.

Barcelona, R. G. (2015) 'Renewable Energy with Volatile Prices: Why NPV Fails to Tell the Whole Story', *Journal of Applied Corporate Finance*, 27(1), pp. 101–109. doi: 10.1111/jacf.12109.

Bass, F. M. (1969) 'A new product growth for model consumer durables', *Management Science*, 15(5), pp. 215–227.

Bellman, R. (1954) 'The Theory of Dynamic Programming', *Bulletin of the American Mathematical Society*, pp. 503–515. doi: 10.1090/S0002-9904-1954-09848-8.

Benassy-Quere, A. *et al.* (2019) *Economic Policy: Theory and Practice*. 2nd edn. Oxford University Press.

Bequette, B. W. (2003) *Process control: modeling, design, and simulation*. Prentice Hall.

Bergek, A., Mignon, I. and Sundberg, G. (2013) 'Who invests in renewable electricity production? Empirical evidence and suggestions for further research', *Energy Policy*. Elsevier, 56, pp. 568–581. doi: 10.1016/j.enpol.2013.01.038.

Bird, L., Cochran, J. and Wang, X. (2014) 'Wind and Solar Energy Curtailment: Experience and Practices in the United States', *National Renewable Energy Laboratory (NREL)*, (March), p. 58. doi: 10.2172/1126842.

BMWi and AGEE-Stat (2021) *Time series for the development of renewable energy sources in Germany (Status: February 2020), Federal Environment Agenc*. Available at: https://www.erneuerbare-energien.de/EE/Redaktion/DE/Downloads/zeitreihen-zur-entwicklung-der-erneuerbaren-energien-in-deutschland-1990-2019-en.pdf?__blob=publicationFile&v=10.

De Boeck, L. *et al.* (2016) 'Comparison of support policies for residential photovoltaic systems in the major EU markets through investment profitability', *Renewable Energy*. Elsevier Ltd, 87, pp. 42–53. doi: 10.1016/j.renene.2015.09.063.

Brohé, A. and Burniaux, S. (2016) 'The impact of the EU ETS on firms' investment decisions: Evidence from a survey', *Carbon Management*, 6(5–6), pp. 221–231. doi: 10.1080/17583004.2015.1131384.

Bui, H. P. (2017) 'Coal-fired power, waste, and cooling water', *Energy Journal of Vietnam*, 142, pp. 12–14.

Burger, B. (2021) *Net Public Electricity Generation in Germany in 2020*, *Energy-Charts*.

Available at: https://energy-charts.info/?l=en&c=DE (Accessed: 7 June 2021).

Carbone, R. and Longini, R. L. (1977) 'A Feedback Model for Automated Real Estate Assessment', *Management Science*, 24(3), pp. 241–248. doi: 10.1287/mnsc.24.3.241.

Chang, Y., Fang, Z. and Li, Y. (2016) 'Renewable energy policies in promoting financing and investment among the East Asia Summit countries: Quantitative assessment and policy implications', *Energy Policy*. Elsevier, 95, pp. 427–436. doi: 10.1016/j.enpol.2016.02.017.

Chow, G. C. (1976) 'The Control of Nonlinear Econometric Systems with Unknown Parameters', *Journal of the Econometric Society*, 44(4), pp. 685–695.

Chu, B. *et al.* (2012) 'Using Economic Model Predictive Control to Design Sustainable Policies for Mitigating Climate Change', *51st IEEE Conference on Decision and Control*, pp. 1–6.

Chu, B. *et al.* (2013) 'Analysis and control design of sustainable policies for greenhouse gas emissions', *Applied Thermal Engineering*. Elsevier Ltd, 53(2), pp. 420–431. doi: 10.1016/j.applthermaleng.2012.04.022.

Climate Policy Initiative (2016) 'Policy and investment in German renewable energy', (April), p. 84.

Couture, T. and Gagnon, Y. (2010) 'An analysis of feed-in tariff remuneration models: Implications for renewable energy investment', *Energy Policy*. Elsevier, 38(2), pp. 955–965. doi: 10.1016/j.enpol.2009.10.047.

Cox, S. and Esterly, S. (2016) *Renewable Electricity Standards: Good Practices and Design Considerations. A Clean Energy Regulators Initiative Report*.

*Daily EU ETS carbon market price* (2021) *EMBER*. Available at: https://ember-climate.org/data/carbon-price-viewer/ (Accessed: 7 May 2021).

Danish Energy Agency *et al.* (2019) *Vietnam Technology Catelogue 2019*.

Darmani, A., Niesten, E. and Hekkert, M. (2014) 'Which Investors Drive the Development of Wind Energy?', *Industrial Economics and Management Electronic Working Paper Series*.

Derakhshan, M. (2015) 'Control Theory and Economic Policy Optimization : The Origin, Achievements and the Fading Optimism from a Historical Standpoint', *International Journal of Business and Development Studies*, 7(1), pp. 5–29.

Dorf, R. C. and Bishop, R. H. (2011) *Modern Control Systems*. Prentice Hall.

Doyle, J., Francis, B. and Tannenbaum, A. (1990) 'Feedback Control Theory', *Design*, 134(6), p. 219. doi: 10.1016/0005-1098(86)90018-X.

Drury, E., Denholm, P. and Margolis, R. (2011) *The Impact of Different Economic Performance Metrics on the Perceived Value of Solar Photovoltaics*, *Technical Report (NREL/TP-6A20-52197)*.

*Effective interest rates for banks/new business/housing loans to private households, initial fixed interest rate over ten years* (no date) *German Federal Bank*. Available at: https://www.bundesbank.de/dynamic/action/de/statistiken/zeitreihen-datenbanken/zeitreihen-datenbank/723452/723452?https=1&https=1&https=1&https=1&https=1&https=1&tsId=BBK01.SUD119 (Accessed: 17 June 2021).

Egli, F., Steffen, B. and Schmidt, T. S. (2018) 'A dynamic analysis of financing conditions for renewable energy technologies', *Nature Energy*. Springer US, 3(12), pp. 1084–1092. doi: 10.1038/s41560-018-0277-y.

Egli, P. and Lecuyer, O. (2017) 'Quantifying the net cost of a carbon price floor in Germany', *Energy Policy*. Elsevier Ltd, 109(July), pp. 685–693. doi: 10.1016/j.enpol.2017.07.035.

*EU Emissions Trading System (EU ETS)* (no date) *European Union*. Available at: https://ec.europa.eu/clima/policies/ets_en (Accessed: 16 June 2021).

European Commission (2015) *EU ETS Handbook*, *Climate Action*. Available at: http://ec.europa.eu/clima/publications/docs/ets_handbook_en.pdf.

European Environment Agency (2017) *Energy and climate change*. Available at: https://www.eea.europa.eu/signals/signals-2017/articles/energy-and-climate-change (Accessed: 16 May 2021).

Federal Government of Germany (2019) *Climate protection program 2030 of the federal government for the implementation of the climate protection plan 2050*.

Federal Ministry for Economic Affairs and Energy (BMWi) (2020) *2020 Federal Report on Energy Research*.

Federal Ministry for the Environment Nature Conversion and Nuclear Safety (BMU) (2020) *Climate Action in Figures: Facts, Trends, and Incentives for German Climate Policy*.

Federal Network Agency (2021a) *Archived EEG tariff rates and data reports*. Available at: https://www.bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen_Institutionen/ErneuerbareEnergien/ZahlenDatenInformationen/EEG_Registerdaten/ArchivDatenMeldgn/ArchivDatenMeldgn_node.html (Accessed: 6 June 2021).

Federal Network Agency (2021b) *Completed tenders of onshore wind power*. Available at: https://www.bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen_Institu tionen/Ausschreibungen/Wind_Onshore/BeendeteAusschreibungen/BeendeteAusschreibungen_node.html (Accessed: 7 May 2021).

Federal Network Agency (2021c) *Completed tenders of solar power*. Available at: https://www.bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen_Institutionen/Ausschreibungen/Solaranlagen1/BeendeteAusschreibungen/BeendeteAusschreibungen_node.html) (Accessed: 7 May 2021).

Finon, D., Menanteau, P. and Lamy, M.-L. (2002) 'Price-based versus quantity-based approaches for stimulating the development of renewable electricity: new insights in an old debate', *Paper prepared for the 25th Annual International Conference of the IAEE (International Association of Energy\rEconomics)*, (September 2001). Available at: http://www.iaee.org/documents/.

Flachsland, C. *et al*. (2018) 'Five myths about an EU ETS carbon price floor', *CEPS Policy Insights*, (October), pp. 1–14.

Fraunhofer Institute for Solar Energy Systems (Fraunhofer ISE) (2020) *Press release: German net electricity generation in the first half of 2020: Renewables reach record share of 55.8 percent*.

Fraunhofer Institute for Solar Energy Systems (ISE) (2020) *Photovoltaics Report*.

Gawel, E., Korte, K. and Tews, K. (2015) 'Distributional Challenges of Sustainability Policies — The Case of the German Energy Transition', (September), pp. 16599–16615.

Georgakellos, D. A. and Macris, A. M. (2009) 'Application of the semantic learning approach in the feasibility studies preparation training process', *Information Systems Management*, 26(3), pp. 231–240. doi: 10.1080/10580530903017708.

German Federal Parliament (2000) *Renewable Energy Source Act (EEG 2000)*.

German Federal Parliament (2004) *Renewable Energy Source Act (EEG 2004)*.

German Federal Parliament (2009) *Renewable Energy Sources Act (EEG 2009)*. doi: 10.1007/978-3-658-07554-5_2.

German Federal Parliament (2010) *PV Act 2010*.

German Federal Parliament (2012) *Renewable Energy Sources Act (EEG 2012)*.

German Federal Parliament (2014) *Renewable Energy Sources Act (EEG 2014)*.

German Federal Parliament (2017) *Renewable Energy Sources Act (EEG 2017)*.

German Federal Parliament (2018) *Law amending of the Renewable Energy Sources Act, the*

*Combined Heat and Power Act, the Energy Industry Act and other energy regulations*.

Government of Vietnam (2011) *Decision 37/2011/QD-TTg on the mechanisms to encourage the development of wind power projects in Vietnam*.

Government of Vietnam (2016a) *Decision 428/QD-TTg on the Approval of the revised National Power Development Plan for the period from 2011 to 2020, with a vision to 2030*.

Government of Vietnam (2016b) 'Decision on the Approval of the revised national power development master plan for the 2011 - 2020 period with the vision on 2030'.

Government of Vietnam (2017a) *Decision 24/2017/QD-TTg on the mechanism for mean retail electricity price adjustment*.

Government of Vietnam (2017b) *Decree 94/2017/ND-CP on goods, services, geographical areas that exercise state monopoly in commercial activities*.

Government of Vietnam (2018) *Decision 39/2018/QD-TTg on the compensation regulation of the mechanisms to encourage the development of wind power projects in Vietnam*.

Grafström, J., Fellow, O.-S. A. and Poudineh, R. (2021) *A critical assessment of learning curves for solar and wind power technologies*.

Grau, T. (2014) 'Responsive feed-in tariff adjustment to dynamic technology development', *Energy Economics*. Elsevier B.V., 44, pp. 36–46. doi: 10.1016/j.eneco.2014.03.015.

Grubler, A. and Nakicenovic, N. (1991) 'Long waves, technology diffusion, and substitution', *Review (Fernand Braudel Center)*, 14(2), pp. 313–343.

Gupta, M. M. (1979) 'A Confluence of Feedback Loops in Social and Educational Structure: (in the Context of Developing and Developed Countries)', *IFAC Proceedings Volumes*. Elsevier, 12(6), pp. 221–229. doi: 10.1016/S1474-6670(17)65697-0.

Gy, M. and Gerencser, L. (2002) 'BIBO stability of linear switching systems', *IEEE Transactions on Automatic Control*, 47(11). doi: 10.1109/TAC.2002.804470.

Hawkins, R. J., Speakes, J. K. and Hamilton, D. E. (2015) 'Monetary policy and PID control', *Journal of Economic Interaction and Coordination*, 10(1), pp. 183–197. doi: 10.1007/s11403-014-0127-3.

Hayashi, F. (2000) *Econometrics*. Princeton University Press.

Heidarinejad, M., Liu, J. and Christofdes, P. D. (2011) 'Economic Model Predictive Control of Nonlinear Process Systems Using Lapunove Techniques', *AIChE Journal*, 59(4), pp. 215–228. doi: 10.1002/aic.

Heiskanen, E. *et al.* (2017) 'Small streams, diverse sources: Who invests in renewable energy in Finland during the financial downturn?', *Energy Policy*. Elsevier Ltd, 106(February 2016), pp. 191–200. doi: 10.1016/j.enpol.2017.03.013.

Hiep, D. T. and Hoffmann, C. (2018) 'Innovation of price adjustment mechanisms to support investment in solar power in Germany', *E3S Web of Conference*, 64. doi: https://doi.org/10.1051/e3sconf/20186402007.

Hiep, D. T. and Hoffmann, C. (2019a) 'A Power Development Planning for Vietnam under the CO2 Emission Reduction Targets', *Energy Reports*. Elsevier Ltd, 6(September), pp. 19–24. doi: 10.1016/j.egyr.2019.11.036.

Hiep, D. T. and Hoffmann, C. (2019b) 'Estimation of the Future Electricity Price Surcharge for the Integration of Wind and Solar Power into the Vietnamese Electricity System', *2019 IEEE Asia Power and Energy Engineering Conference (APEEC)*. IEEE, pp. 263–268. doi: 10.1109/APEEC.2019.8720702.

Hirst, D. (2018) *Carbon Price Floor (CPF) and the price support mechanism, House of Commons Library Briefing Paper*. Available at: https://researchbriefings.parliament.uk/ResearchBriefing/Summary/SN05927.

Hochberg, M. and Poudineh, R. (2018) *Renewable Auction Design in Theory and Practice: Lessons from the Experiences of Brazil and Mexico, Oxford Institute for Energy Studies*.

Hove, A. *et al.* (2020) *China Energy Transition Status Report 2020*.

Hurlin, C. (2018) 'Chapter 3. Panel Threshold Regression Models', *Lecture Slides*, (May).

*Information on Hour-Ahead Market, date 03 March 2020* (no date) *National Load Dispatch Center of Vietnam (NLDC)*. Available at: https://www.nldc.evn.vn/FullNewsg/100/Thong-tin-thi-truong-dien/default.aspx (Accessed: 26 June 2021).

Intergovernmental Panel on Climate Change (IPCC) (2018) 'Annex I: Glossary [Matthews, J.B.R. (ed.)]', in *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,*.

International Renewable Energy Agency (2020) *Green bonds - Renewable Energy Finance Brief 03*. Available at: www.irena.org/publications.

Investopedia (2021) *Internal Rate of Return (IRR) Definition & Formula*. Available at: https://www.investopedia.com/terms/i/irr.asp (Accessed: 1 June 2021).

IRENA (2016) *Unlocking Renewable Energy Investment: The Role of Risk Mitigation and Structured Finance.*

IRENA (2018) *Renewable Power Generation Costs in 2018*, *International Renewable Energy Agency*. doi: 10.1007/SpringerReference_7300.

IRENA (2019a) *Future of Solar Photovoltaic: Deployment, investment, technology, grid integration and socio-economic aspects, International Renewable Energy Agency (IRENA).* Available at: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Oct/IRENA_Future_of_wind_2019.pdf.

IRENA (2019b) *Future of Wind: Deployment, investment, technology, grid integration and socio-economic aspects (A global energy transformation paper)*, *International Renewable Energy Agency*. Available at: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Oct/IRENA_Future_of_wind_2019.pdf.

IRENA (2020) *Renewable Power Generation Costs in 2019*, *International Renewable Energy Agency*. Available at: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2018/Jan/IRENA_2017_Power_Costs_2018.pdf.

IRENA and CEM (2015) *Renewable Energy Auctions - A Guide to Design*. Available at: www.irena.org.

Kersten, F. *et al.* (2011) 'PV Learning Curves: Past and Future Drivers of Cost Reduction', *Proc. 26th European Photovoltaic Solar Energy Conference*, (September), pp. 4697–4702. doi: 10.4229/26thEUPVSEC2011-6CV.1.63.

Kim, K., Park, H. and Kim, H. (2017) 'Real options analysis for renewable energy investment decisions in developing countries', *Renewable and Sustainable Energy Reviews*. Elsevier, 75(October 2015), pp. 918–926. doi: 10.1016/j.rser.2016.11.073.

Kim, Y. C., Keel, L. H. and Manabe, S. (2002) 'Controller design for time domain specifications', *IFAC Proceedings Volumes (IFAC-PapersOnline)*. IFAC, 35(1), pp. 37–42. doi: 10.3182/20020721-6-es-1901.01232.

Kitzing, L. *et al.* (2016) *Recommendations on the role of auctions in a new renewable energy directive*.

Klein, A. *et al.* (2010) *Evaluation of Different Feed-in Tariff Design Options: Best Practice Paper for the International Feed-in Cooperation*, *Energy Economics Group & Fraunhofer Institute Systems and Innovation Research, Germany*. Available at: http://www.renewwisconsin.org/policy/ARTS/MISC

Docs/best_practice_paper_2nd_edition_final.pdf.

Klein, M. and Deissenroth, M. (2017) ‘When do households invest in solar photovoltaics? An application of prospect theory’, *Energy Policy*. Elsevier Ltd, 109(June), pp. 270–278. doi: 10.1016/j.enpol.2017.06.067.

Kost, C. *et al.* (2018) ‘Levelized Cost of Renewable Energy Technologies’, (March). Available at: http://www.ise.fraunhofer.de/en/publications/veroeffentlichungen-pdf-dateien-en/studien-und-konzeptpapiere/study-levelized-cost-of-electricity-renewable-energies.pdf.

Kostarakos, I. and Kotsios, S. (2017) ‘Feedback policy rules for government spending: an algorithmic approach’, *Journal of Economic Structures*. Springer Berlin Heidelberg, 6(1), pp. 1–10. doi: 10.1186/s40008-017-0065-z.

Kotler, P. (1996) *Marketing Management: Analysis, Planning, Implementation, and Control*. 9th edn.

Koyck, L. M. (1954) *Distributed Lags, and Investment Analysis*. Amsterdam, The Netherlands: North-Holland Publishing Company. doi: 10.1017/S1373971900069778.

Krause, F., Bossel, H. and Mueller-Reissmann, K.-F. (1980) *Energy transition: Growth and prosperity without crude oil and uranium*.

Kreiss, J., Ehrhart, K. M. and Hanke, A. K. (2017) ‘Auction-theoretic analyses of the first offshore wind energy auction in Germany’, *Journal of Physics: Conference Series*, 926(1). doi: 10.1088/1742-6596/926/1/012015.

Kuphaldt, T. R. (2018) ‘Chapter 33. Process dynamics and PID controller tuning’, in *Lessons in Industrial Instrumentation*. Creative Commons Attribution 4.0 International Public License.

Lantz, E., Wiser, R. and Hand, M. (2012) *IEA Wind Task 26: The past and future cost of wind energy, National Renewable Energy Laboratory*.

Le, P. V. (2019) ‘Energy demand and factor substitution in Vietnam: evidence from two recent enterprise surveys’, *Journal of Economic Structures*. Springer Berlin Heidelberg, 8(1). doi: 10.1186/s40008-019-0168-9.

Ledzewicz, U. and Schättler, H. (2004) ‘Application of control theory in modeling cancer chemotherapy’, in *International Conference on Control, Automation, and Systems*. Available at: http://www.siue.edu/~uledzew/papers/pprBangkok.pdf.

Leff, P. E. E. (2000) *Introduction of Feedback Control Systems, Coronado Systems*.

*List of solar projects in Vietnam* (2021) *DEVI Renewable Energies*. Available at:

https://docs.google.com/spreadsheets/d/1SYraolsm8s_23xyfVf-7bHzlblDHEMa_T_HMZyRdJUQ/edit?ts=5c453484#gid=182466376 (Accessed: 17 June 2021).

*List of wind projects in Vietnam* (2021a) *DEVI Renewable Energies*. Available at: https://docs.google.com/spreadsheets/d/1hQNS0W-EDO5DDw6TppV7pyYdyagCDmHuASHHZBxQHxo/edit#gid=182466376 (Accessed: 25 June 2021).

*List of wind projects in Vietnam* (2021b) *DEVI Renewable Energies*. Available at: https://docs.google.com/spreadsheets/d/1hQNS0W-EDO5DDw6TppV7pyYdyagCDmHuASHHZBxQHxo/edit#gid=182466376 (Accessed: 17 June 2021).

Liu, X. and Zeng, M. (2017) 'Renewable energy investment risk evaluation model based on system dynamics', *Renewable and Sustainable Energy Reviews*. Elsevier Ltd, 73(April 2016), pp. 782–788. doi: 10.1016/j.rser.2017.02.019.

Liviatan, N. (1963) 'Consistent Estimation of Distributed Lags', *International Economic Review*, 4(1), pp. 44–52.

Mahajan, V., Bretschneider, S. I. and Bradford, J. W. (1980) 'Feedback Approaches to Modeling Structural Shifts in Market Response', *Journal of Marketing*, 44(1), p. 71. doi: 10.2307/1250037.

Martin, R., Muûls, M. and Wagner, U. (2011) 'Climate Change, Investment and Carbon Markets, and Prices – Evidence from Manager Interviews', *Carbon Pricing for Low-Carbon Investment Project*, (January), pp. 1–30.

Masini, A. and Menichetti, E. (2012) 'The impact of behavioural factors in the renewable energy investment decision making process: Conceptual framework and empirical findings', *Energy Policy*. Elsevier, 40(1), pp. 28–38. doi: 10.1016/j.enpol.2010.06.062.

Ministry of Finance of Vietnam (2019) *Official dispatch on Incentive policies for rooftop solar power projects with an installed capacity of not exceeding 50 kW*. Available at: http://www.mof.gov.tw/ct.asp?xItem=58412&ctNode=657&mp=1.

Ministry of Industry and Trade of Vietnam (2018) *Circular 45/2018/TT-BCT on regulations on operating the competitive wholesale electricity market.pdf*.

Ministry of Industry and Trade of Vietnam (2019) *Decision 648/QD-BCT on the Adjustment of the mean retail price and the regulation on electricity price*. Available at:

https://www.evn.com.vn/d6/news/Quyet-dinh-so-648QD-BCT-ngay-2032019-ve-dieu-chinh-muc-gia-ban-le-dien-binh-quan-va-quy-dinh-gia-ban-dien-9-130-23316.aspx.

Ministry of Industry and Trade of Vietnam (2020) *Draft National Power Development Plan for the period from 2021 to 2030, with a Vision towards 2045*.

Ministry of Industry and Trade of Vietnam (2021) *National energy master plan for the period 2021-2030, vision 2050*.

Ministry of Natural Resources and Environment of Vietnam (2017) *The second biennial updated report of Vietnam to the United Nations framework convention on climate change*.

Morris, C. (2018a) *Share of German citizen renewable energy shrinking*, *Energy Transition*. Available at: https://energytransition.org/2018/02/share-of-german-citizen-renewable-energy-shrinking/ (Accessed: 10 May 2021).

Morris, C. (2018b) *Share of German citizen renewable energy shrinking*, *Energy Transition*. Available at: https://energytransition.org/2018/02/share-of-german-citizen-renewable-energy-shrinking/ (Accessed: 7 June 2021).

Moura, S. (2018) 'Chapter 1: Modeling and Systems Analysis', in *Energy Systems and Control*, pp. 1–28.

*National Business Registration Portal* (2021). Available at: https://dangkykinhdoanh.gov.vn/en/Pages/default.aspx (Accessed: 17 June 2021).

Neck, R. (2009) 'Control theory and economic policy: Balance and perspectives', *Annual Reviews in Control, Elsevier*, 33, pp. 79–88. doi: 10.1016/j.arcontrol.2009.03.004.

Neck, R. and Karbuz, S. (1997) 'Optimal control of fiscal policies for Austria: Applications of a stochastic control algorithm', *Nonlinear Analysis, Theory, Methods and Applications*, 30(2), pp. 1051–1061. doi: 10.1016/S0362-546X(97)00134-X.

Neuhoff, K. (2011) 'Carbon Pricing for Low-Carbon Investment: Executive Summary', *Climate Policy*, (January), p. 9. Available at: http://climatepolicyinitiative.org/wp-content/uploads/2011/12/Carbon-Pricing-Exec-Summary.pdf.

Newbery, D., Reiner, D. and Ritz, R. (2018) *When is a carbon price floor desirable?*, *Cambridge Working Paper in Economics*.

Ogata, K. (2005) 'Mathematical Modelling of Control Systems', *Modern control Engineering*, pp. 13–62.

Onatski, A. and Stock, J. H. (2002) 'Robust monetary policy under model uncertainty in a small model of the U.S. economy', *Macroeconomic Dynamics*, 6(1), pp. 85–110. doi: 10.1017/S1365100502027050.

Ostojic, I. (2010) *Bass innovation diffusion model and its application in policy analysis for the adoption of renewable energy technologies*.

Owayjan, M., Daou, R. A. Z. and Moreau, X. (2015) 'A comparison between frequency domain and time domain controller synthesis: Position control of a DC motor', *2015 3rd International Conference on Technological Advances in Electrical, Electronics and Computer Engineering, TAEECE 2015*, (July), pp. 201–206. doi: 10.1109/TAEECE.2015.7113627.

Paschalia, D. G. (2012) *The non-linear Bass diffusion model on Renewable Energy Technologies in European countries*. Aristotle University of Thessaloniki.

Phillips, A. W. (1957) 'Stabilisation policy and the time-forms of lagged responses', *Economic Journal*, pp. 169–183. doi: 10.1017/cbo9780511521980.019.

Prime Minister of Vietnam (2015) *Decision on Vietnam's Renewable Energy Development Strategy up to 2030 with outlook to 2050*.

Prime Minister of Vietnam (2016) *Decision 403/QD-TTg on Approval and Adjustment of Vietnam Coal Industry Development Plan to 2020, with a Vision to 2030*.

Prime Minister of Vietnam (2017a) *Decision 11/2017/QD-TTG on the mechanisms to encourage the development of solar power projects in Vietnam*.

Prime Minister of Vietnam (2017b) *Decision 60/QD-TTg on Approval of Vietnam Gas Industry Development Plan to 2025, with a Vision to 2035*.

Prime Minister of Vietnam (2020) *Decision 13/2020/QD-TTg on Support Mechanisms for Solar Power in Vietnam.*

Ramstein, C. *et al.* (2019) *State and Trends of Carbon Pricing 2019*, *State and Trends of Carbon Pricing 2019*. doi: 10.1596/978-1-4648-1435-8.

Rao, K. U. and Kishore, V. V. N. (2010) 'A review of technology diffusion models with special reference to renewable energy technologies', *Renewable and Sustainable Energy Reviews*, 14(3), pp. 1070–1078. doi: 10.1016/j.rser.2009.11.007.

Rayner, M. E. and Bender, E. A. (2008) *An Introduction to Mathematical Modelling*. doi: 10.2307/3615903.

Rehber, E. (1999) 'Financial Analysis of Investment Alternatives', in *Guidelines for the Emerging Economies: University for Economic Activities, Warsaw, Poland*, pp. 137–150. doi:

10.2307/2977324.

Renewable Energy Policy Network for the 21st century (REN21) (2020) *Renewables 2020: global status report*.

Renewable Energy Policy Network for the 21st century (REN21) (2021) *Renewables 2021 Global Status Report, REN21*. Available at: https://www.ren21.net/wp-content/uploads/2019/05/gsr_2020_full_report_en.pdf%0Ahttp://www.ren21.net/resources/publications/.

Ricke, K. *et al.* (2018) 'Country-level social cost of carbon', *Nature Climate Change*, 8(10), pp. 895–900. doi: 10.1038/s41558-018-0282-y.

Robinson, D. T. (2007) 'Control theories in sociology', *Annual Review of Sociology*, 33, pp. 157–174. doi: 10.1146/annurev.soc.32.061604.123110.

Rogers, E. M. (1983) *Diffusion of Innovations*. Third Edit. The Free Press.

*Rooftop Solar Market Update (Until May 2020)* (no date) *The Rooftop solar*. Available at: http://rooftopsolar.com.vn/rooftop-solar-market-update-until-feb-20201.html (Accessed: 17 June 2021).

Sach, T., Lotz, B. and Bluecher, F. von (2019) *Auctions for the support of renewable energy in Germany Main results and lessons learnt*.

Sanseverino, E. R. *et al.* (2020) 'Review of Potential and Actual Penetration of Solar Power in Vietnam', *Energies*, pp. 7–9. doi: 10.3390/en13102529.

Shalabh, I. K. (2018) 'Chapter 1. Introduction to Econometrics', in *Econometrics*, pp. 1–12.

Shepherd, D., Torres, R. I. M. and Saridakis, G. (2018) 'Monetary policy rules with PID control features: Evidence from the UK, USA and EU', *International Review of Applied Economics*.

Taylor, J. B. (1993) *Macroeconomic policy in a world economy: from econometric design to practical operation, Stanford University*. doi: 10.1016/s0164-0704(96)80017-6.

Taylor, J. B. (1999) 'A Historical Analysis of Monetary Policy Rules', *NBER Chapters*, I(January), pp. 319–348.

Taylor, J. B. and Wieland, V. (2012) *Surprising Comparative Properties of Monetary Models: Results from a New Model Database*.

Taylor, J. B. and Williams, J. C. (2010) *Simple and Robust Rules for Monetary Policy*.

The central executive committee of Vietnam (2020) *Resolution of the political regarding the strategic orientations for the national energy development in Vietnam up to 2030 with a vision* *to 2045*.

The Vietnamese national assembly (2004) 'Electricity law', pp. 1–45.

Thure, T., Claudia, K. and Jochen, D. (2011) 'German electricity prices: Only modest increase due to renewable energy expected', *Deutsches Institut für Wirtschaftsforschung (DIW)*, 7(6), pp. 37–46.

Togeby, M. (2017) *Macroeconomic Cost-Benefit Analysis for Renewable Energy Integration*.

*Total energy supply (TES) by source, Germany 1990-2019* (no date) *IEA*. Available at: https://www.iea.org/countries/germany (Accessed: 17 June 2021).

*Total energy supply (TES) by source, Vietnam 1990-2019* (no date) *IEA*. Available at: https://www.iea.org/countries/viet-nam (Accessed: 7 June 2021).

Tustin, A. (1953) *The Mechanism of Economic Systems: An Approach to the Problem of Economic Stabilisation from the Point of View of Control-System Engineering*, *London: William Heinemann Ltd*. doi: 10.2307/1925755.

U.S Energy Information Administration (2020) *Electric Power Monthly with Data for December 2019*.

United Nations Framework Convention on Climate Change (2016) *Report of the Conference of the Parties on COP 21*, *Conference of the Parties on its twenty-first session (COP 21).* Available at: https://unfccc.int/process-and-meetings/conferences/past-conferences/paris-climate-change-conference-november-2015/cop-21.

US Environmental Protection Agency (2016) *Chapter 5. Renewable Portfolio Standards*.

Viet, N. Q. (2021) *Developing credit for renewable energy in Vietnam*, *Finance Magazine.* Available at: https://tapchitaichinh.vn/ngan-hang/phat-trien-tin-dung-cho-nang-luong-tai-tao-o-viet-nam-332668.html (Accessed: 21 June 2021).

*Vietnam's Economy Expanded by 6.8 Percent in 2019 but Reforms are Needed to Unleash the Potential of Capital Markets* (2019) *The World Bank*. Available at: https://www.worldbank.org/en/news/press-release/2019/12/17/vietnams-economy-expanded-by-68-percent-in-2019-but-reforms-are-needed-to-unleash-the-potential-of-capital-markets (Accessed: 17 June 2021).

Vietnam, G. of (2016) *Plan for implementation of the Paris agreement*.

Wanders, S. (2010) *Kirchhoff ' s Voltage Law*.

Wang, P. *et al.* (2019) 'Estimates of the social cost of carbon: A review based on meta-analysis', *Journal of Cleaner Production*. Elsevier Ltd, 209, pp. 1494–1507. doi: 10.1016/j.jclepro.2018.11.058.

Werner, L. and Scholtens, B. (2017) ‘Firm Type, Feed-in Tariff, and Wind Energy Investment in Germany: An Investigation of Decision-Making Factors of Energy Producers Regarding Investing in Wind Energy Capacity’, *Journal of Industrial Ecology*, 21(2), pp. 402–411. doi: 10.1111/jiec.12443.

Wiesenthal, T. *et al.* (2012) *Technology Learning Curves for Energy Policy Support, For the European Union*. doi: 10.2790/59345.

Wietschel, M. *et al.* (2018) *Sektorkopplung – Definition, Chancen und Herausforderungen*.

Windeurope (2016) *WindEurope views on curtailment of wind power and its links to priority dispatch, Windeurope*.

World Bank Group (2017) *Linking Up: Public-Private Partnerships in Power Transmission in Africa*.

World Nuclear Association (2011) *Comparison of Lifecycle Greenhouse Gas Emissions of Various Electricity Generation Sources*.

Yohe, G. *et al.* (2007) *Perspectives on Climate Change and Sustainability. Climate Change 2007: Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press*.

Zapata, H. and Gauthier, W. (2003) ‘Threshold Models in Theory and Practice’, *Southern Agricultural Economics Association Annual Meeting*, p. 17. Available at: https://ageconsearch.umn.edu/bitstream/35147/1/sp03za06.pdf.

Zhang, M. M. *et al.* (2016) ‘Optimal feed-in tariff for solar photovoltaic power generation in China: A real options analysis’, *Energy Policy*. Elsevier, 97, pp. 181–192. doi: 10.1016/j.enpol.2016.07.028.

Zhang, W. and Semmler, W. (2003) ‘Monetary policy rules under uncertainty: Empirical evidence, adaptive learning, and robust control’, *Macroeconomic Dynamics*, 9(5), pp. 651–681. doi: 10.1017/S1365100505040332.

Ziegler, M. (2011) *Photovoltaic price index, photovoltaik-guide.de*. Available at: https://www.photovoltaik-guide.de/photovoltaik-preisindex-24386 (Accessed: 14 June 2021).

# Appendices

Appendix 1. Data of solar power investment in Germany between 2000 and 2020 (BMWi and AGEE-Stat, 2021)

| **Year** | **Total new investment cost** | **Annually installed capacity** | **Average new specific investment cost** | **Average new specific O&M costs** | **Average electricity price for new investment** | **Average full-load hours of new installation** |
|---|---|---|---|---|---|---|
| | Million Euro | MW/year | Million Euro/MW | Million Euro/MW | Euro cents/kWh | Hours |
| 2000 | 260 | 44 | 5.91 | 0.118 | 50.62 | 1,000 |
| 2001 | 360 | 62 | 5.81 | 0.116 | 50.62 | 1,000 |
| 2002 | 680 | 120 | 5.67 | 0.113 | 48.10 | 1,000 |
| 2003 | 760 | 139 | 5.47 | 0.109 | 45.70 | 1,000 |
| 2004 | 3,530 | 670 | 5.27 | 0.105 | 54.60 | 1,000 |
| 2005 | 4,840 | 951 | 5.09 | 0.102 | 51.87 | 1,000 |
| 2006 | 4,010 | 843 | 4.75 | 0.095 | 49.28 | 1,000 |
| 2007 | 5,330 | 1,271 | 4.17 | 0.083 | 46.82 | 1,000 |
| 2008 | 7,970 | 1,950 | 4.10 | 0.082 | 44.48 | 1,000 |
| 2009 | 13,570 | 4,446 | 3.06 | 0.061 | 40.91 | 1,000 |
| 2010 | 19,580 | 7,440 | 2.63 | 0.053 | 34.73 | 1,000 |
| 2011 | 15,860 | 7,910 | 2.00 | 0.040 | 27.33 | 1,000 |

| Year | Total new investment cost | Annually installed capacity | Average new specific investment cost | Average new specific O&M costs | Average electricity price for new investment | Average full-load hours of new installation |
|---|---|---|---|---|---|---|
| | Million Euro | MW/year | Million Euro/MW | Million Euro/MW | Euro cents/kWh | Hours |
| 2012 | 11,980 | 8,161 | 1.47 | 0.029 | 19.08 | 1,000 |
| 2013 | 3,380 | 2,633 | 1.27 | 0.025 | 14.50 | 1,000 |
| 2014 | 1,450 | 1,190 | 1.22 | 0.024 | 12.48 | 1,000 |
| 2015 | 1,480 | 1,324 | 1.27 | 0.025 | 10.67 | 1,000 |
| 2016 | 1,570 | 1,455 | 1.08 | 0.022 | 10.53 | 1,000 |
| 2017 | 1,660 | 1,614 | 1.03 | 0.021 | 9.55 | 1,000 |
| 2018 | 2,580 | 2,865 | 1.00 | 0.020 | 9.68 | 1,000 |
| 2019 | 3,540 | 3,889 | 0.91 | 0.018 | 9.09 | 1,000 |
| 2020 | 4,220 | 4,801 | 0.88 | 0.018 | 9.58 | 1,000 |

Appendix 2. The profitability of solar power investment in Germany between 2000 and 2020 (*Effective interest rates for banks/new business/housing loans to private households, initial fixed interest rate over ten years*, no date; Egli, Steffen and Schmidt, 2018, our calculation)

| **Year** | **Estimated IRR** | **Desired IRR** | **Profitability** |
|---|---|---|---|
| 2000 | 2.75% | 5.10% | -2.35% |
| 2001 | 2.99% | 4.90% | -1.91% |
| 2002 | 2.62% | 4.70% | -2.08% |
| 2003 | 2.41% | 4.48% | -2.07% |
| 2004 | 5.49% | 4.37% | 1.13% |
| 2005 | 5.25% | 3.88% | 1.37% |
| 2006 | 5.50% | 4.02% | 1.47% |
| 2007 | 6.64% | 4.28% | 2.36% |
| 2008 | 6.22% | 4.32% | 1.90% |
| 2009 | 9.56% | 3.89% | 5.68% |
| 2010 | 9.31% | 3.47% | 5.84% |
| 2011 | 9.86% | 3.49% | 6.37% |
| 2012 | 9.04% | 2.83% | 6.21% |
| 2013 | 6.83% | 2.62% | 4.22% |
| 2014 | 5.32% | 2.36% | 2.96% |
| 2015 | 3.87% | 1.85% | 2.02% |
| 2016 | 4.60% | 1.71% | 2.90% |
| 2017 | 3.89% | 1.74% | 2.15% |
| 2018 | 5.72% | 1.74% | 3.98% |
| 2019 | 4.95% | 1.40% | 3.55% |
| 2020 | 6.25% | 1.13% | 5.12% |

Appendix 3. Predicted data of new power plants in Vietnam in 2020 (Danish Energy Agency et al., 2019)

| **Technology** | **Capital cost** | **Years to build** | **Lifetime** | **Max full-load hours** | **Interest rate** | **Variable O&M cost** | **Fixed O&M cost** | **Total of O&M cost** | **Efficiency** |
|---|---|---|---|---|---|---|---|---|---|
| | USD/kW | Years | Years | Hours/year | | US cents/kWh | US cents/kWh | US cents/kWh | |
| Subcritical coal | 1,120 | 3 | 30 | 6,000 | 10% | 0.07 | 0.45 | 0.52 | 35% |
| Supercritical coal | 1,380 | 4 | 30 | 6,000 | 10% | 0.01 | 0.47 | 0.48 | 37% |
| Ultra-supercritical coal | 1,510 | 4 | 30 | 6,000 | 10% | 0.01 | 0.65 | 0.66 | 42% |
| SCGT | 590 | 1.5 | 25 | 4,000 | 10% | 0.00 | 0.26 | 0.26 | 33% |
| CCGT | 770 | 2.5 | 25 | 4,000 | 10% | 0.05 | 0.34 | 0.38 | 52% |
| Small hydro | 1,750 | 3 | 50 | 6,658 | 10% | 0.05 | 0.48 | 0.53 | 95% |
| Large hydro | 1,500 | 4 | 50 | 3,154 | 10% | 0.07 | 0.43 | 0.50 | 95% |
| Solar PV | 1,100 | 1 | 25 | 1,500 | 10% | 0.00 | 0.13 | 0.13 | |
| Onshore wind | 1,600 | 1.5 | 27 | 2,540 | 10% | 0.42 | 0.46 | 0.88 | |
| Offshore wind | 2,360 | 3 | 27 | 3,500 | 10% | 0.37 | 0.57 | 0.94 | |
| Diesel | 800 | 1 | 25 | 2,000 | 10% | 0.64 | 0.09 | 0.73 | 45% |

Appendix 4. Predicted data of new power plants in Vietnam in 2030 (Danish Energy Agency et al., 2019)

| **Technology** | **Capital cost** | **Years to build** | **Lifetime** | **Max full-load hours** | **Interest rate** | **Variable O&M cost** | **Fixed O&M cost** | **Total of O&M cost** | **Efficiency** |
|---|---|---|---|---|---|---|---|---|---|
| | USD/kW | Years | Years | Hours/year | | US cents/kWh | US cents/kWh | US cents/kWh | |
| Subcritical coal | 1,210 | 3 | 30 | 6,000 | 10% | 0.07 | 0.45 | 0.52 | 35% |
| Supercritical coal | 1,390 | 4 | 30 | 6,000 | 10% | 0.01 | 0.47 | 0.48 | 37% |
| Ultra-supercritical coal | 1,490 | 4 | 30 | 6,000 | 10% | 0.01 | 0.65 | 0.66 | 42% |
| SCGT | 570 | 1.5 | 25 | 4,000 | 10% | 0.00 | 0.26 | 0.26 | 33% |
| CCGT | 690 | 2.5 | 25 | 4,000 | 10% | 0.05 | 0.34 | 0.38 | 52% |
| Small hydro | 1,750 | 3 | 50 | 6,658 | 10% | 0.05 | 0.48 | 0.53 | 95% |
| Large hydro | 1,500 | 4 | 50 | 3,154 | 10% | 0.07 | 0.43 | 0.50 | 95% |
| Solar PV | 840 | 1 | 25 | 1,500 | 10% | 0.00 | 0.13 | 0.13 | |
| Onshore wind | 1,310 | 1.5 | 27 | 2,540 | 10% | 0.42 | 0.46 | 0.88 | |
| Offshore wind | 2,250 | 3 | 27 | 3,500 | 10% | 0.37 | 0.57 | 0.94 | |
| Diesel | 800 | 1 | 25 | 2,000 | 10% | 0.64 | 0.09 | 0.73 | 45% |

Appendix 5. Fuel cost for power plants in Vietnam in 2020 (Government of Vietnam, 2016b)

| | **Fuel price** | **Unit** | **Net fuel rate** | **Unit** | **Fuel cost** | **Unit** |
|---|---|---|---|---|---|---|
| Coal | 6.3 | US cents/kg | 0.478 | kg/kWh | 3.01 | US cents/kWh |
| Natural gas | 810 | US cents/mil BTU | 0.00625 | mil BTU/kWh | 5.06 | US cents/kWh |
| Diesel oil | 112.27 | US cents/kg | 0.29205 | kg/kWh | 32.79 | US cents/kWh |

Appendix 6. Fuel cost for power plants in Vietnam in 2030 (Government of Vietnam, 2016b)

| | **Fuel price** | **Unit** | **Net fuel rate** | **Unit** | **Fuel cost** | **Unit** |
|---|---|---|---|---|---|---|
| Coal | 7.1 | US cents/kg | 0.478 | kg/kWh | 3.39 | US cents/kWh |
| Natural gas | 1,090 | US cents/mil BTU | 0.00625 | mil BTU/kWh | 6.81 | US cents/kWh |
| Diesel oil | 156.77 | US cents/kg | 0.29205 | kg/kWh | 45.78 | US cents/kWh |

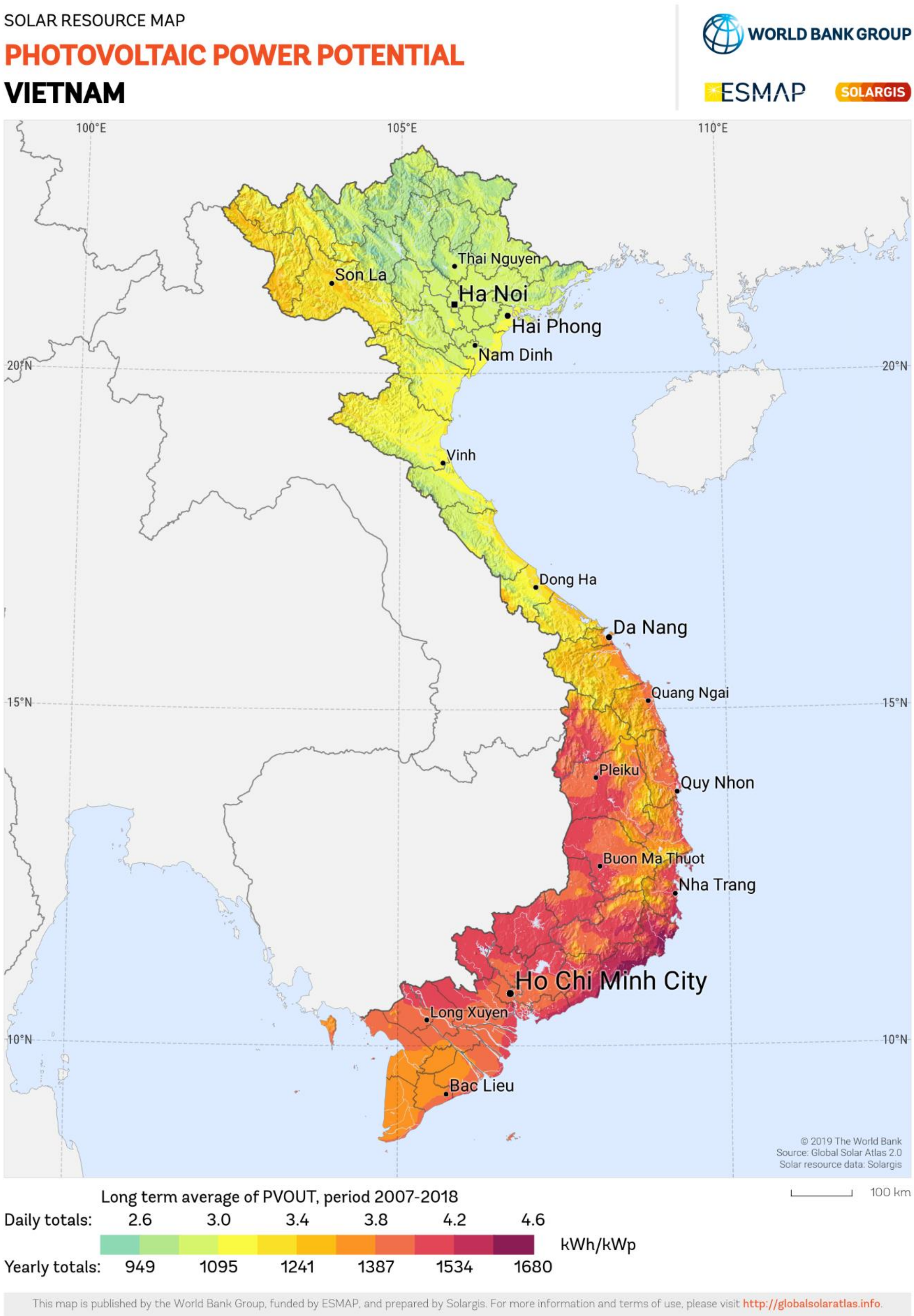
Appendix 7. Technical solar power potential by region in Vietnam (Togeby, 2017)

| **Area** | **The annual average of daily global horizontal irradiation** | **Theoretical potential** | **Technical potential** | **The average number of sunshine hours** |
|---|---|---|---|---|
| | KWh/m$^2$/day | MWp | MWp | Hour |
| Hong Delta river | 3.4 - 3.6 | 613,906 | 30,695 | 1,600 - 1,750 |
| Highland and mountainous in the North | 3.1 - 3.6 | 2,033,466 | 101,673 | 1,750 - 1,800 |
| North of Central and coastal areas | 3.5 - 5.7 | 2,132,840 | 106,642 | 1,700 - 2,000 |
| Highland Central | 3.4 - 4.0 | 808,973 | 40,449 | 2,000 - 2,600 |
| Eastern of South region | 3.8 - 4.5 | 397,493 | 19,875 | 2,200 - 2,500 |
| Mekong Dental river | 4.8 - 5.5 | 805,880 | 40,294 | 2,200 - 2,500 |
| Total | | 6,792,558 | 339,628 | |
| Average | | | | 1,700 - 2,500 |

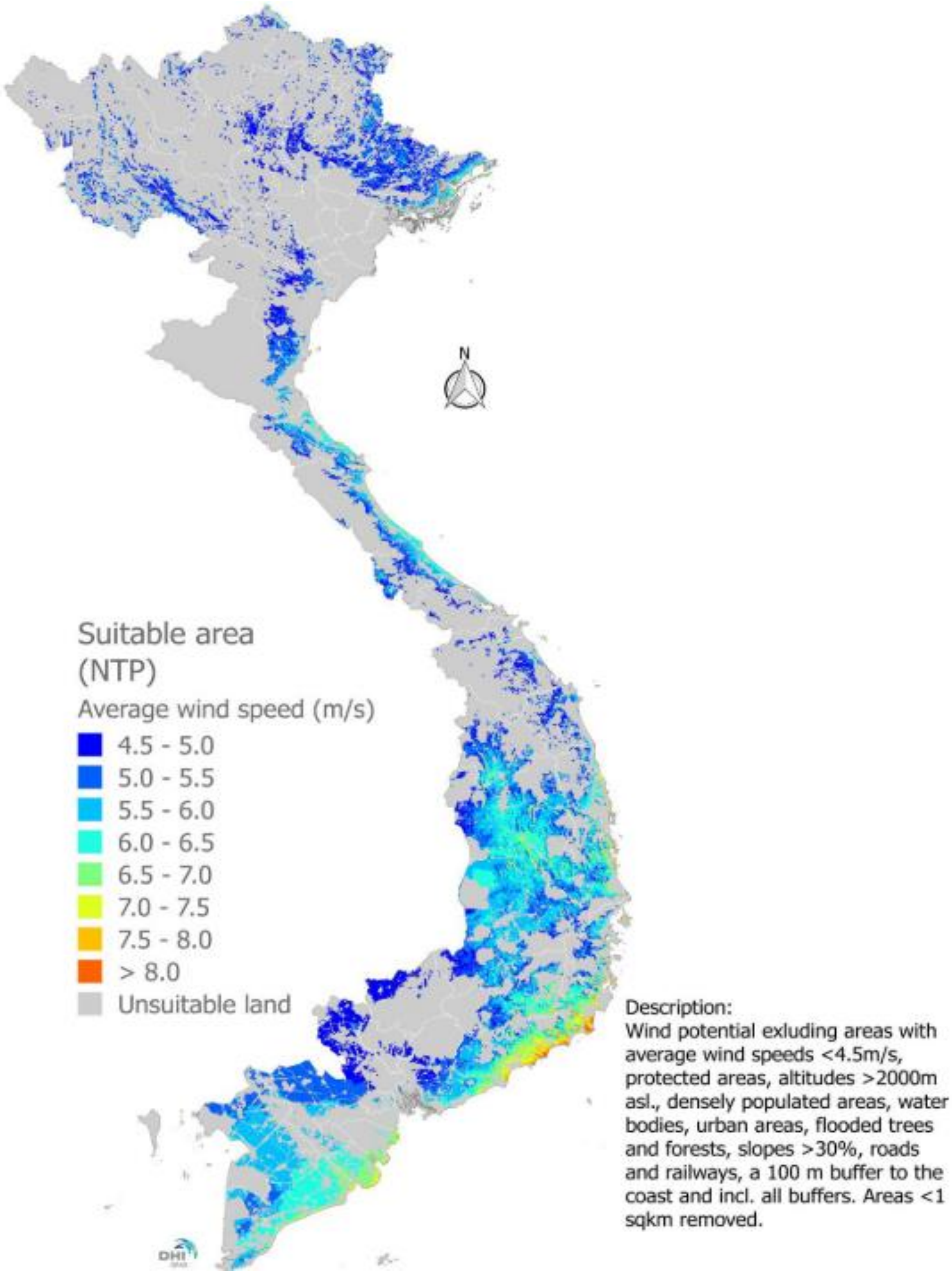
Appendix 8. Technical onshore wind power potential by wind speed range in Vietnam (Togeby, 2017)

| **Wind speed** | **Area** | **Share of area** | **Capacity** | **Share of capacity** |
|---|---|---|---|---|
| M/s | $Km^2$ | | MW | |
| 4.5 - 5.0 | 13,832 | 19.33% | 41,496 | 19.33% |
| 5.0 - 5.5 | 18,637 | 26.04% | 55,911 | 26.04% |
| 5.5 - 6.0 | 21,681 | 30.30% | 65,043 | 30.30% |
| 6.0 - 6.5 | 11,492 | 16.06% | 34,476 | 16.06% |
| 6.5 - 7.0 | 3,540 | 4.95% | 10,620 | 4.95% |
| 7.0 - 7.5 | 1,550 | 2.17% | 4,650 | 2.17% |
| 7.5 - 8.0 | 564 | 0.79% | 1,692 | 0.79% |
| over 8.0 | 265 | 0.37% | 795 | 0.37% |
| Total | 71,561 | | 214,683 | |

Appendix 9. Solar power potential map in Vietnam (Global Solar Atlas 2.0, Solargis)



Appendix 10. Onshore wind power potential map in Vietnam (Togeby, 2017)



Appendix 11. List of solar power plants in Vietnam (*List of solar projects in Vietnam*, 2021, updated from press releases)

| **No.** | **Commercial Operation Date** | **Project** | **Location** | **Installed capacity (MW)** | **Installed capacity (MWp)** | **Owner** |
|---|---|---|---|---|---|---|
| 1 | Nov-18 | TTC Phong Dien | Thua Thien Hue | 35 | 48 | GEC/TTC |
| 2 | Dec-18 | TTC Krong Pa | Gia Lai | 49 | 69 | GEC/TTC |
| 3 | Mar-19 | BP Solar 1 | Ninh Thuan | 37.5 | 46 | Bac Phuong JSC |
| 4 | Jun-19 | VPS Binh Thuan II | Binh Thuan | 26.5 | 33.1 | VSP Binh Thuan II Solar Power |
| 5 | Jan-19 | Srêpôk 1 | Daklak | 42.1 | 50 | Dai Hai Investment and Development JSC |
| 6 | Jan-19 | Quang Minh Solar | Daklak | 40.9 | 50 | Dai Hai Power and Srepok Solar |
| 7 | Apr-19 | TTC1 Solar | Tay Ninh | 68.8 | 70 | TTC Green Energy |
| 8 | May-19 | TTC2 Solar | Tay Ninh | 48.8 | 50 | TTC Green Energy |
| 9 | May-19 | BIM 1 | Ninh Thuan | 25 | 30 | Bim Group |
| 10 | May-19 | BIM 2 | Ninh Thuan | 199.3 | 250 | Bim Group |
| 11 | May-19 | BIM 3 | Ninh Thuan | 41.2 | 50 | Bim Group |
| 12 | Apr-19 | Yen Dinh Solar | Thanh Hoa | 30 | 38 | Song Lam Son La Energy JSC |
| 13 | Apr-19 | Vinh Tan Phase 1 | Binh Thuan | 4.4 | 5 | EVNPECC2 |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 14 | Jun-19 | Vinh Tan Phase 2 | Binh Thuan | 34.9 | 42.7 | EVNPECC2 |
| 15 | May-19 | Ham Phu II | Binh Thuan | 40.8 | 49 | GEC/TTC |
| 16 | Apr-19 | Duc Hue 1 | Long An | 40.8 | 49 | GEC/TTC |
| 17 | Apr-19 | Trung Nam Ninh Thuan | Ninh Thuan | 204 | 258 | Trung Nam JSC |
| 18 | Jun-19 | Da Mi Floating | Binh Thuan | 42 | 47.5 | EVNGENCO1 |
| 19 | Jun-19 | Da Bac Solar Power | Ba Ria Vung Tau | 48 | 61 | Tai Tien LTD |
| 20 | May-19 | Da Bac 2 Solar Power | Ba Ria Vung Tau | 48 | 61 | Tai Tien LTD |
| 21 | May-19 | Da Bac 3 Solar Power | Ba Ria Vung Tau | 42 | 50 | Green HC LTD |
| 22 | Jun-19 | Điện mặt trời Đá Bạc 4 | Ba Ria Vung Tau | 42 | 50 | Dong A Chau JSC |
| 23 | Jun-19 | Dau Tieng Solar Power 1, 2 | Tay Ninh | 350 | 420 | B. Grimm Power + Xuan Cau |
| 24 | Jun-19 | Dau Tieng Solar Power 3 | Tay Ninh | 60 | 71 | DT3 Energy JSC |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 25 | Jun-19 | Hoa Hoi solar power | Phu Yen | 214 | 257 | B. Grimm Power + Truong Thanh Group |
| 26 | May-19 | BMT Solar Power | Daklak | 25 | 30 | AMI and AC Energy |
| 27 | May-19 | Jang Pong Solar Power | Daklak | 8.6 | 10 | Cao Nguyen IE JSC |
| 28 | Apr-19 | Duc Minh Solar Farm | Quang Ngai | 19 | 19.2 | Thien Tan Group |
| 29 | May-19 | Binh Nguyen Solar Farm | Quang Ngai | 40.8 | 49.6 | Truong Thanh Quang Ngai |
| 30 | May-19 | LIG Quang Tri | Quang Tri | 41.2 | 49.5 | LICOGI 13 JSC |
| 31 | Jun-19 | Cat Hiep | Binh Dinh | 42 | 49.5 | Truong Thanh Group + Quadran International |
| 32 | Jun-19 | Thuan Nam 19 Solar PV | Ninh Thuan | 49 | 61.1 | Tasco |
| 33 | Jun-19 | Ha Do (Hong Phong 4) | Binh Thuan | 44 | 48 | Ha Do Group |
| 34 | May-19 | AMI Khanh Hoa | Khanh Hoa | 47.5 | 49.9 | AMI Khanh Hoa Energy JSC |
| 35 | May-19 | Song Giang | Khanh Hoa | 45.9 | 50 | Song Giang Solar Power JSC |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 36 | Jun-19 | BCG Bang Duong phase 1 | Long An | 34.4 | 40.6 | Bamboo Capital Group |
| 37 | Jun-19 | Sao Mai PV1 | An Giang | 96.9 | 104 | Sao Mai Group |
| 38 | Jun-19 | Mui Ne | Binh Thuan | 35.8 | 40 | Duc Thanh Mui Ne JSC |
| 39 | Jun-19 | CMX Renewable Vietnam | Ninh Thuan | 131.3 | 168 | CMX RE Sunseap Vietnam |
| 40 | May-19 | Phuoc Huu - Dien luc 1 | Ninh Thuan | 28.1 | 30.2 | Phuoc Huu Power JSC |
| 41 | Jun-19 | TTC Truc Son | Dak Nong | 36.5 | 44.4 | TTC Group |
| 42 | Jun-19 | EuroPlast Long An | Long An | 40.8 | 50 | Sao Mai + EU Plastics |
| 43 | Jul-19 | EuroPlast Phu Yen | Phu Yen | 44.7 | 50 | EU Plastics |
| 44 | Jun-19 | My Son - Hoan Loc Viet | Ninh Thuan | 41.3 | 50 | My Son - Hoan Loc Viet JSC |
| 45 | May-19 | Phong Dien 2 | Thua Thien Hue | 48 | 50 | Doan Son Thuy JSC |
| 46 | May-19 | Cu Jut Solar Power | Dak Nong | 50 | 62 | Central Hydropower JSC |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 47 | Jun-19 | Nhi Ha Bitexco phase 1 | Ninh Thuan | 41.2 | 50 | Bitexco Group (Solar Power Ninh Thuan LTD) |
| 48 | Jul-19 | Nhi Ha - Thuan Nam 13 | Ninh Thuan | 48 | 50 | Sijar Power Ninh Thuan |
| 49 | Jun-19 | Ninh Phuoc 6.1, 6.2 | Ninh Thuan | 49 | 58.3 | NITSA (Renewable energy and Agriculture Ninh Thuan |
| 50 | Jun-19 | Fujiwara Binh Dinh | Binh Dinh | 40 | 50 | Fujirawa Binh Dinh LTD |
| 51 | Jun-19 | Chu Ngoc - LIGICO 16 | Gia Lai | 12.8 | 15 | LICOGI 16 Gia Lai Renewable Energy Investment |
| 52 | Jun-19 | Trung Nam Tra Vinh | Tra Vinh | 140.8 | 165 | Trungnam Group |
| 53 | May-19 | Phong Phu | Binh Thuan | 38 | 42 | Solar Power Investment Company |
| 54 | May-19 | Vinh Hao Solar Farm | Binh Thuan | 30 | 34.2 | Vinh Hao Solar Power JSC |
| 55 | Jun-19 | Vinh Hao 4 Solar Farm | Binh Thuan | 36.8 | 39 | Quynh Quang Real Estate Company |
| 56 | Jun-19 | Vinh Hao 6 Solar Farm | Binh Thuan | 40 | 50 | FECON |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 57 | Jun-19 | Bau Ngu lake | Ninh Thuan | 37.4 | 45.8 | Truong Thanh Investment and Construction JSC |
| 58 | Jun-19 | Van Giao 2 Solar Power | An Giang | 40 | 50 | Van Giao Solar Power JSC |
| 59 | Jun-19 | Van Giao 1 Solar Power | An Giang | 40 | 50 | Van Giao Solar Power JSC |
| 60 | May-19 | Gelex Binh Thuan | Ninh Thuan | 42 | 50 | Gelex Ninh Thuan JSC |
| 61 | Jun-19 | Phuoc Huu | Ninh Thuan | 50 | 65 | Vinh Nha Trang Investment JSC |
| 62 | Jul-19 | Solar Park 02 | Long An | 40.8 | 50 | Hoan Cau |
| 63 | May-19 | Song Luy 1 | Binh Thuan | 39 | 46.7 | Quang Dien Binh Thuan Investment JSC |
| 64 | Jun-19 | Cam Hoa Solar Farm | Ha Tinh | 43.8 | 50 | Hoanh Son Group Company |
| 65 | Jun-19 | Xuan Tho 1 | Phu Yen | 45.9 | 49.6 | Phu Khanh Solar Power JSC |
| 66 | Jun-19 | Xuan Tho 2 | Phu Yen | 45.9 | 49.6 | Phu Khanh Solar Power JSC |
| 67 | Jun-19 | Hong Phong 1A | Binh Thuan | 150 | 195 | Vietracimex |
| 68 | Jun-19 | Hong Phong 1B | Binh Thuan | 100 | 130 | Vietracimex |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 69 | May-19 | Tan Chau Solar | Tay Ninh | 25 | 30 | Bach Khoa A Chau Tay Ninh JSC |
| 70 | May-19 | Tri Viet 1 | Tay Ninh | 25 | 30 | Tri Viet Tay Ninh JSC |
| 71 | Jun-19 | HCG Tay Ninh | Tay Ninh | 40 | 50 | Hoang Thai Gia Trust Investment and Management LTD |
| 72 | Jun-19 | Hoang Thai Gia Tay Ninh | Tay Ninh | 40 | 50 | Hoang Thai Gia Trust Investment and Management LTD |
| 73 | Jun-20 | Eco Seido Tuy Phong | Binh Thuan | 40 | 51 | Green Energy LTD |
| 74 | Jun-19 | Cam Lam | Khanh Hoa | 45 | 49.6 | Cam Lâm Solar LTD |
| 75 | Jun-19 | KN Cam Lam | Khanh Hoa | 45 | 49.5 | Cam Lâm Solar LTD |
| 76 | Jun-19 | Phan Lam 1 Solar Power | Binh Thuan | 30 | 36.72 | Pha Lam Energy LTD |
| 77 | Jun-19 | Binh Hoa Solar PV | An Giang | 10 | 12 | Pacific Energy Network |
| 78 | Jun-19 | Son My 3.1 Solar PV | Binh Thuan | 43 | 50 | Son My Renewable Energy JSC |
| 79 | Jul-19 | Long Thanh Solar Power 1 | Daklak | 43.8 | 50 | Long Thanh Investment LTD |
| 80 | Jun-19 | Tuan An Solar Power | Khanh Hoa | 9.6 | 11.7 | Tuan An Energy Group JSC |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 81 | May-19 | Mo Duc Solar Power | Quang Ngai | 17.6 | 19 | Thien Tan Group |
| 82 | Jul-19 | Tuy Phong Solar Power | Binh Thuan | 30 | 39 | Power Plus Vietnam LTD |
| 83 | Oct-19 | Thinh Long Solar Power - AAA Phu Yen | Phu Yen | 43.8 | 50 | Thinh Long Phu Yen Solar Power JSC |
| 84 | Jun-19 | Chau Duc Industrial Zone Solar Power | | 58 | 70 | Halla E&C + Hyosung Group |
| 85 | Jun-19 | EVNCPC solar power_phase 1 | Khanh Hoa | 9 | 10 | EVNCPC |
| 86 | Dec-20 | EVNCPC solar power_phase 2 | Khanh Hoa | 41.9 | | EVNCPC |
| 87 | Jun-19 | Binh An solar power | Binh Thuan | | 50 | Green Energy LTD |
| 88 | Jun-19 | GAIA solar power | Long An | 100.4 | 100.5 | Bamboo Capital Group |
| 89 | Jun-19 | Ham Kiem | Binh Thuan | 45 | 49 | Truong Thanh Binh Thuan solar power LTD |
| 90 | Dec-19 | Sinenergy Ninh Thuan 1 | Ninh Thuan | 50 | 50 | Sinenergy Holdings Singapore |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 91 | Jun-19 | Solar Park 01 | Long An | 50 | 50 | Hoan Cau Long An LTD |
| 92 | Jun-19 | Solar Park 02 | Long An | 50 | 50 | VietnamSolar JSC |
| 93 | Jul-20 | Solar Park 03 | Long An | 50 | 50 | Long An Solar Park JSC |
| 94 | Aug-20 | Solar Park 04 | Long An | 50 | 50 | Long An Solar Energy JSC |
| 95 | Jun-19 | Thuan Minh 2 | Binh Thuan | 50 | 50 | SD Truong Thanh JSC |
| 98 | Dec-19 | Thuan Nam Duc Long | Ninh Thuan | 50 | 50 | Ninh Thuan DLG solar power JSC |
| 99 | Feb-20 | Thien Tan Solar Ninh Thuan | Ninh Thuan | 50 | 50 | Thien Tan Solar Ninh Thuan JSC |
| 100 | Feb-20 | Xuan Thien Thuan Bac_phase 1 | Ninh Thuan | 125 | 125 | Xuan Thien JSC |
| 101 | Feb-20 | Xuan Thien Thuan Bac_phase 2 | Ninh Thuan | 75 | 75 | Xuan Thien JSC |
| 102 | Jun-20 | Phuoc Ninh | Ninh Thuan | 45 | 45 | Ninh Thuan energy industry LTD |
| 103 | Aug-20 | Phuoc Thai 1 | Ninh Thuan | 50 | 50 | EVNPMB3 |
| 104 | Dec-18 | My Son 1 | Ninh Thuan | 50 | 62 | Hoang Son Energy |
| 105 | Dec-19 | My Son 2 | Ninh Thuan | 50 | 50 | Hoang Son Energy |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 106 | Sep-20 | Thuan Nam 12 | Ninh Thuan | 49 | 49.92 | Thanh Vinh solar power JSC |
| 107 | Sep-20 | SP Infra 1 | Ninh Thuan | 49 | 50 | Surya Prakash VN energy LTD |
| 108 | Dec-18 | Trung Nam Thuan Nam | Ninh Thuan | 450 | 450 | Trung Nam Thuan Nam solar power LTD |
| 109 | Dec-20 | Adani Phuoc Minh | Ninh Thuan | 27.3 | 27.3 | Adami Phuoc Minh solar power LTD |
| 110 | Jul-20 | Tan Chau 1 | Tay Ninh | 50 | 50 | Tan Chau energy JSC |
| 112 | Nov-20 | Se San 4 | Kon Tum | 49 | 49 | EVNPMB2 |
| 113 | Nov-20 | Gio Thanh 1 | Quang Tri | 50 | 50 | Gio Thanh energy JSC |
| 114 | Nov-20 | Gio Thanh 2 | Quang Tri | 50 | 50 | SECO JSC |
| 115 | Nov-20 | Thanh Long Phu Yen | Phu Yen | 50 | 50 | Thanh Long Phu Yen energy JSC |
| 116 | Dec-20 | Long Son | Khanh Hoa | 170 | 170 | Long Son energy JSC |
| 117 | Nov-20 | Easup 3 | Daklak | 100 | 100 | Ea Sup 3 JSC |
| 118 | Dec-20 | Ho Nui Mot 1 | Ninh Thuan | 50 | 50 | Truong Thanh Construction Investment and Development JSC |
| 119 | Dec-20 | Thac Mo | Binh Phuoc | 50 | 50 | EVNGENCO2 |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 120 | Nov-20 | Easup 5 | Daklak | 150 | 150 | Ea Sup 5 JSC |
| 121 | Nov-20 | Easup 1 | Daklak | 100 | 100 | Ea Sup 1 JSC |
| 122 | Dec-20 | KN Van Ninh | Khanh Hoa | 100 | 100 | KN Van Ninh power solar Investment and Development LTD |
| 123 | Nov-20 | Easup 2 | Daklak | 100 | 100 | Easup 2 JSC |
| 124 | Nov-20 | Easup 4 | Daklak | 150 | 150 | Easup 4 JSC |
| 125 | Dec-20 | My Hiep | Binh Dinh | 50 | 50 | Vietnam Renewable Energy JSC |
| 126 | Dec-20 | Phan Lam 2 | Binh Thuan | 49 | 49 | Phan lam Energy LTD |
| 127 | Dec-20 | Phu My 1 | Binh Dinh | 120 | 120 | BCG Energy |
| 128 | Dec-20 | Phu My 2 | Binh Dinh | 110 | 110 | BCG Energy |
| 129 | Feb-21 | Phu My 3 | Binh Dinh | 110 | 110 | BCG Energy |
| 130 | Dec-20 | Dam Tra O | Binh Dinh | 50 | 50 | Vietnam Renewable Energy JSC |
| 131 | Dec-20 | Loc Ninh 1 | Binh Phuoc | 200 | 200 | Loc Ninh Energy JSC |
| 132 | Dec-20 | Loc Ninh 2 | Binh Phuoc | 200 | 200 | Loc Ninh Energy JSC |

| No. | Commercial Operation Date | Project | Location | Installed capacity (MW) | Installed capacity (MWp) | Owner |
|---|---|---|---|---|---|---|
| 133 | Dec-20 | Loc Ninh 3 | Binh Phuoc | 150 | 150 | Loc Ninh Energy JSC |
| 134 | Dec-20 | Hong Liem 3 | Binh Thuan | 50 | 50 | Truong Loc - Binh Thuan solar power LTD |
| 135 | Dec-20 | Loc Ninh 4 | Binh Phuoc | 200 | 200 | Loc Ninh 4 Energy JSC |
| 136 | Dec-20 | Loc Ninh 5 | Binh Phuoc | 50 | 50 | Loc Ninh 4 Eenergy JSC |
| 137 | Dec-20 | DowHa Le Thuy | Bhuy Phuoc | 49.5 | 49.5 | Dohwa Green Energy LTD |
| 138 | Jul-20 | Nhon Hai Solar Farm | Barm Phuoc | 35 | 35 | LICOGI 16 Ninh Thuan Renewable Energy JSC |
| 139 | Aug-20 | Bau Zon | Ninh Thuan | 25.031 | 25.031 | TT SUNGLIM solar power LTD |
| 140 | Dec-20 | Ho Tam Bo | Ba Ria Vung Tau | 35 | 35 | CY Energy Development LTD |
| 141 | Dec-20 | Ho Gia Hoet 1 | Ba Ria Vung Tau | 35 | 35 | DTD Natural Energy LTD |
| 142 | Dec-20 | Hau Giang | Hau Giang | 35 | 35 | VKT - Hoa An solar power JSC |
| 143 | Dec-20 | Trung Son | Khanh Hoa | 35 | 35 | Trung Son Energy Development JSC |
| Total | | | | 8,837 | 9,746 | |

Appendix 12. List of wind power plants in Vietnam (*List of wind projects in Vietnam*, 2021, updated from press releases)

| **No.** | **Year of comercial operation** | **Project** | **Location** | **Installed capacity (MW)** | **Owner** |
|---|---|---|---|---|---|
| 1 | 2011 | REVN | Binh Thuan | 30 | Vietnam Renewable Energy JSC (REVN) |
| 2 | 2012 | Phu Quy | Binh Thuan | 6 | Petrolimex Vietnam |
| 3 | 2012 | Cong Ly phase 1 | Bac Lieu | 16 | Cong Ly Construction-Trading-Tourism Co. |
| 4 | 2013 | Cong Ly phase 2 | Bac Lieu | 83.2 | Cong Ly Construction-Trading-Tourism Co. |
| 5 | 2016 | Phu Lac | Binh Thuan | 24 | Thuan Binh Wind Power JSC (TBW) |
| 6 | 2017 | Huong Linh 2 | Quang Tri | 30 | Tan Hoan Cau JSC |
| 7 | 2017 | Dam Nai phase 1 | Ninh Thuan | 6 | The Blue Circle PTE LTD and TSV Invest and Development |
| 8 | 2018 | Dam Nai phase 2 | Ninh Thuan | 38 | The Blue Circle PTE LTD and TSV Invest and Development |
| 9 | 2018 | Tay Nguyen phase 1 | Ninh Thuan | 28.8 | HBRE Wind Power Solution LTD |
| 10 | 2019 | Trung Nam phase 1 | Ninh Thuan | 40 | Trung Nam Wind Power |
| 11 | 2019 | Mui Dinh | Daklak | 37.6 | EAB New Energy Gmbh |

| No. | Year of comercial operation | Project | Location | Installed capacity (MW) | Owner |
|---|---|---|---|---|---|
| 12 | 2020 | Phuong Mai 3 | Binh Dinh | 21 | Central Wind Power JSC |
| 13 | 2020 | Huong Linh 1 | Quang Tri | 30 | Tan Hoan Cau JSC |
| 14 | 2020 | Dai Phong | Binh Thua | 40 | The Blue Circle PTE LTD and TSV Invest and Development |
| | Total | | | 430.6 | |