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Towards avoiding microgrid design failures arising from an unrealistic operating strategy: an anticipative White Box model versus a responsive Black Box model

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RESUME – Cet article compare deux approches déterministes et stochastiques pour le dimensionnement des micro-réseaux : un modèle *White Box (WB) anticipatif* qui optimise à la fois le dimensionnement et l'opération du micro-réseau sous l'hypothèse d'une prévision parfaite de la consommation et de la production des énergies renouvelables, et un modèle *Black Box (BB) réactif* qui optimise de manière heuristique le dimensionnement du micro-réseau avec une stratégie d'opération réaliste basée sur des règles dynamiques. Ce travail souligne l'importance d'optimiser le dimensionnement du micro-réseau avec la politique de gestion qui sera mise en œuvre et évalue les écarts technico-économiques par rapport à un dimensionnement basé sur l'hypothèse de connaissance parfaite du futur. Les résultats du cas d'étude montrent que le modèle BB est adapté au dimensionnement des micro-réseaux avec des temps de calcul inférieurs à ceux du modèle WB.

ABSTRACT – This paper provides a comparison of two deterministic and stochastic approaches for microgrid sizing: an *anticipative White Box (WB) model* that optimizes both microgrid sizing and operation assuming a perfect forecasting of load and renewable energy production profiles, versus a *responsive Black Box (BB) model* that heuristically optimizes microgrid sizing with a realistic rule-based operation strategy. This work underlines the importance of optimizing microgrid design with the operating policy that will be implemented and assesses the techno-economic gaps compared to a sizing approach that assumes the perfect knowledge of the future. The case study results show that BB model is suitable for microgrid sizing with less computational requirements than the WB model.

KEYWORDS – microgrid, optimal design, operating strategy, uncertainties, stochastic programming, linear programming.

1. Introduction

Today's society is critically dependent on a secure energy supply. The increasing integration of intermittent renewable energy sources and electric vehicles into the conventional electric grid incites the transition from passive to active distribution networks. Thus, the implementation of radically new system concepts is incontrovertible. Microgrids, also known as the « building blocks of smart grids », are perhaps the most promising, novel network structure [1]. They are expected to become part of the next electric power system evolution, both in rural remote areas and in urban zones. As microgrids can lower the costs of energy supply and enhance the utility grid reliability and resilience, their planning and design must be optimized to ensure long-term stability. There are two key factors influencing the microgrid sizing: the **operation strategy**, which determines the power flows in the microgrid, and the **uncertainties** on the input data [2].

The stochastic nature of renewable power generation, the impossibility of predicting with total accuracy future energy prices, and the uncertainty of the long-term energy demand patterns and climate outlook, all highlight the importance of **uncertainty** considerations. To tackle this issue, Stochastic Programming (SP) is the most widely used approach to develop microgrid design models for decision-making under uncertainty [3].

In terms of solutions, microgrid **operation strategies** can be divided into two types: rule-based and optimization-based operation strategies [2], [4]. *In the rule-based operation strategies*, a set of priority-rules determines, at each time step, the state (on/off) and the production level of the microgrid's energy sources and storage units. As in HOMER Pro, a widely used software for microgrids sizing [5], there are two traditional strategies for scheduling: Load Following (LF) and Cycle Charging (CC). These rules prioritize renewable generation capacity, followed by storage units and finally fuel-fired generators. Each time a generator operates, it produces only enough power to meet the load when LF is used, while it operates at full output power when CC is used. *In the optimization-based operation strategies*, the operational

variables are optimized with perfect foresight over the entire operation horizon. The optimization methods can be further classified in two categories: Mathematical Programming (MP) techniques such as mixed-integer programming (MIP) and heuristic optimization methods such as Particle Swarm Optimization (PSO) which are suitable for solving non-linear and non-convex problems [6]. These two operation strategies mainly differ regarding their real-life implementation capability. A rule-based simulator has a realistic operation policy that accesses to past and current information. Conversely, an optimization-based control strategy is anticipative over a project's lifetime and therefore unrealistic for real-time application, as it requires full access to past, current, and future information. Long-term look-ahead control strategy may differ from the one implemented in real life.

Concerning microgrid design, components sizing can be chosen from a set of discrete values or optimized using MP or heuristic methods. The paper [7] presents a comparison of two deterministic methods for rural mini-grid design: a mixed-integer linear programming model that optimizes the mini-grid sizing and operation assuming perfect prediction of load and generation profiles, and a heuristic PSO method that implements classical dispatch strategies (LF, CC). Nevertheless, to the best of our knowledge, there are no existing studies that evaluate the gaps between the two models' solutions and computation times when the number of decision variables is increased and when uncertainties are considered.

Among all the possible combinations of sizing and operation co-optimization methods, we are interested in comparing two approaches. The first one, which we call **White Box (WB)**, optimizes both the microgrid sizing and operation using MP. In the second one, which we call **Black Box (BB)**, the sizing is optimized using heuristic optimization algorithm, and the operation is rule-based. We thus aim to study the impact on microgrid optimization when operating it in a non-realistic manner and to compare the computation time of the two methods in both deterministic and stochastic cases.

The paper is organized as follows. Section 2. describes the mathematical formulation of the WB model, while section 3. details the BB model. Then, section 4. presents the case study and results. Finally, conclusions are drawn in section 5.

2. White Box (WB) model

2.1 Description

The purpose of this section is to describe the mathematical formulation of the WB optimization problem to obtain the most cost-effective design of a microgrid composed of a photovoltaic plant (PV), battery storage, and a diesel generator. This WB model, illustrated in Figure 1.a, conjointly optimizes both the design and operation of the microgrid by means of Linear Programming (LP), a mathematical model represented by linear dependencies that can achieve the global optimum. The objective is to minimize the Levelized Cost of Energy (*LCOE*) of the system. *LCOE* accounts for both the investment and operating costs, and the energy served to the load. Operating charges are evaluated considering a typical year's simulation at an hourly resolution, which is a reasonable trade-off between problem tractability and results optimality. The model is written in YALMIP, a MATLAB toolbox for optimization modeling, and solved using the "linprog" solver from MATLAB optimization toolbox.

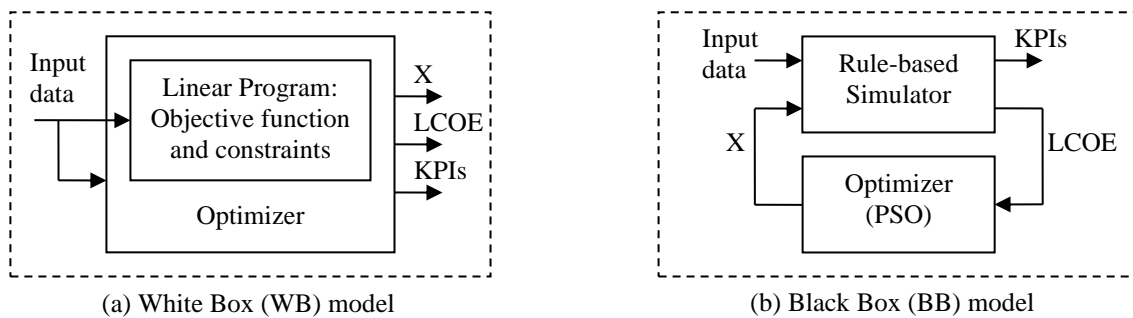


Figure 1. Diagrams of White Box (a) and Black Box (b) models for microgrid design optimization.

2.2 Mathematical formulation

2.2.1 Deterministic case

This subsection presents the deterministic WB model, where all parameters are known with absolute certainty. Model's decision variables X are both design and operation variables. The *design variables* are the size of the microgrid assets: maximum energy capacity of the battery N_{bat} , and maximum power of PV N_{pv} and diesel generator N_{gen} . The *operation variables* are the power flows or production of generation and storage units at every time step: charging $P_{bat,in}$ and discharging $P_{bat,out}$ power from the battery, state of charge of the battery $E_{bat,soc}$, and hourly production of PV P_{pv} and diesel generator P_{gen} .

$$X = \{N_{bat}, N_{pv}, N_{gen}, P_{bat,in}, P_{bat,out}, E_{bat,soc}, P_{pv}, P_{gen}\} \quad (1)$$

The objective is to minimize the *LCOE* of the system, shown in Eq. (2), which reflects the cost of consumed electrical energy. The *LCOE* is the ratio of the total annualized cost C_{tot} to the annual electricity delivered to the load E_{serv} . C_{tot} is the sum of all costs over the chosen period, including the annualized investment costs C_{cap} as well as the fixed and variable operation and maintenance (O&M) costs C_{op} .

$$LCOE = \frac{C_{tot}}{E_{serv}} = \frac{C_{cap} + C_{op}}{E_{serv}} \quad (2)$$

$$C_{cap} = N_{gen} \times annuity_{gen} + N_{pv} \times annuity_{pv} + N_{bat} \times annuity_{bat} \quad (3)$$

$$annuity_{tec} = \frac{r \times c_{cap,tec}}{1 - (1 + r)^{-T_{tec}}} \quad (4)$$

$$C_{op} = N_{gen} \times fOM_{gen} + N_{pv} \times fOM_{pv} + N_{bat} \times fOM_{bat} + \sum_h P_{gen,h} \times vOM_{gen} \quad (5)$$

$$vOM_{gen} = F_{slope} \times c_{fuel} \quad (6)$$

Where $annuity_{gen}$, $annuity_{pv}$ and $annuity_{bat}$ are the annualized investment costs of the generator, PV, and battery; r is the discount rate; T_{tec} is the technology (generator, PV, battery) lifetime and $c_{cap,tec}$ is its capital cost; fOM_{gen} , fOM_{pv} and fOM_{bat} represent fixed O&M costs of the generator, PV and battery; $P_{gen,h}$ is the generator production at hour h ; vOM_{gen} represents variable O&M cost of the generator related to fuel consumption and is evaluated as the slope of fuel consumption curve F_{slope} multiplied by the fuel price c_{fuel} : the underlying assumption is that diesel efficiency is considered constant whatever the generator operating point.

Eq. (7)-(14) are the model's constraints required to describe the system's energy balance and other operational and technical constraints. Eq. (7) guarantees that the operational decisions are made for balancing the energy production and demand at each time step h . If enough electricity is generated to meet the demand, the excess can be stored in the battery or curtailed.

$$P_{gen,h} + P_{pv,h} \geq P_{demand,h} + P_{bat,in,h} - P_{bat,out,h} \quad (7)$$

According to Eq. (8), the energy stored by the battery at time $h + 1$ is equal to the energy stored at time h added to the difference between the incoming and outgoing energy of the battery at time h , considering the round-trip conversion efficiency $\eta_{rt} \in [0,1]$. The cyclicity constraint given by Eq. (9) applies to the first hour of the year and states that the stored energy at the beginning of the year must be equal to the stored energy at the end of the year. This constraint is useful as we optimize only over one year and then extrapolate over the project lifetime by treating all years as identical.

$$E_{bat,soc,h+1} = E_{bat,soc,h} + P_{bat,in,h} \times \sqrt{\eta_{rt}} - \frac{P_{bat,out,h}}{\sqrt{\eta_{rt}}} \quad (8)$$

$$E_{bat,soc,0} = E_{bat,soc,8759} + P_{bat,in,8759} \times \sqrt{\eta_{rt}} - \frac{P_{bat,out,8759}}{\sqrt{\eta_{rt}}} \quad (9)$$

As the time step selected for optimization is fixed to one hour, the relationship between hourly-production and installed capacity can be derived using Eq. (10)-(13), where P_{bat} is the battery storage capacity. Eq. (14) limits the available energy volume that can be stored by the battery.

$$0 \leq P_{gen} \leq N_{gen} \quad (10)$$

$$0 \leq P_{pv} \leq N_{pv} \quad (11)$$

$$0 \leq P_{bat,in} \leq P_{bat} \quad (12)$$

$$0 \leq P_{bat,out} \leq P_{bat} \quad (13)$$

$$0 \leq E_{bat,soc} \leq N_{bat} \quad (14)$$

2.2.2 Stochastic case

When the input uncertainties are considered, the microgrid optimal design becomes an uncertain optimization problem. The decision-making structure involved in this issue can be captured in a two-stage SP model, which splits the decisions into first- and second-stage decisions, representing decisions that must be taken respectively before and after uncertainty is revealed [3],[8]. Our application of the two-stage SP for optimal microgrid design is a scenario-based approach, which assumes that the parameters' uncertainty can be represented by a finite number of N_s scenarios. Each scenario s is assumed to have a probability p_s .

The first stage involves design and operation variables X_{stage_1} with no information on the realization of uncertainty. The second stage involves also design and operation decisions X_{stage_2} that need to be made according to the actual realization of uncertain parameters, but also to the first-stage decisions. To show the dependency between both stages' decisions, the second-stage decisions cannot discard the PV installed in the first stage, given that diesel and battery lifetimes are reached by the end of the first stage. One can only keep the PV or increase the installed power. It is worth noting that, in the deterministic WB model, single values are calculated for the design variables and single vectors holding time step values are calculated for the operation variables. In the stochastic case, the same procedure is applied in the first stage, generating a single $LCOE$. While in the second stage, these variables must be computed for each individual uncertain scenario s , thus generating a $LCOE$ for each scenario, noted $LCOE_s$. Eventually, the number of decision variables is multiplied by $N_s + 1$.

$$X_{stage_1} = \{N_{bat_1}, N_{pv_1}, N_{gen_1}, P_{bat,in_1}, P_{bat,out_1}, E_{bat,soc_1}, P_{pv_1}, P_{gen_1}\} \quad (15)$$

$$X_{stage_2} = \{N_{bat_{2,s}}, N_{pv_{2,s}}, N_{gen_{2,s}}, P_{bat,in_{2,s}}, P_{bat,out_{2,s}}, E_{bat,soc_{2,s}}, P_{pv_{2,s}}, P_{gen_{2,s}}\} \quad (16)$$

As it is commonly the case in two-stage SP, the final objective function, which is the $LCOE$ in our model, is stated as the sum of the first-stage $LCOE$ and the expected value of the second-stage $LCOE$, as shown in Eq. (17).

$$LCOE = LCOE_{stage_1} + E_s[LCOE_s] = LCOE_{stage_1} + \sum_{s=1}^{N_s} (p_s \times LCOE_s) \quad (17)$$

Constraints that include only first-stage variables are expressed similarly to deterministic models Eq. (7)-(14). However, constraints that also contain second-stage variables are indexed per scenario s . Given the objective function and the constraints, the WB model simultaneously optimizes the first- and second-stage decision variables.

3. Black Box (BB) model

3.1 Description

The proposed BB model, illustrated in Figure 1.b, is a heuristic approach which, in our case, is based on a PSO algorithm. The objective function is identical to the WB one that minimizes the $LCOE$. Unlike the WB, in which the operation variables are optimized assuming perfect forecasting of load and renewable profiles over the optimization period, the BB operation strategy is based on priority-rules. In this paper, we only consider the LF strategy, which is the most common operating strategy used in real-life applications owing to its modest hardware and computational requirements [7]. Thereafter, the PSO procedure iteratively generates multiple size configurations for the microgrid components. The rule-based simulator simulates the system operation of each configuration for the entire year and subsequently evaluates the corresponding costs. Afterwards, the method calculates the $LCOE$ of the system and other Key Performance Indicators (KPIs). Once the convergence criteria of the PSO are reached, the procedure stops, and the optimal components are evaluated.

3.2 Mathematical formulation

3.2.1 Deterministic case

This subsection presents the deterministic BB model, in which the decision variables X are only the design variables (size of the assets detailed in 2.2.1) of the microgrid. The objective function, shown in Eq. (19), is to minimize the $LCOE$ of the system. To ensure energy balance, a penalty on load shedding is added to the objective function. Hence, the PSO algorithm will seek to find the design that minimizes the $LCOE$ while ensuring a 100% load supply rate.

$$X = \{N_{bat}, N_{pv}, N_{gen}\} \quad (18)$$

$$LCOE = \frac{C_{tot}}{E_{serv}} \quad (19)$$

At each time step, a rule-based control strategy determines the operating variables without considering future load and PV production profiles. Hence, the BB model does not include the constraints presented in the WB (Eq. (7)-(14)).

3.2.2 Stochastic case

To include uncertainties in the microgrid design, the BB model employs the same scenario-based approach used in the WB model (2.2.2). Clearly, design variables are the only first- and second-stage variables. The BB technique is applied to the first stage and to each individual scenario s in the second stage: the iterative routine between the PSO optimizer and the rule-based simulator is applied $N_s + 1$ times in order to optimize X_{stage_1} and X_{stage_2} and the corresponding $LCOE$. Finally, the total objective function is calculated using Eq. (16).

$$X_{stage_1} = \{N_{bat_1}, N_{pv_1}, N_{gen_1}\} \quad (20)$$

$$X_{stage_2} = \{N_{bat_{2,s}}, N_{pv_{2,s}}, N_{gen_{2,s}}\} \quad (21)$$

4. Case study

4.1 Description

The proposed WB and BB sizing methodologies are tested on a real microgrid composed of a PV, a battery, and a fuel-fired generator. The demand and PV production profiles were estimated using real data, with a yearly peak demand of 2084 kW. We assumed a 30-year time horizon with 5% discount rate. Also, we assumed linear specific costs: 1200 \$/kWp for the PV, 350 \$/kWh for the battery, and 400 \$/kW for the generator. Maintenance costs are expressed as yearly values proportional to the size component: 20 \$/kWp/y for the PV, 10 \$/kWh/y for the battery, and 20 \$/kW/y for the generator for an average of 1000 working hours per year and a cost of 0.02 \$/kW/h. The components' lifetimes are as follows: 30 years for the PV, 15 years for the battery, and 15 years for the generator. The battery round-trip efficiency is considered 90%. The fuel price is assumed to be 1 \$/L and the fuel consumption curve slope is 0.24 L/kW.

The same economic and technical parameters, load and renewable generation profiles were considered for both WB and BB models so that the two methods could be compared on equal basis. Calculation time step is one hour. The optimization period is the typical year based on which the multi-year behavior of the system is approximated.

4.2 Results

4.2.1 WB versus BB – Deterministic case

The deterministic optimal microgrid design is first obtained with the LP WB model, and then with the PSO-based BB with a LF strategy. The resulting designs are included in the techno-economic comparison shown in Table 1, where NPC , τ_{shedd} and τ_{EnR} are the Net Present Cost, the load shedding rate and the renewable energy share rate, respectively. It is worth noticing that the components sizing is quite different in the two models. The fuel generator in BB optimal design, equal to the yearly peak demand, is reduced using the WB model. Indeed, since WB scans the possible system behavior in advance, a smaller genset can be used and operated to charge a much larger battery. This also implies that the WB global optimum stands theoretically for the lowest value with respect to rule-based strategies: BB solution is 1.512% higher than WB solution in terms of LCOE. Yet, BB allows significant execution time reduction by a factor of 4.7.

Besides, we calculated the LCOE in the case where the system is sized based on the WB operation strategy and then operated with the BB operation strategy. The simulation results depicted in Table 2 underline the drawbacks of using an anticipative operation strategy in the optimization phase different than the one actually used: a 0.81% increase in LCOE and 0.25% load shedding. Note that, in real life, τ_{shedd} could be higher due to the lack of switching equipment close to the users.

Table 1. Optimal microgrid design with deterministic WB and BB models.

Model	Time [s]	$N_{gen}[kW]$	$N_{pv}[kWp]$	$N_{bat}[kWh]$	$LCOE[\$/MWh]$	$NPC[k\$]$	$\tau_{shedd}[\%]$	$\tau_{EnR}[\%]$
WB	33	1548	2643	2794	227.7	24553	0	32.3
BB	7	2084	1828	89	231.1	24924	0	21.8

Table 2. Simulation of the microgrid designed with an optimization-based strategy and operated with a rule-based one (LF).

Simulation strategy	Design obtained with	$LCOE[\$/MWh]$	$NPC[k\$]$	$\tau_{shedd}[\%]$	$\tau_{EnR}[\%]$
BB	WB	229.6	24690	0.25	32.5

4.2.2 WB versus BB – Stochastic case

For a simplified stochastic case, we only consider fuel price uncertainty. Annual variations of fuel price were not considered in this study. The cost remains constant (1 \$/L) until the 15th year, from that point it can either decrease by 90%, remain constant or increase by 90% over the remaining 15 years of the project lifetime. These three realizations, corresponding to scenarios s_1 , s_2 and s_3 , are taken as equiprobable. The results presented in Table 3 show the dependency between the first- and second-stage designs. In s_3 , a larger PV and battery are installed in both WB and BB to reduce the consumption of fuel whose price increases. Nevertheless, a large generator is still required to satisfy the peak load in the BB. As in the deterministic case, optimal component sizes are different between the two models with an overall LCOE of 1.502% higher in the BB than in the WB. Also, note that the WB is more time-consuming than BB by a factor of 3.5.

Table 3. Optimal microgrid design with stochastic WB and BB models.

Model	Time [s]	Stage	$N_{gen}[kW]$	$N_{pv}[kWp]$	$N_{bat}[kWh]$	$LCOE[\$/MWh]$	$NPC[k\$]$	$\tau_{shedd}[\%]$	$\tau_{EnR}[\%]$
WB	184	1	1765	1758	1044	229.0	24691	0	23.4
		2- s_1	2084	1758	0	60.9	6565.8	0	21.2
		2- s_2	1548	2643	2794	227.7	24553	0	32.3
		2- s_3	1279	5472	7754	337.9	36432	0	54.4
BB	52	1	2084	1491	0	231.7	24983	0	19.4
		2- s_1	2084	1491	0	57.6	6209.3	0	19.4
		2- s_2	2084	1823	84	231.1	24924	0	21.8
		2- s_3	2084	5357	7399	349.3	37667	0	53.8

5. Conclusion

This paper compares two approaches for microgrid sizing. Firstly, we presented **an anticipative LP WB model** that conjointly optimizes microgrid sizing and operation assuming perfect knowledge of load and renewable patterns over the project lifespan. Then, we presented **a responsive PSO-based BB model** that heuristically optimizes the sizing of microgrid whose operation is controlled by a rule-based simulator that determines at each time step the optimal generation dispatch. The microgrid sizing and operation are obtained by solving the deterministic and two-stage stochastic forms of the two models. The case study results highlighted the importance of selecting a sizing method that copes with the actual operating strategy of the project to avoid design failures and costs increase. Furthermore, the results showed that BB outperformed the WB in terms of computational requirements. Among the avenues for future work, we would like to validate this comparison by studying other microgrid projects and by testing the sensitivity of the models' computational requirements when the number of decision variables is expanded, and other uncertainties are considered.

References

- [1] N. Hatziaargyriou, *Microgrid: architectures and control*. Chichester, West Sussex, United Kingdom: Wiley, 2013.
- [2] B. Li, R. Roche, D. Paire, et A. Miraoui, « Sizing of a stand-alone microgrid considering electric power, cooling/heating, hydrogen loads and hydrogen storage degradation », *Appl. Energy*, vol. 205, p. 1244-1259, nov. 2017, doi: 10.1016/j.apenergy.2017.08.142.
- [3] G. Mavromatidis, K. Orehounig, et J. Carmeliet, « Design of distributed energy systems under uncertainty: A two-stage stochastic programming approach », *Appl. Energy*, vol. 222, p. 932-950, juill. 2018, doi: 10.1016/j.apenergy.2018.04.019.
- [4] A. Ehsan et Q. Yang, « Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques », *Appl. Energy*, vol. 210, p. 44-59, janv. 2018, doi: 10.1016/j.apenergy.2017.10.106.
- [5] T. Lambert, P. Gilman, et P. Lilienthal, « Micropower System Modeling with Homer », in *Integration of Alternative Sources of Energy*, F. A. Farret et M. G. Simões, Éd. Hoboken, NJ, USA: John Wiley & Sons, Inc., 2006, p. 379-418. doi: 10.1002/0471755621.ch15.
- [6] S. Twaha et M. A. M. Ramli, « A review of optimization approaches for hybrid distributed energy generation systems: Off-grid and grid-connected systems », *Sustain. Cities Soc.*, vol. 41, p. 320-331, août 2018, doi: 10.1016/j.scs.2018.05.027.
- [7] A. Micangeli, D. Fioriti, P. Cherubini, et P. Duenas-Martinez, « Optimal Design of Isolated Mini-Grids with Deterministic Methods: Matching Predictive Operating Strategies with Low Computational Requirements », *Energies*, vol. 13, n° 16, p. 4214, août 2020, doi: 10.3390/en13164214.
- [8] J. R. Birge et F. Louveaux, *Introduction to Stochastic Programming*. New York, NY: Springer New York, 2011. doi: 10.1007/978-1-4614-0237-4.