

Review of Methodologies for the Assessment of Feasible Operating Regions at the TSO–DSO Interface

Georgios Papazoglou  and Pandelis Biskas * 

School of Electrical and Computer Engineering, Aristotle University of Thessaloniki, 541 24 Thessaloniki, Greece; papazoglou@ece.auth.gr

* Correspondence: pbiskas@auth.gr; Tel.: +30-6973-841753

Abstract: The Feasible Operating Region (FOR) is defined as a set of points in the PQ plane that includes all the feasible active and reactive power flows at the Transmission System Operator (TSO)–Distribution System Operator (DSO) interconnection. Recent trends in power systems worldwide increase the need of cooperation between the TSO and the DSO for flexibility provision. In the current landscape, the efficient and accurate estimation of the FOR could unlock the potential of the DSO to provide flexibility to the TSO. To that end, much existing research has tackled the problem of FOR estimation, which is a challenging problem. However, no research that adequately organizes the literature exists. This work aims to fill this gap. Three categories of FOR estimation methods were identified: Geometric, Random Sampling, and Optimization-Based methods. The basic principles behind each method are analyzed and the most significant works involving each method are presented. For the reviewed works, we focus on the types of flexibility providing units included in the FOR estimation, the examination of time dependence, and the monetization of the FOR. Finally, the strengths and weaknesses of each category of methods are compared, providing a holistic review of the available FOR estimation methods.

Keywords: feasible operating region; TSO–DSO coordination; active distribution networks; flexibility aggregation; network capability charts; flexibility cost maps; interconnection power flow



Citation: Papazoglou, G.; Biskas, P. Review of Methodologies for the Assessment of Feasible Operating Regions at the TSO–DSO Interface. *Energies* **2022**, *15*, 5147. <https://doi.org/10.3390/en15145147>

Academic Editor: Abu-Siada Ahmed

Received: 24 June 2022

Accepted: 12 July 2022

Published: 15 July 2022

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1. Introduction

1.1. Motivation

1.1.1. Challenges Posed by the Energy Transition

The ongoing energy transition of the global energy sector, whose aim is the reduction of carbon emissions in order to combat the climate crisis [1], is causing major changes in energy systems worldwide. These changes are manifested through the rapid integration of Renewable Energy Sources (RES) and other forms of Distributed Energy Resources (DERs) in power systems, as well as the electrification of various industries and aspects of human life [1]. In Europe, recent developments have led to policies that further accelerate the roll-out of RES and electrification (i.e., the REPowerEU plan [2]), further amplifying the impact of the energy transition and making it imminent. The impact of these changes poses new challenges to the Transmission System Operators (TSOs) and the Distribution System Operators (DSOs), but also creates new opportunities for stakeholders [3].

TSOs are responsible for the secure and reliable operation of the Transmission Network (TN), and for maintaining the balance between supply and demand in the power system at every instance. On the supply side, in traditional power systems, the bulk of electricity is generated by conventional and hydro power plants that are connected in the TN. Conventional and hydro power plants are dispatchable, meaning that their output can be adjusted (e.g., by regulating their fuel consumption), thus their output is predictable and they are able to offer flexibility (the term “flexibility” has received many definitions in the literature [3]). In this paper, we refer to flexibility as the ability of an asset (or an aggregation

of assets) to change its power output according to dispatch instructions) services to the TSO. On the demand side, several methods have been developed that enable its forecast with reasonable accuracy [4]. Therefore, in order to keep supply and demand in balance (i.e., to offset mismatches between forecasted and actual demand), the TSO would rely on the flexibility provided by conventional and hydro generators, and the reserves it keeps to safeguard the system against unexpected events (e.g., line or generator outages) [5].

The proliferation of RES means that a significant share of energy is now generated by renewable sources. RES generation depends on environmental conditions (e.g., wind speed or irradiance), and thus is non-dispatchable, variable, and difficult to accurately forecast [4]. Therefore, the residual demand (total demand minus RES generation) that conventional generation has to accommodate is characterized by increased variability and different ramping patterns [5], which means that the system has greater flexibility needs [3]. Since many conventional power plants are being decommissioned, their roles in the energy mix are being reduced (e.g., incentivized by REPowerEU [2] and Fit for 55 [6] plans in Europe), and due to their inherent high operational costs, TSOs have to turn elsewhere for procurement of the required flexibility.

The changes caused by the ongoing energy transition along with recent advancements in information and communication technologies mean that the Distribution Network (DN) can be transformed into a major source of flexibility for the system [3,7]. Traditionally, DNs were passive and featured limited amounts of flexibility. However, the integration of DERs on the DN level, the rapid adoption of electric vehicles (EVs), and the expected rollout of smart meters and smart appliances transform DNs into Active Distribution Networks (ADNs) that feature many control options and much flexibility potential [5,7]. Hence, TSOs could rely on the flexible assets of DNs (or ADNs as a whole) for the procurement of the required flexibility to solve their operational problems. Via this scheme, TSOs do not only rely on flexibility provided by generators, but also on demand-side flexibility, which is already starting to emerge in Europe [8].

What complicates matters is the fact that DSOs also have new challenges to overcome. Traditional power systems were organized under the assumption that power was generated in the TN and would then flow through the DN towards the end users. Since a large number of DERs and RES has been introduced in the DN, this assumption is being challenged. As a result, DNs are being subject to flows they have not been designed to withstand. Moreover, due to the increasing electrification of human activities and industries, and the emergence of EVs, DNs are being increasingly loaded. Consequently, DSOs face operational challenges such as reverse flows, voltage violations and line congestions that pose threats to the secure and reliable operation of the DN [9]. The traditional way of mitigating these issues would be the capital-intensive solution of network reinforcement. An alternative and cost-effective solution would be the utilization of the flexibility that lies within the DN by the DSO in order to alleviate its operational issues.

The problem that arises stems from the fact that both the TSOs and the DSOs need to access the same flexibility resources, for different (and potentially even conflicting) objectives. Thereby, coordination between the TSO and the DSOs (which is referred to as “TSO–DSO coordination” in the literature) is required to achieve optimal use of flexibility and the operational objectives of both the TSO and the DSOs.

1.1.2. TSO–DSO Coordination Models

The topic of TSO–DSO coordination has received a lot of attention recently from various entities, such as the European Commission (e.g., [10]), ENTSO-E (e.g., [11,12]) and CIGRE (e.g., [13]), and is an active field of research amongst academics. Many TSO–DSO coordination schemes have been proposed in the literature ([14,15] provide a comprehensive review), and can be split into three categories: TSO-managed models, TSO–DSO hybrid-managed models, and DSO-managed models [14,15].

In TSO-managed models, a central entity (in all three TSO–DSO coordination categories, the role of the central entity is usually assumed by the TSO, but could also be

assumed by an independent market operator [14]) is responsible for the dispatch of both the assets of the TN and the DNs, while respecting the TN and DN constraints ([16] is an example of this implementation). The main advantage of this method is the simplification of the TSO–DSO coordination, as the role of the DSO is limited to the communication of operational data to the central entity. The disadvantages of this method stem from the size of the optimization problem that the central entity has to solve (which has to include all the assets of the TN and the DNs, as well as all of their operational constraints, posing computational and modeling challenges), and the amounts of operational data transfer required amongst the TSO, the DSOs and the central entity [14,15].

In TSO–DSO hybrid-managed models, a central entity is responsible for the dispatch of both the assets of the TN and the DNs, but only considers the TN constraints during the dispatch. That is because, according to this method, each DSO performs a validation of the bids submitted by the assets that lie in their network, to guarantee the feasibility of the dispatch in the DN. Only the validated bids are included in the optimization problem that the central entity solves. An example of this implementation can be found in [17]. Advantages of this method include the reduction of the computational and modeling burden undertaken by the central entity and the elimination of the communication of operational DSO data to the central entity. Disadvantages arise from the complication of the TSO–DSO coordination (since decision processes are no longer centralized in one entity), and the computational and modeling challenges DSOs face (considering that DSO entities have less expertise in these issues, when compared to TSOs) [14,15].

Finally, in DSO-managed models, a central entity is responsible for the dispatch of the assets of the TN and the aggregated dispatch of the assets of the DNs. The dispatch of each individual asset of each DN is undertaken by the respective DSO, as in this method the DSO acts as an aggregator (or a central coordinator) for the assets in its DN. Thus, the DSO provides validated bids to the central entity that correspond to aggregated volumes, and receives aggregated dispatch instructions from the central entity that must then disaggregate on an asset basis. Details of this implementation can be found in [18] and in the following sections of this paper. This method owns all the advantages and disadvantages as the TSO–DSO hybrid-managed method [14,15]. Additional advantages of this method include its compatibility with distribution-level markets and its potential to achieve the highest level of efficiency for the assets that lie in the DN [14]. The latter advantage can be attributed to the fact that, since the DSO performs the disaggregation of the flexibility, in case the requested flexibility is less than the flexibility available within the DN, the DSO can re-optimize its network before dispatch, to achieve greater efficiency [14].

According to [19], limitations in the definition of system operator responsibilities, in regulatory frameworks, in privacy aspects and in information technology, along with its potential to achieve the highest efficiency in flexibility provision, make DSO-managed models the best method for TSO–DSO coordination in the current landscape.

1.1.3. Feasible Operating Regions

At the core of the DSO-managed models lies the Feasible Operating Region (FOR). The FOR (which is also called the capability chart of the ADN, the PQ flexibility area or map and the equivalent PQ capability) is used to represent the aggregated flexibility potential of a DN, by charting the feasible active and reactive power flows of the DN at the TSO–DSO interconnection. This approach to describe the flexibility potential of the DN was first introduced in [20]. In order to determine the FOR, the DSO must take into account the available flexibility of the assets that lie in the DN, the current status of the DN, as well as the physical constraints of the DN. The shape of a typical FOR can be seen in Figure 1.

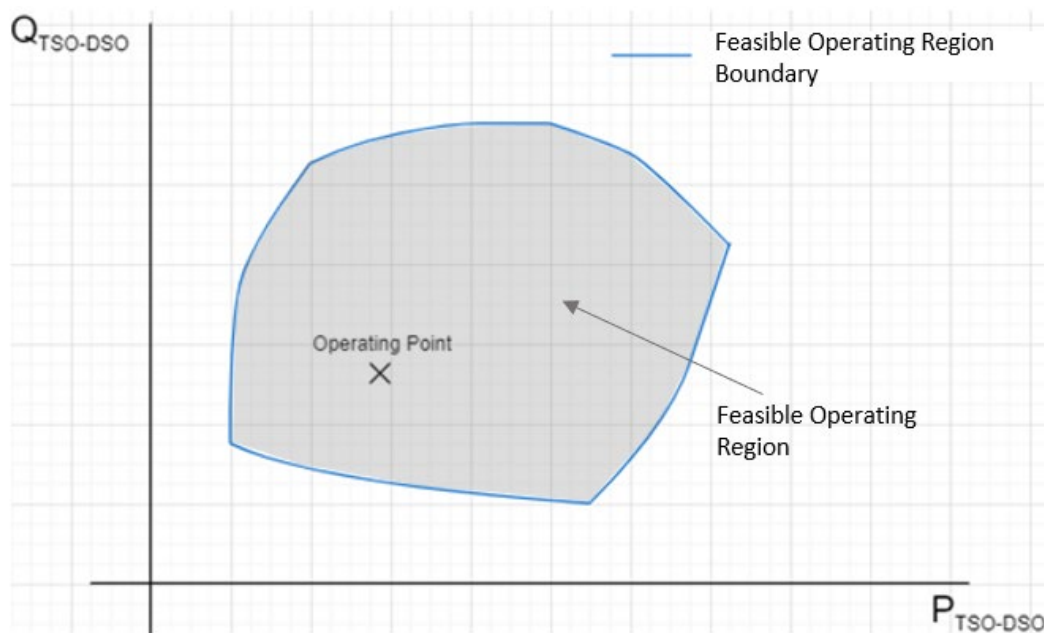


Figure 1. A typical FOR.

Therefore, using the FOR, the DSO is able to aggregate the flexibility within its system in a way that internalizes the constraints of the DN. What is more, the DSO can include its own assets in the calculation of the FOR (e.g., compensators or On-Load Tap Changing (OLTC) transformers) on top of the Flexibility Providing Units (FPUs) in the DN. Therefore, the DSO can communicate the FOR to the TSO, as it contains all the information the TSO needs in order to use it in the context of managing the operational issues of the TN. Importantly, via this process, the need for the communication of the topology or the operational status of the DN by the DSO is circumvented. Moreover, the monetization of the FOR (which is discussed in the following sections) can provide a clear pathway to the pricing of the flexibility provided by the DSO to the TSO [19,21].

The determination of the FOR is a challenging problem and has received significant academic interest. A lot of different algorithms exist in the literature that propose ways for its accurate and efficient estimation (most of them are discussed in the following sections). According to the literature [19,22,23], the different approaches fall into one of the following three categories: Geometric methods, Random Sampling (RS) methods, and Optimization-based (OB) methods. Each method presents several advantages and disadvantages, and different approaches to the application of each method can have their own strengths and weaknesses, as is discussed in the following sections.

As a final remark, the depth of the literature surrounding the calculation of the FOR can be interpreted as a further testament to the promise DSO-managed models show as the preferred means of TSO–DSO coordination in the existing landscape, as the efficient estimation of the FOR is key to its further adoption.

1.1.4. Types of Flexibility-Providing Units at the Distribution Network

The shape of the FOR is determined by the characteristics of the DN and the characteristics of the FPUs that are connected in the DN. The capability charts of the FPUs determine the amount of flexibility they can provide, which in turn determines the shape of the FOR. Refs. [23,24] provide an overview of the capability charts of the six major types of FPUs that are located in the DN, namely: generic FPUs, controllable loads, battery storage systems, wind generators, photovoltaic generators, and synchronous generators. The capability charts of these types of assets are parameterized in these works and can be seen in Figure 2.

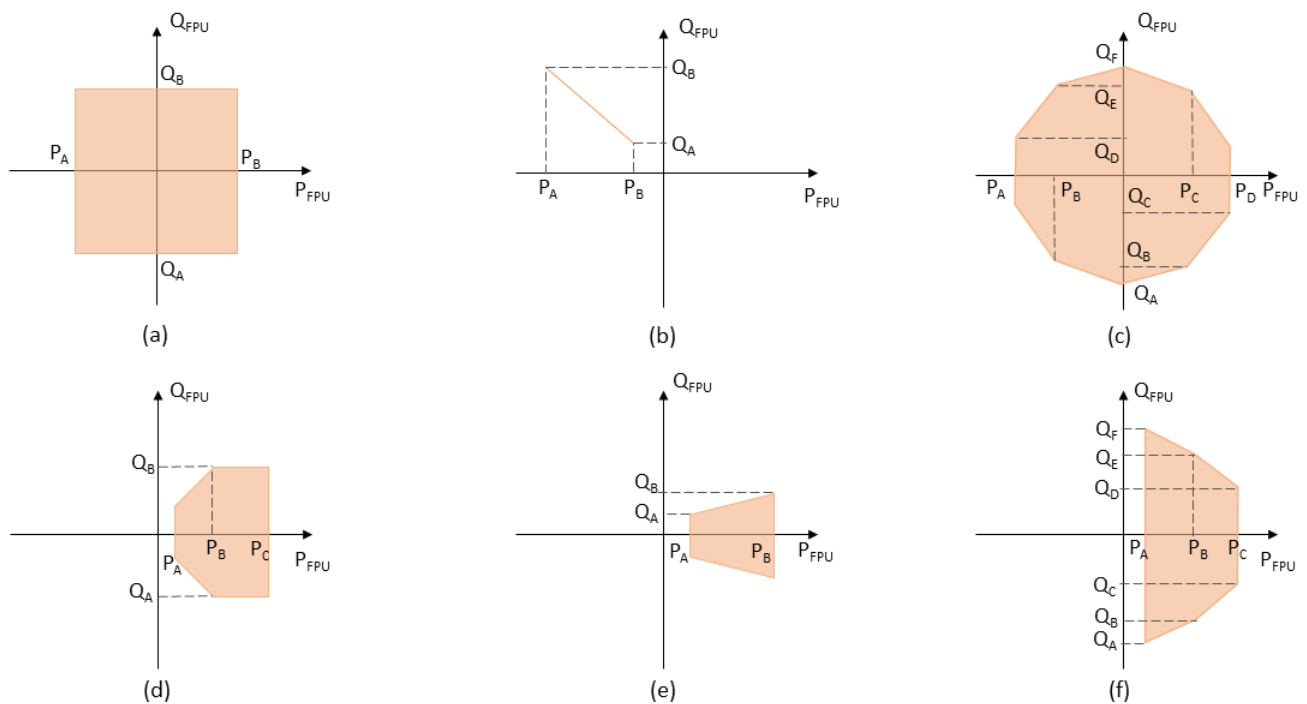


Figure 2. Capability charts of different types of FPUs: (a) generic FPU, (b) controllable load, (c) battery storage system, (d) wind generator, (e) photovoltaic generator, and (f) synchronous generator.

The categorization introduced by [23,24] is also adopted in this work. Moreover, in this work we refer to the works that incorporate FPU flexibility in the form of step-wise or piece-wise bids as “FPU-agnostic”.

1.2. Similar Works and Contribution

There are a few existing review papers on the estimation of the FOR in the literature [19,22,23]. A summary and comparison of these review papers can be found in Table 1. These review papers have made good contributions in organizing the literature surrounding FOR estimation and summarizing much of the related research. However, these papers leave some knowledge gaps regarding FOR estimation that this paper aims to address.

Table 1. A summary of the existing review papers on FOR estimation.

Reference	FOR Estimation Categories Reviewed	Types of FPUs Analyzed	Time Dependence Examined	Monetization of FOR Examined
[19]	RS OB	No	No	Yes
[22]	Geometric	Yes	Yes	No
[23]	Geometric RS OB	Yes	No	No
This work	Geometric RS OB	Yes	Yes	Yes

Specifically, in some of the existing review papers, not all three FOR estimation categories are analyzed, with some limiting their analysis to just one category. While these papers can provide crucial insights to the inner workings of the categories of the FOR estimation methods that they review, they do not provide a platform for the comparison of the advantages and disadvantages of the application of all three categories.

Moreover, some papers (e.g., [19]) do not provide details regarding the type of FPUs that exist in the reviewed works. The type of FPUs plays a significant role in the formu-

lation of the FOR estimation problem and should be addressed before choosing the FOR estimation method to use. Two more important aspects that are not adequately addressed in the existing works have to do with the time-dependence aspect of the FOR estimation, and the monetization of the FOR.

Therefore, this paper aims to fill the following gaps:

1. To provide a detailed review of the existing methods for the estimation of the FOR for all three available categories of methods (Geometric, RS and OB methods);
2. To include the type of FPU of the reviewed works;
3. To examine whether the reviewed methods account for the time dependence some FPU exhibit, and calculate the FOR for multiple time periods;
4. To examine whether the reviewed methods can provide information regarding the monetization of the FOR; and
5. To provide a comparison between the three categories of FOR estimation methods, focusing on their respective strengths and weaknesses, and make recommendations on the use cases that better suit each category of methods.

The remainder of this paper is organized as follows. In Section 2, Geometric methods are discussed. Section 3 presents RS methods, and Section 4 presents OB methods. For each category of methods, an overview of the central ideas behind the method is presented, and existing works that apply them for FOR estimation are discussed. Finally, in Section 5, the advantages and disadvantages of the three categories of FOR estimation methods are discussed and, in Section 6, the conclusions are drawn.

2. Geometric Methods

2.1. Overview

In mathematical terms, flexibility of an FPU can be described as the set containing all the power profiles an FPU can achieve, based on its current setpoint. Geometrically, this set is a polytope on the PQ plane [22]. In order to calculate the FOR, one has to aggregate the flexibilities of all the available FPUs, by combining them in a way that reflects the total available flexibility. To that end, Geometric methods use the Minkowski sum (M-sum, also known as the Minkowski addition, dilation, or point-wise sum). The M-sum is an operation between two sets that calculates their point-wise sum. Given two sets $A, B \in \mathbb{R}^N$, their M-sum (which is denoted as $A \oplus B$) is the set

$$A \oplus B = \{a + b | a \in A, b \in B\}. \quad (1)$$

A simple example of the calculation of an M-sum can be seen in Figure 3, where the M-sum is calculated between the set of the elements contained in the triangle ABC and the set of the elements contained in the square $DEFG$. The resulting M-sum is the polygon $HJKLM$. Further details on the M-sum can be found in mathematical textbooks such as [25].

Existing algorithms for M-sum calculation are computationally expensive and not scalable enough for application in modern DNs that contain up to thousands of FPUs [26]. Consequently, approximations of the M-sum are used in the literature to calculate the aggregated flexibility of the FPUs [22].

Assuming that M is the set that contains the exact M-sum of two sets A, B , the M-sum can be approximated either with an Inner Approximation (IA) or an Outer Approximation (OA). OAs overestimate the aggregated flexibility, meaning that if M_{OA} is the set containing the outer approximation of the M-sum, then $M_{OA} \supseteq M$. On the other hand, IAs underestimate the aggregated flexibility, meaning that if M_{IA} is the set containing the inner approximation of the M-sum, then $M_{IA} \subseteq M$. The differences between the M-sum, the IA of the M-sum and the OA of the M-sum can be seen in Figure 4. FORs calculated using OAs therefore overestimate the aggregated flexibility of the DN and can lead to points of the FOR that cannot be disaggregated amongst individual FPUs. Conversely, FORs calculated using IAs underestimate the aggregated flexibility of the DN, which leads to some flexibility being lost [22].

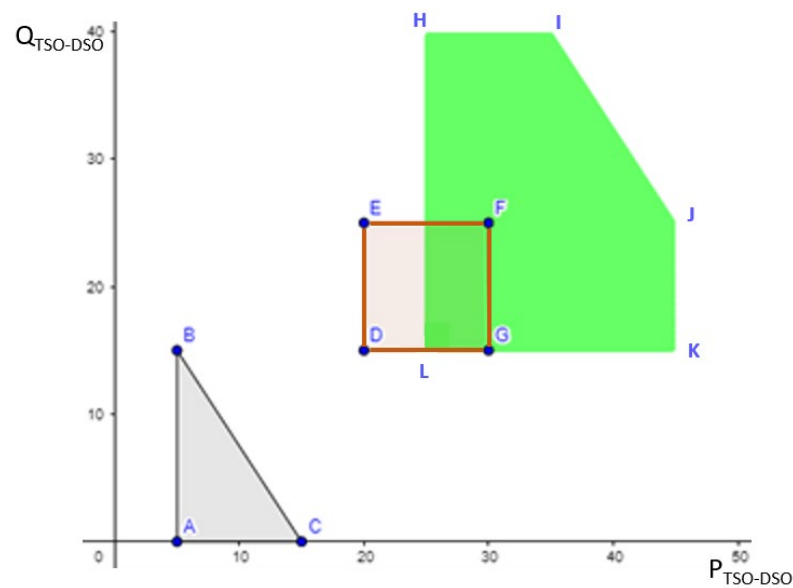


Figure 3. A simple example of the calculation of the M-sum.

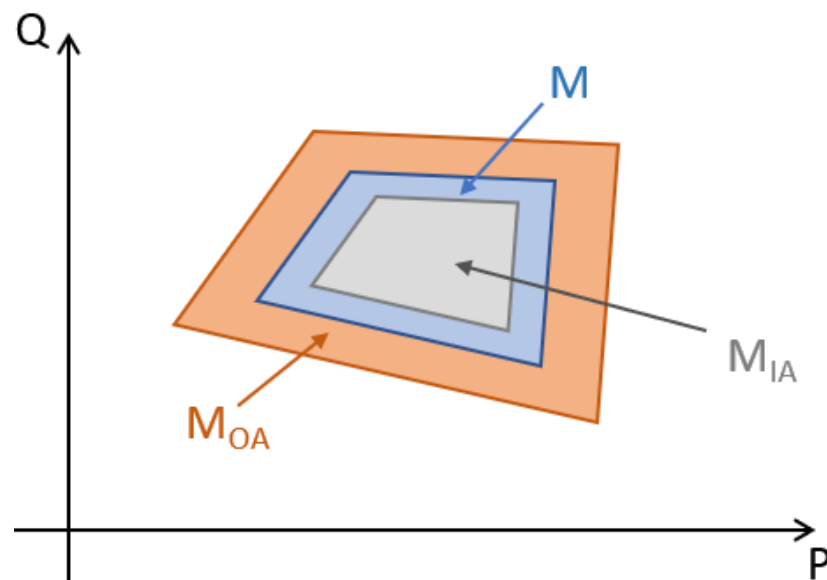


Figure 4. Visual comparison of the M-sum, the IA of the M-sum and the OA of the M-sum.

2.2. Related Works

Numerous works that use M-sum or M-sum approximations for the estimation of the FOR exist in the literature. The seminal work of Geometric methods for the estimation of the FOR is [27]. In [27], the authors recognize Thermostatically Controlled Loads (TCLs) as an important class of assets that can provide flexibility through demand response. Flexibility of each individual TCL in a heterogenous population of TCLs is represented by a polytope, and the FOR is estimated using a subset and a superset of the M-sum of the individual flexibilities. Hence, for each FPU the OA and IA is calculated. The FOR is estimated using the OA and IA approximations, by restricting the approximation sets to be the homothets of the prototype set. The method is found to be very efficient, and is able to improve the FOR estimation accuracy drastically compared to similar methods.

Ref. [28] expands on the work of [27] by extending the zonotope- and homothet-based approaches for computing M-sums. The focus of this work is on the calculation of IAs of the M-sum, so that the feasibility of the resulting FORs is guaranteed. The method presented is applied on inverter-interfaced devices and controllable loads. To account for

the exponential growth of the size of the problem in case of multiple FPU's [26], techniques to limit the complexity of the proposed methods, and the trade-off of accuracy versus complexity, are investigated.

In [29], a novel OA of the M-sum is developed, which can be computed in polynomial time. The method is based on the representation of polytopes as intersections of collections of half spaces, which allow for their expression as a set of linear inequalities. The parameters of the linear inequalities are then used for the OA of the M-sum in a computationally tractable way, as it relies only on linear algebra and linear programming. The methodology is shown to be able to capture a wide range of demand-side FPU's (the only requirement is that the represented FPU's can be modelled by convex polytopes), and its application is demonstrated to capture the flexibility of TLCs and deferrable loads. A similar method that includes preconditioning of the problem is discussed in [30]. Crucially, these works extend the FOR calculation for multiple time periods, making it compatible for use in Optimal Power Flow (OPF) problems. In their follow-up work [31], the same authors expand their methodology to also capture flexibility from FPU's modeled by second-order cone and semidefinite constraints, showcasing the application of the method for electric vehicles.

In an effort to increase the computational efficiency of the M-sum calculations, the authors in [32] use zonotopes to obtain the IA of the M-sum. The use of zonotopes (that are centrally symmetric polytopes) lowers memory requirements and time complexity. The presented methodology allows for the inclusion of any FPU's that can be modeled by linear constraints, and for multiple time periods. In their subsequent work [33], the authors enhanced and expanded their method to also provide a cost function of the FOR.

In [34], the authors propose a method that is agnostic about the type and model of FPU's, in an effort to introduce a scalable, "plug-and-play" approach to the estimation of the FOR for DNs with multiple, heterogeneous DERs. The methodology uses both the IA and the OA of the M-sum, and proposes metrics to evaluate the accuracy of the calculated FOR. The method is showcased in a test case consisting of batteries, inverter-interfaced photovoltaics, inverter-interfaced wind generators, and air conditioners.

Ref. [35] provides a complete framework for the real-time control of power grids. In the context of this framework, the FOR is calculated as the M-sum, by approximating the flexibility of FPU's with convex polygons. The method is FPU-agnostic, and a method to calculate the cost function of the FOR is proposed.

Aggregated flexibilities of FPU's can also be represented as virtual batteries (a process called virtual battery modeling). In [36,37], the authors developed approximations based on virtual batteries, in which the battery parameters were derived to obtain IA and OA M-sum approximations. These works considered a heterogeneous collection of TCLs as FPU's. Virtual battery modeling can be viewed as a special case of [27], if the prototype set is chosen to be a virtual battery model.

For more information regarding the mathematics involved in the calculation of the M-sum and its various approximation strategies in the context of FOR estimation, the reader is referred to [22]. Table 2 provides a summary of the reviewed Geometric methods of FOR estimation.

2.3. Discussion

Geometric methods for the estimation of the FOR aggregate the flexibilities of FPU's using the M-sum, or M-sum approximations. The calculation of the M-sum is computationally expensive, and cannot be applied in realistic DNs that contain up to thousands of FPU's. Many methodologies that approximate the M-sum have been developed. IAs underestimate flexibility, causing some flexibility to be lost, while OAs overestimate flexibility, leading to potentially infeasible operating points of the DN. Some of the existing methods account for the time dependence of FPU's, and extract the cost function of the FOR. This allows them to be integrated within OPF formulations in a TN level, or within market-based approaches.

Table 2. A summary of the reviewed Geometric methods.

Reference	Method	Type of FPU's Supported	Multi-Period Support	Monetization of FOR
[27]	IA and OA of M-sum	TCLs	No	No
[28]	IA of M-sum (zonotope and homothet-based)	Inverter-interfaced loads and TCLs	No	No
[29]	OA of M-sum	FPU's that can be modeled as convex polytopes	Yes	No
[30,31]	OA of M-sum	FPU's that can be modeled by linear, second-order cone or semidefinite constraints	Yes	No
[32]	Zonotope-based IA of M-sum	FPU's that can be modeled by linear constraints	Yes	No
[33]	Zonotope-based IA of M-sum	FPU's that can be modeled by linear constraints	Yes	Yes
[34]	Homothet-based OA and IA of M-sum	FPU-agnostic	Yes	No
[35]	M-sum	FPU-agnostic	No	Yes
[36,37]	Homothet-based OA and IA of M-sum modelled as virtual battery	TCLs	Yes	No

A major drawback of the Geometric methods is their failure to integrate the constraints of the DN, which can potentially lead to infeasibilities during dispatch [23]. Even so, Geometric methods remain an important tool in FOR estimation, and can complement RS and OB methods by being used to aggregate the flexibilities of FPU's that are connected to the same bus [21].

3. Random Sampling Methods

3.1. Overview

RS methods for the estimation of the FOR are also known in the literature as Monte-Carlo, Stochastic or Data-driven methods. The main idea behind RS methods (which was introduced in [20]) consists of simulating the Interconnection Power Flow (IPF) at the TSO–DSO interface for many different scenarios of the operational status of the DN. To create the different scenarios, the assets of the DN are split into two categories: non-flexible assets and FPU's. Non-flexible assets are considered to operate in the same setpoint in each scenario, since their injection/offtake is assumed to be non-dispatchable. FPU's, on the other hand, assume a different setpoint in each scenario, which is generated randomly, by assigning different values to it from its capability chart.

Then, for each scenario, the resulting IPF is calculated (which is a point of the FOR) by running a Power Flow (PF) analysis. The only modification needed in this PF analysis, compared to a vanilla PF analysis [23], is the formulation of the active/reactive power injection/offtake at each bus as

$$P_i = \sum_{j \in M_i} P_j + \sum_{f \in F_i} P_f, \quad (2)$$

$$Q_i = \sum_{j \in M_i} Q_j + \sum_{f \in F_i} Q_f, \quad (3)$$

where i is the index of each bus, M_i is the set containing the indexes j of the non-flexible assets connected at bus i , F_i is the set containing the indexes f of the FPU's connected at bus

i , and P_i , P_j , P_f (Q_i , Q_j , Q_f) are the active (reactive) power injections/offtakes (positive values for injections and negative for offtakes) at bus i , of the non-flexible asset j , and of the FPU f , respectively. As already mentioned, values of P_f , Q_f are generated randomly using Probability Density Functions (PDFs) within the FPU capability charts, while values of P_j , Q_j are assumed to be constant in each scenario. An overview of the capability charts for different types of FPUs can be found in [23,24].

The results of the PF are ex-post-examined for violations of the constraints of the DN. In case violations exist, the IPF is discarded from the FOR point cloud. In the opposite case, the IPF is considered to be feasible, and thus is added to the FOR point cloud. The FOR is then defined by the contour of the FOR point cloud. This process is repeated until the maximum number of samples is reached. The process can be summarized in the flowchart shown in Figure 5.

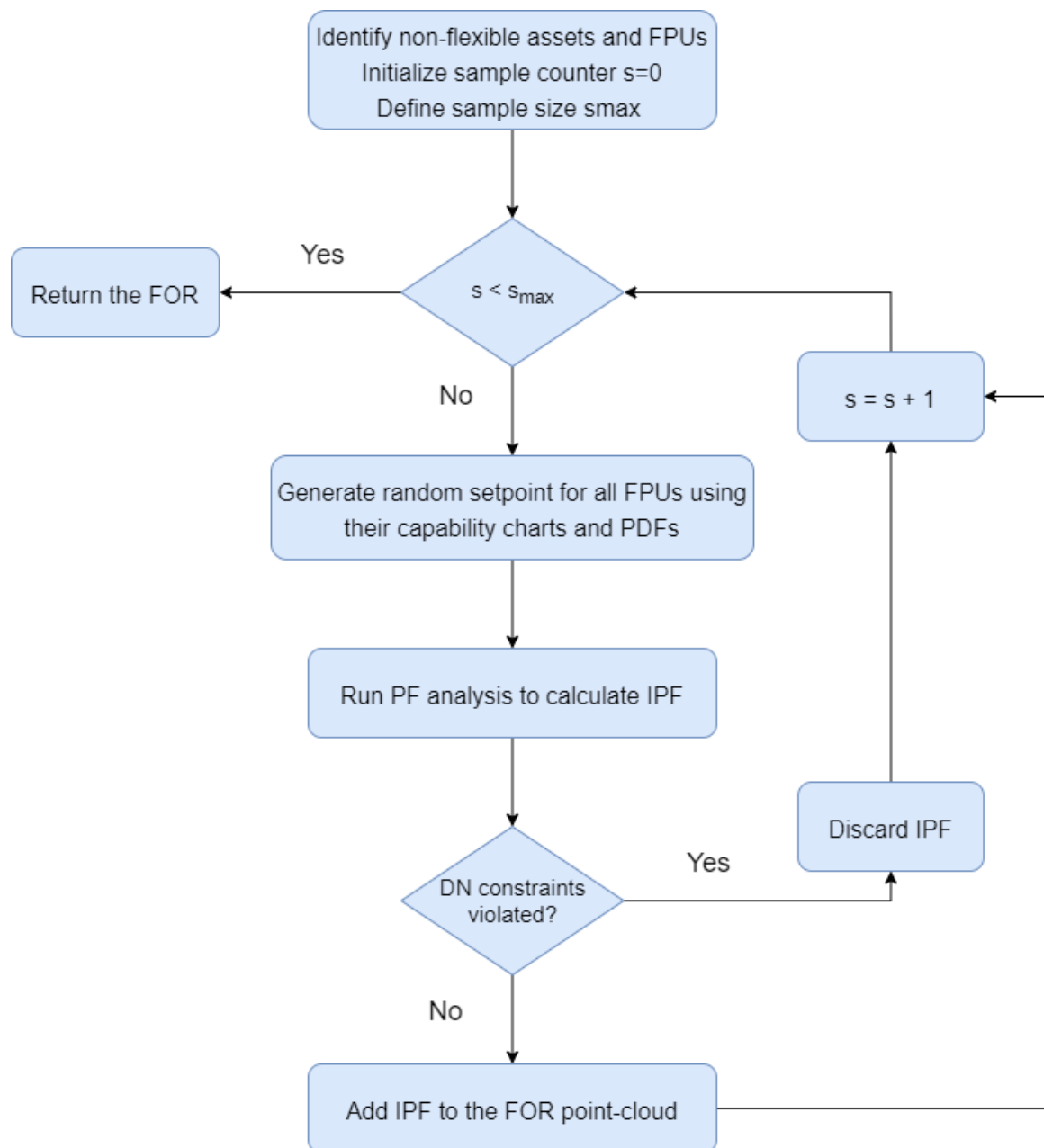


Figure 5. Flow chart of summary of RS methods.

3.2. Related Works

RS methods for the estimation of the FOR have received moderate research interest. The seminal work on RS methods is [20], which lays the foundation for RS methods and introduces the concept of the FOR. In this work, two different approaches were adopted with regard to the sampling process of the FPU setpoints. In the first approach, an independent random variable was associated with each FPU. In the second approach, FPUs located at the same bus featured a negative correlation between them (i.e., when generation increased, load decreased). Both approaches included network-controllable assets, including flexibility featuring discrete controls (e.g., OLTC transformers), whose setpoint was also sampled using a discrete uniform probability distribution. The method is FPU-agnostic, and no limitations regarding the shape of the FPU capability chart are mentioned. The authors discuss the potential of the application of these approaches to multi-period timeframes, but do not provide details about the potential complications (e.g., how the intertemporal constraints would be handled). This work also discusses the extraction of Flexibility Cost Maps (FCMs), in an effort to monetize the FOR. According to the authors, for each sample, the associated flexibility cost can be calculated (simply by summing the associated costs of the setpoint of each FPU), thus transforming the FOR into an FCM, by associating a cost to each IPF in the FOR point cloud. When comparing the two approaches, the authors found that the approach featuring the negative correlation performs better, by being able to capture for a wider FOR and having lower flexibility costs (in both cases, the sample size was the same).

The authors in [38] extend the concepts introduced in [20]. According to [38], apart from the state of the DN and its operational limits, the shape of the FOR is dependent on the time-varying characteristics of the non-flexible devices of the DN, and the time-dependent capability charts of the FPUs. Therefore, the authors set out to estimate the trajectory of the FOR (the variation of its position, shape and area) over time, using a probabilistic approach, to describe the probability that a particular IPF setpoint will be available in the future. This estimation is done using the RS method with independent random variables introduced by [20]. The FOR for each time step was successfully approximated by a polygon in the PQ plane. However, unlike in [20], the monetization of the FOR is not discussed.

In [39], the authors set out to make an important distinction between Feasibility and Flexibility Operating Regions (referred to as FOR and FXOR, respectively). According to them, the concepts of flexibility and feasibility are used interchangeably, while they should not be. FORs and FXORs coincide only if all the FPUs have sub-second response times, which is not a realistic assumption. Therefore, the temporal ability of FPUs to move between setpoints should also be taken into account. Thus, the FXOR is always a subset of the FOR in realistic applications. Again, in [39], the FOR and FXOR estimation is done using the RS method with independent random variables introduced by [20]. In this work too, however, additional constraints are added to account for the ramp rates of the FPUs and the target intervals of the flexibility activation. The monetization of the FOR is not examined.

Ref. [40] uses the methodology introduced by [41], in which four different PDFs for sampling are introduced, to generate the FOR and include it in an economic dispatch problem. The time dependence of flexibility is not examined, nor is the monetization of the FOR, as the inclusion of the FOR in the economic dispatch problem is done using fixed costs. The parameters of the PDFs of sampling distributions are chosen based on heuristics.

In [42], the authors identify the naïve sampling strategies as the main cause of the shortcomings of the RS methods, and argue that improved sampling strategies would enhance the capabilities of RS methods. Naïve sampling strategies according to [42] suffer from the so-called “convolution problem”, as the PDF of the sum of two or more independent random variables is the convolution of their respective PDFs. The convolution problem is demonstrated to be exacerbated as the number of FPUs increases. The work does not introduce a novel sampling strategy to mitigate this issue, but works as a basis for the recognition of the problem, urging for its solution. The authors point towards

the successive sampling method proposed by [43] and the formulation of sampling as a distributed optimization problem, as proposed by [44], as potential solutions.

In [45], the authors argue that RS methods that use uniform distributions during sampling tend to underestimate the size of the FOR. The reason for this is that the extreme scenarios that lead to points close to the contour of the FOR are unlikely to be generated using uniform distributions, resulting in conservative FORs. As a solution to these problems, the use of a novel “beta” PDF is introduced that prioritizes the sampling of extreme values of the capability charts of FPU. The proposed PDF features parameters that can be tuned by the user according to the desired aggressiveness of the sampling. Finally, in [23], the same authors follow up on their work and introduce two more novel sampling methods for FOR estimation. The first approach emulates the bivariate beta PDF and the second emulates the Rademacher PDF. The first approach is found to be a minor improvement compared to the uniform PDF, and the second poses a significant improvement. In both works, time dependence of flexibility and the monetization of the FOR are not examined.

Table 3 provides a summary of the reviewed RS methods of FOR estimation.

Table 3. A summary of the reviewed RS methods.

Reference	Method	Type of FPU. Supported	Multi-Period Support	Monetization of FOR
[20]	RS with independent random variables or negative correlation between loads and generation	FPU-agnostic	Yes	Yes
[38]	RS with independent random variables and time dependence	FPU-agnostic	Yes	No
[39]	RS with independent random variables and time dependence	FPU-agnostic	Yes	No
[40]	RS with PDFs from [41]	FPU-agnostic	No	No
[42]	RS with independent random variables	FPU-agnostic	No	No
[45]	RS with “beta” PDF	FPU-agnostic	No	No
[23]	RS with bivariate beta PDF and RS with Rademacher PDF	FPU-agnostic	No	No

3.3. Discussion

RS methods were the first to tackle the problem of FOR estimation. RS methods are relatively easy to implement; however, they are computationally expensive to execute. It should be noted that the PF analyses that need to be run can be parallelized, therefore a significant reduction of the computation time can be achieved.

The major problem regarding RS methods has to do with sampling strategies. As discussed in [42], the convolution problem that comes with the use of uniform PDFs leads to the conservative estimation of the FOR. Thus, research on RS methods should be focused on finding better and more sophisticated sampling strategies, such as the ones suggested by [42]. The authors in [23] further highlight the need for better sampling strategies, as according to their analysis, the increase in the number of samples shows marginal improvement on the estimation of the FOR, also posing an extra computational burden, while the choice of a better sampling strategy drastically improves the quality of the estimation.

A major advantage of RS methods has to do with their ability to handle the non-linear constraints imposed by the DN and all types of FPU. Since a PF is solved for each sample,

the physics of the system are accurately reflected, without the need of linearizations or other types of approximations. Moreover, as the operating point of each FPU is sampled and inserted in the PF, RS methods are agnostic to the type of FPUs needed, as long as they can be sampled effectively.

As demonstrated by [20], the extraction of the FCM of the FOR is straightforward, allowing for the monetization of the FOR and its inclusion in market-based applications. Additionally, RS methods have been shown capable of incorporating time-dependent and intertemporal constraints of the FPUs, allowing for their use in multi-period settings.

Finally, [42] points out that in practice, it is common that not all topology data are stored or available, which complicates the parametrization of explicit grid models (such as the OB methods discussed in the following section). In such cases, black-box machine learning models can be trained by measurement data (which are expected to be widely available through the adoption of smart meters) to be an alternative to physics-based, explicit grid models. Since RS methods are compatible with this approach, the authors of [42] argue that it is important for further research on RS methods to be conducted, to improve these approaches.

4. Optimization-Based Methods

4.1. Overview

OB methods (also known as deterministic methods or Iterative Optimization-based methods) for the estimation of the FOR involve solving multiple optimization problems to obtain points of the contour of the FOR. The idea of using optimization methods to obtain the capability charts of a power system was introduced 30 years ago in [46], but has received renewed academic interest in recent years in the context of FOR estimation. A generic formulation of an OPF problem that can be used in OB methods follows:

$$\min(-\alpha P_{TSO-DSO} - \beta Q_{TSO-DSO}) \quad (4)$$

Subject to

$$P_i = \sum_{j=1}^N (v_i v_j G_{ij} \cos \theta_{ij} + v_i v_j B_{ij} \sin \theta_{ij}), \quad \forall i, \quad (5)$$

$$Q_i = - \sum_{j=1}^N (v_i v_j B_{ij} \cos \theta_{ij} - v_i v_j G_{ij} \sin \theta_{ij}), \quad \forall i, \quad (6)$$

$$P_f, Q_f \in C_f, \quad \forall f, \quad (7)$$

$$V_i^{\min} \leq v_i \leq V_i^{\max}, \quad \forall i, \quad (8)$$

$$(p_{ij})^2 + (q_{ij})^2 \leq S_{ij,max}^2, \quad \forall (i, j), \quad (9)$$

$$p_{ij} = g_{ij} U_i^2 - U_i U_j (g_{ij} \cos \theta_{ij} + b_{ij} \sin \theta_{ij}), \quad (10)$$

$$q_{ij} = -b_{ij} U_i^2 - U_i U_j (g_{ij} \sin \theta_{ij} - b_{ij} \cos \theta_{ij}), \quad (11)$$

where $P_{TSO-DSO}$, $Q_{TSO-DSO}$ are the active and reactive IPFs, v_i is the voltage magnitude at bus i , θ_{ij} is the difference in voltage angles between bus i and j , $V_i^{\min}$ and $V_i^{\max}$ are the minimum and maximum voltage magnitudes at bus i , p_{ij} and q_{ij} are the active and reactive power flow of line (i, j) , and g_{ij} , b_{ij} are the conductance and susceptance of line (i, j) . P_i and Q_i are the same quantities as introduced in (2) and (3) (and thus defined by the same equations) and C_f is the capability chart of each FPU f (i.e., (7) constrains the range of P_f , Q_f within the acceptable limits as per the capabilities of each FPU). Parameters α and β are used to tune the search direction of the optimization problem, in order to sample vertices on the contour of the FOR. Thereby, sampling is also involved in OB methods, not just RS methods. The two simplest (naïve) sampling methods are analyzed: setpoint-based sampling and angle-based sampling [19].

4.1.1. Setpoint-Based Sampling

In the initial stages of the setpoint-based sampling, the outermost vertices of the FOR are identified by solving the OPF consisting of (4)–(11) for

$$(\alpha, \beta) = \{(1, 0), (1, 1), (0, 1), (-1, 0), (-1, -1), (0, -1), (1, -1), (-1, 1)\}. \quad (12)$$

The results of the initial setpoint-based sampling can be seen in Figure 6. The contour of the true FOR can be seen in blue, while the contour that results by drawing the edges between the vertices obtained by the initial setpoint sampling can be seen in black. In some areas (e.g., between $Q_{TSO-DSO}^{max}$ and $P_{TSO-DSO}^{max}$) the area of the FOR is overvalued, while in other areas (e.g., between $P_{TSO-DSO}^{max}$ and $Q_{TSO-DSO}^{min}$) the area is undervalued. As discussed in Section 2, undervalued areas mean that some flexibility is lost, while overvalued areas can lead to infeasibilities in the dispatch.

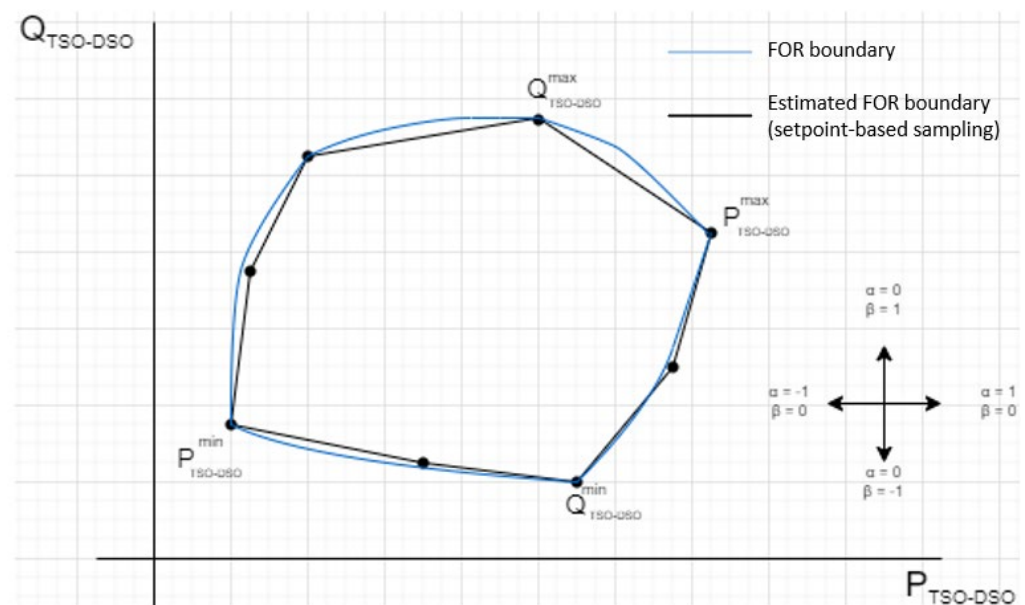


Figure 6. Visualization of setpoint-based sampling.

The results of the initial stages of the setpoint-based sampling are not expected to be satisfactory, and more vertices of the FOR need to be calculated to capture it in more detail. To that end, the sample size s_{max} is defined, and the following values are calculated:

$$\Delta P_{step} = \frac{|P_{TSO-DSO}^{max} - P_{TSO-DSO}^{min}|}{s_{max}}, \quad (13)$$

$$\Delta Q_{step} = \frac{|Q_{TSO-DSO}^{max} - Q_{TSO-DSO}^{min}|}{s_{max}}. \quad (14)$$

ΔP_{step} and ΔQ_{step} are used to define the sampling granularity. Then, for each sampling step, the following quantities are calculated

$$P_s = P_{TSO-DSO}^{min} + \Delta P_{step}s, \quad (15)$$

$$Q_s = Q_{TSO-DSO}^{min} + \Delta Q_{step}s, \quad (16)$$

where s is the current sample, $s = 1, \dots, s_{max}$. Then, the values of P_s and Q_s are added to the optimization problem, by replacing the applicable FPU capability limits imposed by (7). The search direction is specified by the values of the parameters α and β in (4), as seen in Figure 6.

4.1.2. Angle-Based Sampling

Each point on the contour of the FOR represents a specific relationship between $P_{TSO-DSO}$ and $Q_{TSO-DSO}$, which can be described by the angle θ as:

$$\tan\theta = \frac{Q_{TSO-DSO}}{P_{TSO-DSO}} = \frac{\beta}{\alpha}. \quad (17)$$

The sample size is again defined as s_{max} and is used to divide the unit circle in different sampling angles. Each angle size is then specified as

$$\theta = s\Delta\theta = s \frac{2\pi}{s_{max}}. \quad (18)$$

In this formulation, the objective function (4) is slightly altered. Parameter $\alpha = 1$, and the objective function becomes:

$$\min(flow) = \begin{cases} \min(-P_{TSO-DSO} - |\tan\theta|Q_{TSO-DSO}), & 0 \leq \theta \leq \pi/2 \\ \min(P_{TSO-DSO} - |\tan\theta|Q_{TSO-DSO}), & \pi/2 \leq \theta \leq \pi \\ \min(P_{TSO-DSO} + |\tan\theta|Q_{TSO-DSO}), & \pi \leq \theta \leq 3\pi/2 \\ \min(-P_{TSO-DSO} + |\tan\theta|Q_{TSO-DSO}), & 3\pi/2 \leq \theta \leq 2\pi \end{cases} \quad (19)$$

Thus, in this approach the optimization problem consists of minimizing the objective function (19), subject to the constraints imposed by (5)–(11). The procedure is visualized in Figure 7. As can be easily understood, for both methods analyzed in this section, the accuracy of the estimated FOR is increased as the value of s_{max} increases. Using angle-based sampling results in accurate estimation of the FOR, only if the FOR is convex. Finally, the procedure followed in angle-based sampling can be fully parallelized, resulting in potential speed gains.

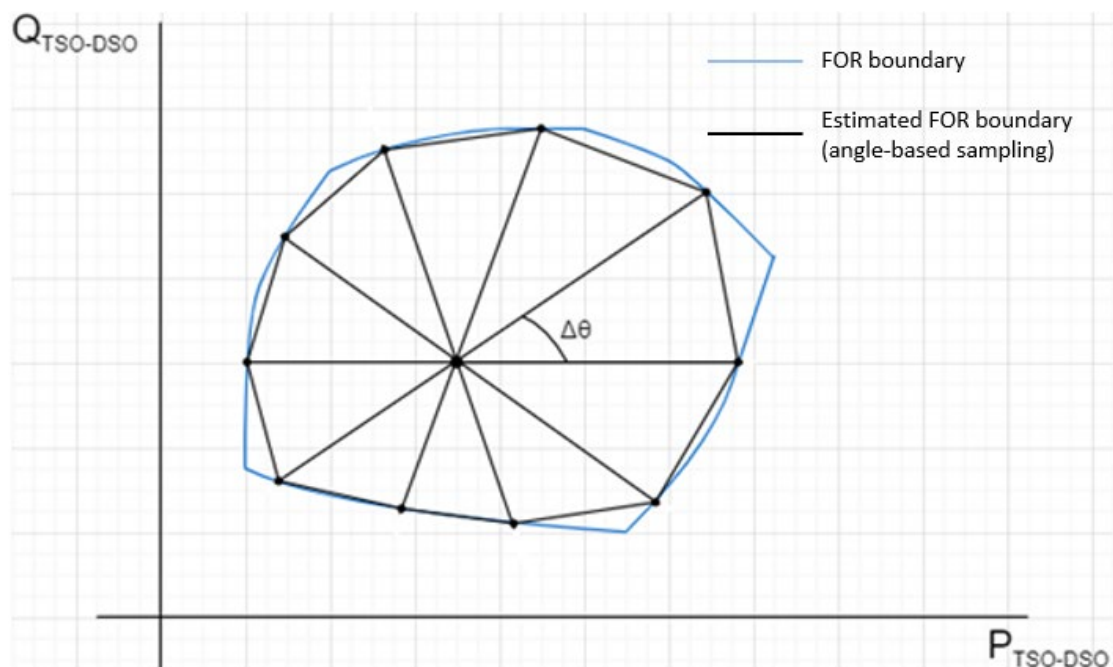


Figure 7. Visualization of angle-based sampling.

4.2. Related Works

OB methods have received significant research interest due to the promise they show for accurate and efficient estimation of the FOR. Research interest surrounding OB methods focuses on the determination of efficient sampling techniques (that would lead to a decrease

in the total number of optimization problems that need to be solved) or on the efficient solution of the resulting optimization problems (e.g., through linearizations).

Starting from the methods that were analyzed in the beginning of this section, the setpoint-based sampling method was analyzed in [19], while the angle-based sampling method appears in [19,47,48]. In [47], a method similar to the setpoint-based sampling method is also analyzed, along with a method that introduces a quadratic objective function ($flow = P_{TSO-DSO}^2 + Q_{TSO-DSO}^2$). The authors find that all three methods are capable of accurately estimating the FOR, and the choice of method depends on the problem at hand. Reference [48] performs a deep dive on the angle-based sampling method, examining the effect of various network parameters on the shape of the FOR (e.g., line characteristics, voltage limits, etc.). In both [47,48], the methods are FPU-agnostic, and no analyses are performed on the time dependence of flexibility, or the monetization of the FOR.

The authors in [49] base their approach on the setpoint-based method, but introduce an iterative approach that stops when certain distance-based stopping criteria are triggered, in an effort to guarantee the accuracy of the FOR and reduce the computational burden. The authors explicitly mention the types of FPUs included in the method (loads, generators, OLTC transformers and reactive compensators). An analysis on the cost of the FOR is included, as the inclusion of an extra constraint in the optimization problem on the total cost of flexibility is proposed, based on the flexibility cost the TSO is willing to pay. The resulting problem is a non-linear mixed-integer OPF. The method is found to be superior compared to naïve RS methods, and results from a real-life application where the method was successfully deployed are presented. The time-dependent characteristics of some FPUs are acknowledged, but the intertemporal constraints are not addressed. A variation of the same algorithm is also presented in [50].

In [24], the authors improve the methodology introduced by [49] by reducing the computation time required for the calculation in large DNs. The non-linear AC OPF used in [49] is linearized using first-order Taylor expansions for the power balance and branch flow equations. Moreover, a piecewise linearization of the quadratic inequalities imposed by the thermal line limits that was introduced in [51] is performed. This way, the OPF problem is transformed to a mixed-integer linear problem. An important contribution of this paper also lies in the identification and categorization of five types of FPUs and their respective capability charts: FPUs with small capacity, loads with constant $\cos(\varphi)$, wind generators, photovoltaic generators, and synchronous generators. In [52], the authors of [49] adopt this methodology to investigate the impact of discrete topology variations in the shape of the FOR (e.g., switching lines and adjusting tap positions on OLTC transformers). The paper concludes that closed-ring and meshed topologies have an increased ability of flexibility provision compared to radial topologies. The same method was also applied in [53].

The authors of [24] followed up their work in [54], where they studied the FOR estimation over time for several time steps (up to an entire day). To that end, FPUs were modeled considering time series. Specifically, the authors provide an analysis for photovoltaics, wind generators and storage systems, taking into account time-varying characteristics, and successfully estimating the FOR for several time steps.

The contribution of [55] is twofold. First, the authors identify alternative OPF formulations that can be used in the context of OB methods for the formulation of the FOR. Apart from the AC OPF, the authors suggest the well-established DistFlow algorithm [56], a second-order cone relaxation of the DistFlow, and the LinDistFlow algorithm, which is a linear approximation of the DistFlow. The second contribution lies in the introduction of the QuickFlex algorithm, which is based on the QuickHull algorithm [57]. QuickFlex is an iterative OB algorithm that, in each iteration, searches for new points of the convex hull of the FOR boundary in four vertices. The idea is to select the furthest point from the segment formed by the vertices between the new and the previous point. The algorithm features a distance-based stopping criterion that stops the algorithm when triggered.

In [58], an OB setpoint sampling-based method is introduced. In the first step of the proposed method, the four extreme points of the FOR are calculated ($P_{TSO-DSO}^{min}$, $P_{TSO-DSO}^{max}$, $Q_{TSO-DSO}^{min}$, $Q_{TSO-DSO}^{max}$). Then, $2s_{max}$ more points are calculated, with the search direction being constrained by adding constraints to the $Q_{TSO-DSO}$. By setting the sample size s_{max} according to the needs of the problem, the author argues that the granularity of the estimated FOR can be tuned. The optimization problem that is solved to find each vertex is a non-linear OPF, and the procedure can be parallelized. The accuracy and efficiency of this method are deemed satisfactory. In a subsequent work [59], the author focuses on flexibility provision via OLTC-controlled demand reduction. Only the control of the OLTC transformer ratio at the TSO–DSO interface is considered, which according to the author is a straightforward way of flexibility provision, since it does not require the involvement of anyone but the DSO. The same method as [58] is used for the formulation of the optimization problem, but since the discrete control parameters of OLTC transformer tap ratios are included, the problem is a non-linear mixed-integer OPF.

Reference [60] introduces some new concepts surrounding TSO–DSO coordination. It is argued that calculating the FOR is not enough for the provision of services to the TSO, because for safety and reliability issues the flow at the TSO–DSO interface must satisfy certain requirements. Therefore, the TSO desirability surface, which is defined as the plane representing pairs of values of ($P_{TSO-DSO}$, $Q_{TSO-DSO}$), for which the TN can be operated in a secure way, must also be calculated. The acceptance range of the flow at the TSO–DSO interconnection is thus the intersection of the FOR and the TSO desirability surface. For the calculation of the FOR, the methodology introduced by [24] is used.

In [61], an OB angle sampling-based method is used for the estimation of the FOR. The proposed method is iterative, and calculates new points of the FOR, until the stopping criterion is triggered. The stopping criterion consists of measuring the difference of the angles between neighboring points of the FOR hull. If the difference is smaller than a predefined tolerance, a new point is not calculated. This approach is compared to naïve RS methods, and is found to be superior in both computation time and accuracy. As the OLTC controls are included in the formulation, the optimization problem that is solved is a non-linear mixed-integer OPF.

Authors in [62] tackle the problem of FOR estimation, using alternative OPF formulations to examine their efficiency in handling this problem. The proposed framework both quantifies the amount of flexibility and assesses the ability of the DSO to provide it. A convex approximation is used to solve the OPF problem, which includes a wide range of assets (e.g., assets with discrete variable and voltage-sensitive assets), in an effort to draw consistent conclusions regarding its performance. The introduced convex approximation is compared with a classic non-linear and a convexified branch flow OPF formulation. It is found that the introduced approach and the convexified branch flow formulations outperform the classic OPF formulation, even by an order of magnitude in terms of speed, with relatively small suboptimality. The FOR estimation algorithm itself is an iterative OB setpoint sampling-based, with a distance-based stopping criterion.

Ref. [63] introduces an iterative setpoint-based OB approach for the estimation of the FOR. The approach consists of five steps. In the first two steps, $P_{TSO-DSO}^{min}$, $P_{TSO-DSO}^{max}$, $Q_{TSO-DSO}^{min}$, $Q_{TSO-DSO}^{max}$ are calculated. In the next step, $Q_{TSO-DSO}$ is maximized and minimized, without restricting $P_{TSO-DSO}$. Step four maximizes and minimizes $P_{TSO-DSO}$ iteratively, while constraining $Q_{TSO-DSO}$ between its minimum and maximum values. In the last step, an interpolation between all the calculated points is executed, to obtain the FOR. This method also integrates limitations introduced by directives in the FOR that the DSO communicates to the TSO. An analysis of the capabilities of inverter-interfaced RES in flexibility provision is also included in the work.

In [64], the problem of FOR estimation for inclusion in multi-period OPF problems is considered. Initially, a semidefinite programming problem is solved, to obtain a dynamic ellipsoidal model of the FOR. Then, a look-ahead AC–OPF problem is solved to dispatch the assets of the TN, using the FOR to incorporate the DN in the model. The disaggregation

for the dispatch of the distribution assets is also discussed. The aggregation procedure is repeated as time advances, not allowing the accumulation of errors.

The time-dependent characteristics of the FOR are also analyzed in [65]. The authors claim that most existing methods for FOR estimation have limited applicability, since they estimate the FOR for a specific time instance. For multiple time instances, the impact of time-dependent FPU (e.g., batteries) that these methods ignore must be considered. Ignoring the time dependence results in overestimating the FOR, leading to potentially infeasible points in dispatch. To that end, the authors introduce the concepts of the hourly and the daily FORs. The hourly FOR is calculated using hourly data to find the FOR for a given instance. The daily FOR is defined as the region that includes all feasible combinations of daily active and reactive flows at the TSO–DSO interface. To calculate these FORs, a two-stage approach is adopted. In the first stage, the hourly FOR is estimated using the method introduced in [63]. The second stage is employed to optimally coordinate the FPU in order to meet the power profile at the TSO–DSO interface determined in the previous day’s planning. The validity of the proposed method is demonstrated in various test cases.

An interesting approach is introduced by [19], where the authors use the metaheuristic approach of Particle Swarm Optimization (PSO) to tackle the optimization problem in the context of FOR estimation. The PSO problem requires some modifications compared to PSO algorithms used in classic AC–OPF optimizations, whose aim is to improve FOR estimation, and avoid local convergence. Moreover, ways to punish the particles in order to guarantee a more global search are discussed. The proposed PSO formulation is compared with a classic AC–OPF formulation, and a quadratically constrained linear programming formulation in the context of FOR estimation, using an iterative setpoint-based sampling strategy. The quadratically constrained linear programming formulation is found to produce the smallest FOR. The proposed PSO formulation performs adequately compared to the classic AC–OPF formulation. In subsequent work [21], the authors again use the PSO method introduced in [19] to devise a monetization scheme of the FOR, using the valuable cost information each particle provides during the solution process.

Table 4 provides a summary of the reviewed OB methods for FOR estimation.

4.3. Discussion

The volume of published works surrounding FOR estimation using OB methods showcases the potential these methods have for the efficient and accurate estimation of the FOR. Research around these methods focuses on two areas: finding better sampling techniques for the determination of the points of the FOR contour and enhancing the formulation of the OPF problems to speed up the solution process.

A lot of sampling techniques have been proposed in the literature, with angle-based sampling and setpoint-based sampling being the two main categories. The vanilla sampling methods that were described in the start of this section can produce accurate results, but are very time-consuming. Research has concentrated on iterative methods (e.g., [24,52,53,60]) that use dynamic calculations to find points that contribute to the accuracy of the estimated FOR, and feature stopping criteria that are triggered when the accuracy is deemed satisfactory.

Regarding OPF formulations, research is actively being conducted. Linear OPF formulations were the first to be introduced [24] in an effort to enhance the efficiency of the AC–OPF. Linear OPF formulations have managed to tackle the problem with satisfactory accuracy, achieving significant speed gains [24]. However, the literature warns that linearized OPF formulations can suffer from inaccuracies if the linearization point is not close enough to the final operating point ([51] and c.f. results with flat start and warm start in [24]), which can become a factor in larger DNs. Other works (e.g., [62]) have explored formulations based on convex approximations that also managed to achieve speed gains, with little sacrifice of accuracy. These methods, though, are known for their issues regarding the exactness of their solutions [62], and ways to guarantee the exactness are being heavily

researched. Recently, metaheuristic methods such as the PSO have emerged as viable alternatives [19] and show promise, as they combine the benefits of RS and OB methods.

Table 4. A summary of the reviewed OB methods.

Reference	Method	Type of FPU's Supported	Multi-Period Support	Monetization of FOR
[47]	OB angle sampling OB setpoint sampling OB quadratic	FPU-agnostic	No	No
[48]	OB angle sampling	FPU-agnostic	No	No
[49,50]	Iterative OB setpoint sampling with distance-based stopping criterion	Loads, generators, OLTC transformers and voltage compensators	Yes	No
[24,52,53,60]	Linearized Iterative OB setpoint sampling with distance-based stopping criterion	FPU's with small capacity, loads with constant $\cos\phi$, wind, photovoltaic and synchronous generators, OLTC transformers	No	No
[54]	Linearized Iterative OB setpoint sampling with distance-based stopping criterion	Photovoltaic and wind generators, storage systems	Yes	No
[55]	QuickFlex	FPU-agnostic	No	No
[58]	Iterative OB setpoint sampling with fixed sample size	FPU-agnostic	No	No
[59]	Iterative OB setpoint sampling with fixed sample size	OLTC transformers	No	No
[61]	Iterative OB angle sampling with angle-based stopping criterion	FPU-agnostic and OLTC transformers	No	No
[62]	Convexified Iterative OB setpoint sampling with distance-based stopping criterion	OLTC transformers, variable loads, generators, and voltage-sensitive loads	No	No
[63]	Iterative OB setpoint sampling	Inverter-interfaced RES	No	No
[64]	Ellipsoidal FOR model	Linear modeling of FPU's	Yes	No
[65]	Two-stage approach	Inverter-interfaced RES, batteries	Yes	No
[19]	Iterative OB setpoint-based sampling, solved with PSO	FPU-agnostic	No	Yes
[21]	Iterative OB setpoint-based sampling, solved with PSO	FPU-agnostic	No	Yes

Most researchers agree on the importance of time dependence for FOR estimation, but little research has tackled the issue. Accounting for time dependence allows for the inclusion of the FOR in OPF problems that integrate both the TN and the DNs. Failing to account for it tends to overestimate the FOR, which can lead to infeasibilities in dispatch. The methods introduced in [64,65] successfully integrate the intertemporal constraints in FOR estimation, providing a clear pathway for its further inclusion in other methods.

The monetization of the FOR can lead to its inclusion in market-based applications. A few works touch on this important issue, with [21,49] providing major contributions. Ref. [49] provides a method for the determination of the FOR based on the maximum amount the TSO is willing to pay for flexibility. Ref. [21] provides the framework for the extraction of the FCM for OB methods. While both contributions are significant, OB methods still lack methods to extract piecewise bids from the FOR that can be easily integrated in existing markets.

Even though OB methods have several advantages compared to RS and Geometric methods, they do not come without drawbacks. The major drawback of OB methods, which research has concentrated on addressing, has to do with the trade-off between computation time and accuracy. Both active research fields surrounding OB methods (namely, research on sampling methods and alternative OPF formulations) aim to contribute in finding the

perfect balance between the two. Another limitation of OB methods has to do with the acceptable capability charts of FPU, as some methods (e.g., linear OPF formulations) are not able to accommodate non-linear capability charts. Finally, non-linear formulations have their inherent limitations in incorporating discrete variables in the problem.

5. Comparison of Feasible Operating Region Estimation Methods

The use of any of the three methods has advantages and disadvantages. Geometric methods have the least potential for use in the current landscape, since they fail to integrate the constraints imposed by the DN. Moreover, the calculation of the M-sum is computationally expensive, thus most Geometric-based methods rely on its approximation. IAs of the M-sum underestimate the FOR, so flexibility is lost, while OAs of the M-sum overestimate the FOR and can lead to infeasibilities. Therefore, considering the advances made in RS and OB methods and the promise they show, Geometric methods have limited use in the context of FOR estimation. Their main use focuses on the aggregation of the flexibilities of elements that are connected in the same bus for their inclusion in OB methods [21]. This use is ideal for Geometric methods, since no physical constraints need to be included for the aggregation of flexibilities connected in the same bus, and the number of FPU in the same bus is generally limited, thus the calculation of even the exact M-sum (which accurately represents the aggregated flexibility) is achievable [35].

RS methods are relatively easy to implement. However, the ease of implementation is outweighed by the computational burden imposed by their use. The accurate estimation of the FOR with RS methods cannot be guaranteed even when a very large amount of samples is used. According to [23], increasing the amount of samples only offers marginal improvements to the quality of the estimated FOR; selecting better sampling strategies, on the other hand, that give more weight to choosing extreme operating points drastically improves the quality of the estimated FOR. The authors in [42] also highlight the need for better sampling strategies, by describing the convolution problem that comes with the use of uniform PDFs. Another drawback is the difficulty of the inclusion of the time dependence of flexibility in these methods. Even though some works have attempted tackling this problem (e.g., [20]), the complications introduced by intertemporal constraints have not been fully addressed in RS methods.

RS methods, however, retain some significant advantages. Firstly, RS methods are the easiest to implement. Moreover, since they run a PF analysis for each setpoint, the exact physics of the system are explicitly considered. The PF analysis can also easily accommodate most types of FPU and discrete control variables. In addition, each power flow analysis can be parallelized, achieving significant speed reduction. Moreover, RS methods provide an easy platform for the calculation of the FCM, providing an easy method for the monetization of the FOR. Finally, [42] points out the compatibility of RS methods in settings where grid models are not available, and any modeling must be executed using measurements.

OB methods receive the majority of research interest surrounding FOR estimation, due to the promise they show for the fast and efficient calculation of the FOR. Enhancements are needed in sampling techniques and the formulation of the OPF problem in OB methods in order to live up to their promise. Research is being conducted on both of these fronts: many iterative sampling techniques are being introduced that aim to dynamically calculate points of the hull of the FOR that improve the accuracy, and a lot of OPF formulations are being tested in this setting (e.g., linear, convexified, PSO OPF, etc.). The superiority of OB methods compared to RS methods in terms of accuracy is validated by studies that compare the two methods (e.g., [23,61]).

OB methods are able to capture the intertemporal flexibility constraint better than any of the other methods. Both [64,65] successfully integrate the intertemporal constraints in FOR estimation, providing a clear pathway for its further inclusion in other methods. Integrating intertemporal constraints is crucial, since otherwise the FOR is overestimated.

In addition, OB methods do an adequate job at providing monetization methods for the FOR, allowing for its inclusion in market-based applications (i.e., [21]).

However, OB methods have to balance the trade-off between accuracy and performance. Better sampling strategies result in fewer optimization problems that need to be solved, but add points that enhance the accuracy of the estimated FOR. Alternative OPF formulation (e.g., linearized OPF) reduce the computational complexity of the problem, but come with some sacrifice of accuracy. Researchers must take these trade-offs into consideration before choosing sampling strategies and OPF formulations. In addition, some OPF formulations have inherent limitations to the types of FPU they support. Finally, OB methods are the hardest of the three to implement.

The respective advantages and disadvantages of all three categories are summarized in Table 5.

Table 5. Summary of the advantages and disadvantages of the three FOR estimation categories.

	Geometric Methods	RS Methods	OB Methods
Advantages	-Can be used to aggregate FPU connected at the same bus in RS and OB methods	-Easy to implement -Parallelizable -Accurately captures the physics of the system -Easy to include most types of FPU -Straightforward monetization of the FOR -Parallelizable	-Very accurate -Able to capture intertemporal constraints of flexibility -Can provide monetization of the FOR
Disadvantages	-Exact M-Sum very computationally expensive -OA and IA approximations not accurate enough -Does not capture the physics of the DN	-No guarantees of accuracy, even with large sample sizes -Heavy computational burden -Lack of efficient sampling strategies and convolution problem -Inclusion of time dependence of flexibility is difficult	-Need to balance trade-off between accuracy and efficiency -Some formulations may limit the inclusion of certain types of FPU -Not always parallelizable -Complex implementation

6. Conclusions

Energy transition causes need for extra flexibility in the power system. Recent advancements in technology, the proliferation of DERs connected to the DN and the electrification of various industries have the potential to make the DN a major source of flexibility. However, the utilization of the flexibility of the DN by the TSO presupposes a level of coordination between the TSO and the DSO. From the three different categories of methods of TSO–DSO coordination that were analyzed, the DSO-managed models are suggested to be the best method for TSO–DSO coordination in the current landscape. At the core of this method lies the FOR, which is a set of points in the PQ plane that describes the feasible points of the IPF at the TSO–DSO interface.

In this work, an overview of the three categories of methods of FOR estimation were presented, namely Geometric, RS and OB methods. For each category, an overview of the main ideas of the method was presented, works that belong to each category were analyzed, and each method was extensively discussed. The discussion focused on four axes: the description of the method, the type of FPU each method supports, whether or not the method accounts for multi-period estimation of the FOR, and whether or not each method discusses the monetization of the FOR. The findings of this work are summarized in Table 2 for Geometric methods, in Table 3 for RS methods and in Table 4 for OB methods. Finally, a high-level comparison between the three methods of FOR estimation was presented, with the respective advantages and disadvantages summarized in Table 5.

Author Contributions: Conceptualization, G.P. and P.B.; methodology, G.P. and P.B.; resources, G.P. and P.B.; writing—original draft preparation, G.P. and P.B.; writing—review and editing, G.P. and P.B.; visualization, G.P.; supervision, P.B.; project administration, P.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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