Pontifícia Universidade Católica
do Rio de Janeiro

Gabriel Campos Godinho

Security of Power Supply in Hydrothermal Systems: Assessing Minimum Storage Requisites for Hydroelectric Plants

Dissertação de Mestrado

Dissertation presented to the Programa de Pós–graduação em Engenharia Elétrica of PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Engenharia Elétrica.

Advisor: Prof. Delberis Araújo Lima

Rio de Janeiro
February 2021

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Bibliographic data

Campos Godinho, Gabriel

Security of Power Supply in Hydrothermal Systems: Assessing Minimum Storage Requisites for Hydroelectric Plants / Gabriel Campos Godinho; advisor: Delberis Araújo Lima. – Rio de janeiro: PUC-Rio, Departamento de Engenharia Elétrica, 2021.

v., 86 f: il. color. ; 30 cm

Dissertação (mestrado) - Pontifícia Universidade Católica do Rio de Janeiro, Departamento de Engenharia Elétrica.

Inclui bibliografia

1. Engenharia Elétrica – Teses. 2. Sistemas de Energia Elétrica – Teses. 3. Sistemas Hidrotérmicos;. 4. Despacho Fora-do-Mérito;. 5. Simulação Recursiva;. 6. Segurança de Suprimento;. I. Araújo Lima, Delberis. II. Pontifícia Universidade Católica do Rio de Janeiro. Departamento de Engenharia Elétrica. III. Título.

CDD: 620.11

Agradecimentos

Ao meu orientador, Prof. Delberis Araújo Lima, pela confiança, atenção e pelas orientações fornecidas.

Aos demais professores da PUC-Rio, que através das disciplinas contribuíram para ampliar e solidificar minha base de conhecimentos.

Ao Mario Daher e Maria Aparecida Martinez pela confiança e pela oportunidade de cursar o mestrado. Vocês foram muito importantes para a minha formação profissional.

Ao Vitor Silva Duarte, Nestor Bragagnolo Filho e ao saudoso Alex Nunes de Almeida pelos aprendizados, trocas de ideias e pela motivação na escolha do tema da dissertação.

Aos demais ex-colegas do ONS, em especial da Gerência de Estudos Energéticos, pela amizade, companheirismo e paciência para assumir minhas atividades enquanto estive ausente cursando as disciplinas.

Aos colegas da Nova Energia pelo companheirismo demonstrado em todos os dias de trabalho e por terem me dado condições para que eu pudesse concluir esta etapa.

Aos colegas da PUC, em especial à "turma da PSR", pela amizade, pelos momentos de estudo e pelo incentivo mútuo.

À minha noiva Daniela que me inspira como pesquisadora e que me apoiou de forma incondicional ao longo de todo o mestrado.

À minha família pelo amor e dedicação em toda a minha vida.

Finalmente, agradeço à PUC-Rio, pelos auxílios concedidos, sem os quais este trabalho não poderia ter sido realizado.

O presente trabalho foi realizado com apoio da Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Código de Financiamento 001.

Abstract

Campos Godinho, Gabriel; Araújo Lima, Delberis (Advisor). **Security of Power Supply in Hydrothermal Systems: Assessing Minimum Storage Requisites for Hydroelectric Plants**. Rio de Janeiro, 2021. 86p. Dissertação de mestrado – Departamento de Engenharia Elétrica, Pontifícia Universidade Católica do Rio de Janeiro.

Unfavorable hydrological conditions experienced from 2014 to 2019 led to the depletion of main reservoir systems in Brazil, causing an increase of thermal energy dispatch. However, an important share of the observed thermal generation was out of economic merit, commanded by government entities which risk perception relies mainly on experts' tacit knowledge. Despite the common sense that storage in reservoirs is intrinsically linked to system security, the metrics employed so far failed to compute the system's real needs in terms of required stored energy in hydroelectric plants. By the end of 2019, ONS proposed a new method to assess the need for additional thermal dispatch the Referential Storage Curve (CREF - *Curva Referencial de Armazenamento*). However, it fails as a reference for the security of energy supply since it considers very specific assumptions of rivers' inflows and thermal generation. Besides, based on its iterative 'trial and error' process, it can result in sub-optimal results of minimum storage levels. This work proposes a new method to evaluate the security of power supply in systems with predominance of hydroelectricity. This method is intended to be an evolution to the CREF method, and it is based on the development of an optimization model that computes the minimum secure levels for hydroelectric plants operation in each month, from a recursive simulation of historical inflow series from 1931 to 2018. In addition, based on the simulation results, reference curves were suggested for the continuous monitoring of the reservoirs operation, with the purpose of subsidizing Brazilian government entities decisions on unorthodox thermal generation dispatch. The monitoring of the proposed reference curves is expected to represent a more robust criterion for decisions on out-of-merit thermal generation in Brazilian power system.

Keywords

Hydrothermal Power Systems; Out-of-merit Dispatch; Backward Simulation; Security of Power Supply.

Resumo

Campos Godinho, Gabriel; Araújo Lima, Delberis. **Avaliação dos Requisitos Mínimos de Armazenamento de Usinas Hidrelétricas para Segurança do Suprimento em Sistemas Hidrotérmicos**. Rio de Janeiro, 2021. 86p. Dissertação de Mestrado – Departamento de Engenharia Elétrica, Pontifícia Universidade Católica do Rio de Janeiro.

As condições hidrológicas desfavoráveis vivenciadas entre 2014 e 2019 levaram ao esgotamento dos principais sistemas de reservatórios no Brasil, causando um aumento na geração de energia proveniente de usinas térmicas. Todavia, uma parte relevante da geração térmica verificada foi comandada por entidades governamentais de forma heterodoxa (fora do mérito econômico calculado pelos modelos de otimização), baseada principalmente na percepção de risco tácita. Apesar do senso comum de que o armazenamento dos reservatórios está intrinsecamente ligado à segurança do sistema, as métricas utilizadas até o momento não conseguiram computar as reais necessidades do sistema em termos de energia armazenada mínima nas usinas hidrelétricas. Ao final de 2019, o ONS propôs um novo método para avaliar a necessidade de despacho térmico adicional, chamado Curva Referencial de Armazenamento (CREF). No entanto, este método considera hipóteses muito específicas de afluências e geração térmica, e com base em seu processo iterativo de "tentativa e erro", pode resultar em resultados sub-ótimos para o cálculo dos armazenamentos mínimos necessários. Este trabalho propõe um novo método para avaliar a segurança do fornecimento de energia em sistemas predominantemente hidroelétricos. Este método é uma evolução do método CREF, e é baseado no desenvolvimento de um modelo de otimização que calcula os níveis mínimos de segurança para operação de usinas hidrelétricas em cada mês, a partir de uma simulação recursiva de séries históricas de afluências de 1931 a 2018. Além disso, com base nos resultados da simulação, foram sugeridas curvas de referência para o monitoramento contínuo da operação dos reservatórios, com o objetivo de subsidiar decisões de órgãos do Governo Brasileiro sobre o despacho heterodoxo de geração térmica. Espera-se que o monitoramento das curvas de referência propostas represente um critério mais robusto para decisões sobre geração térmica fora-do-mérito no Sistema Elétrico Brasileiro.

Palavras-chave

Sistemas Hidrotérmicos; Despacho Fora-do-Mérito; Simulação Recursiva; Segurança de Suprimento;

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List of Abreviations

ANA	*Agência Nacional de Águas* (Brazilian National Water Agency)
ANE	Affluent natural energy
BHS	Backward Hydrothermal Simulation Model
CAR	*Curvas de Aversão ao Risco* (Risk-Aversion Curves)
CAR5	Five-Year Horizon Risk-Aversion Curves
CEPEL	*Centro de Pesquisas de Energia Elétrica* (Electrical Energy Research Center)
CME	*Custo Marginal de Expansão* (Marginal expansion cost)
CMSE	*Comitê de Monitoramento do Setor Elétrico* (Power Sector Monitoring Committee)
CMO	*Custo Marginal de Operação* (Marginal operating cost)
CPAMP	*Comissão Permanente para Análise de Metodologias e programas Computacionais do Setor Elétrico* (Permanent Commission for Analysis of Methodologies and Computer Programs for the Electric Sector)
CREF	*Curva Referencial de Armazenamento* (Referential Storage Curve)
CVaR	Conditional value-at-risk
D.C.	Direct current
DECOMP	Medium-Term Operation and Planning Software
DESSEM	Short Term Hydrothermal Dispatch Model
EER	Energy equivalent reservoirs
EPE	*Empresa de Pesquisa Energética* (Energy Research Office)
FCF	Future cost function, also related as cost-to-go function
GDP	Gross Domestic Product
GENCO	Generation company
GW	Gigawatt
HVDC	High-voltage direct current
J	Joule
LOLP	Loss of load probability
MINLP	Mixed Integer Nonlinear Programs
MIP	Mixed Integer Programming
MME	Ministry of Mines and Energy
MW	Megawatt

N	North subsystem
NE	Northeast subsystem
NEWAVE	Strategic Model for Hydrothermal Generation by Equivalent Subsystems
NIS	National Interconnected System
NLBB	Nonlinear Branch-and-Bound
ONS	*Operador Nacional do Sistema Elétrico* (Brazilian National System Operator)
PAR(p)	Periodic autoregressive model of order p
PDE	*Plano Decenal de Expansão de Energia* (EPE's Ten-Year Energy Expansion Plan)
PDP	*Programa Diário de Produção* (Daily Dispatch Scheduling)
PMO	*Programa Mensal da Operação Energética* (Monthly Dispatch Scheduling)
POCP	*Procedimentos Operativos de Curto-Prazo* (Short-term Operating Procedures)
S	South subsystem
SAR	*Superfície de Aversão ao Risco* (Risk-Aversion Surface)
SDDP	Stochastic dual dynamic programming
SE/MW	Southeast/Midwest subsystem
SSDP	Sampling stochastic dynamic programming
VaR	Value-at-risk
VCU	Variable cost per unit
VminOp	*Volume Mínimo Operativo* (Minimum Operating Volumes)

List of Notations

δ	Outflow-volume monthly conversion factor
π	Objective function penalty for constraints violation
ρ_h	Production coefficient in MWh/m^4 per hydroelectric plant h
$A_h(l_h^{up})$	Level x Area polynomial. Calculates area in km^2 for a given level in m
C	Set of problem's constraint
D_i	Total demand of subsystem i
D_i^{net}	Net demand of subsystem i
E_h^{ini}	Initial stored energy in MWmonth for hydroelectric plant h
$\overline{F}_{i,j}$	Maximum energy transfer limit from subsystem i to subsystem j
$f_{i,j}$	Energy transfer from subsystem i to subsystem j
$f_{j,i}$	Energy transfer from subsystem j to subsystem i
$\underline{F}_{i,j}$	Minimum energy transfer limit from subsystem i to subsystem j
$\underline{G}_h$	Minimum generation limit in MWmonth by hydroelectric plant h
$\overline{G}_h$	Maximum generation limit in MWmonth by hydroelectric plant h
g_h	Energy generated in MWmonth by hydroelectric plant h
gt_w	Available generation in MWmonth for thermoelectric plant w
H	Set of hydroelectric plants
H_h^d	Set of plants that divert flow to plant h
H_h^{down}	Set of plants downstream on the same cascade of plant h
H^I	Set of impoundment hydroelectric plants
H^R	Set of run-of-river hydroelectric plants
H_h^{up}	Set of plants immediately upstream of plant h
H_i	Set of hydroelectric plants from subsystem i
I^{sum}	Set of interchange/generation sum constraint c
k_h^{evap}	Monthly reservoir evaporation rate in mm/month for hydroelectric plant h
l_h^{down}	Tailwater level in m for hydroelectric plant h
$L_h^{down}(q_h^{out})$	Outflow x Tailwater Level polynomial. Calculates tailwater level in m for a given outflow in m^3/s
l_h^{up}	Forebay reservoir level in m for hydroelectric plant h
$L_h^{up}(V_h)$	Volume x Level polynomial. Calculates level in m for a given volume in hm^3

LB_c	Lower bound for interchange/generation sum constraint c
$loss_h$	Hydraulic losses in m or % from penstock ducts for hydroelectric plant h
N^{sys}	Number of subsystems
NH_c	Set of hydroelectric plants from generation sum constraint c
NS_i	Not-individually simulated plants generation estimative from subsystem i
NT_c	Set of transmission lines from interchange sum constraint c
q_h^d	Deviated inflow in m^3/s for hydroelectric plant h
q_h^{in}	Total upstream outflow in m^3/s for hydroelectric plant h
q_h^{irrig}	Irrigation in m^3/s for hydroelectric plant h
q_h^l	Lateral inflow in m^3/s for hydroelectric plant h
q_h^{out}	Total outflow in m^3/s for hydroelectric plant h
s_h	Spillage outflow in m^3/s for hydroelectric plant h
u_h	Turbined outflow in m^3/s for hydroelectric plant h
UB_c	Upper bound for interchange/generation sum constraint c
v_h^{evap}	Evaporated volume in hm^3 for hydroelectric plant h
V_h^f	Stored volume in hm^3 for hydroelectric plant h at the end of the stage
V_h^{ini}	Stored volume in hm^3 for hydroelectric plant h at the beginning of the stage
V_h^{min}	Minimum reservoir volume in hm^3 for hydroelectric plant h
W_i^{mc}	Set of thermoelectric plants from subsystem i with VCU equal or lower to a marginal cost mc
x_h^{equiv}	Equivalent net head in meters for hydroelectric plant h
x_h	Net head in meters for hydroelectric plant h
z_c	Total violation of constraint c

'All models are wrong, but some are useful'

George Box, 1987

1 Introduction

The medium and long term operation planning of hydrothermal power systems generally rely on state-of-the-art optimization techniques, such as stochastic dual dynamic programming (SDDP) [1] or sampling stochastic dynamic programming (SSDP) [2], to ensure reliable power supply at minimum cost. Considering the predominance of hydropower generation in the Brazilian electricity matrix (approximately 72% in 2018 [3]), the mid-term operation planning's main concerns are related to the availability of energy resources during persistent droughts. In Brazil, the National System Operator (ONS - *Operador Nacional do Sistema Elétrico*) is the organization responsible for operating the power plants and transmission grid.

The thermal generation dispatched by ONS follows cost-based guidelines provided by NEWAVE (Strategic Model for Hydrothermal Generation by Equivalent Subsystems) and DECOMP (Medium-Term Operation and Planning Software) optimization models [4], taking into account the future cost of present time decisions. While NEWAVE finds the optimal operation policy through a stochastic simulation of 2000 synthetic inflow series in a five-year horizon, DECOMP is a more detailed model that provides the optimal present-time dispatch, considering the possibilities assessed by NEWAVE's future cost function. Thus, according to the current system's conditions and estimates for load, power plants inflows and resources availability, NEWAVE and DECOMP minimize the total operation costs, defining the optimal resources dispatch per load level in each week.

At the beginning of 2020, an even more detailed model called DESSEM (Short Term Hydrothermal Dispatch Model) [5] was implemented at the end of the optimization models chain to define the optimal dispatch of generating units. DESSEM simulates the power system's operation on a semi-hourly basis, assessing the optimal future policies through the future cost function calculated by NEWAVE and DECOMP models. Its main features include the possibility of representing the load curve in greater detail, and network's constraints through a DC power flow model.

The quality of the energy guidelines resulting from the operation planning models has been a concern for power industry entities since the beginning of the 21st century. Between the years of 2001 and 2002, Brazilian consumers faced energy shortage because of low inflows and delays of expansion plans [6]. After that episode, the Brazilian government created the Power Sector Monitoring Committee (CMSE - *Comitê de Monitoramento do Setor Elétrico*), with the objective of permanently monitoring the power supply conditions. Besides, additional risk-aversion procedures, such as the Risk-Aversion Curves (CAR - *Curva de Aversão ao Risco*) [7] and the conditional value-at-risk (CVaR) [8][9], were implemented in operation planning models during the units dispatch optimization, in order to avoid load curtailment and anticipate necessary thermal generation.

However, even with the application of such risk-aversion procedures, unfavorable hydrological conditions experienced during the last 6 years have led to the exhaustion of the main reservoir systems in Brazil [10]. Fig. 1.1 shows the percentage of stored hydropower in the Brazilian interconnected power system, referred as National Interconnected System (NIS), from 2000 to 2019 [3]. By the end of 2018, Brazilian reservoirs reached levels below 20% of stored energy, the lowest ever recorded. As a consequence, larger amounts of thermoelectric generation have had to be dispatched [3], as seen expressed in megawatt-month (MWmonth) in Fig. 1.2.

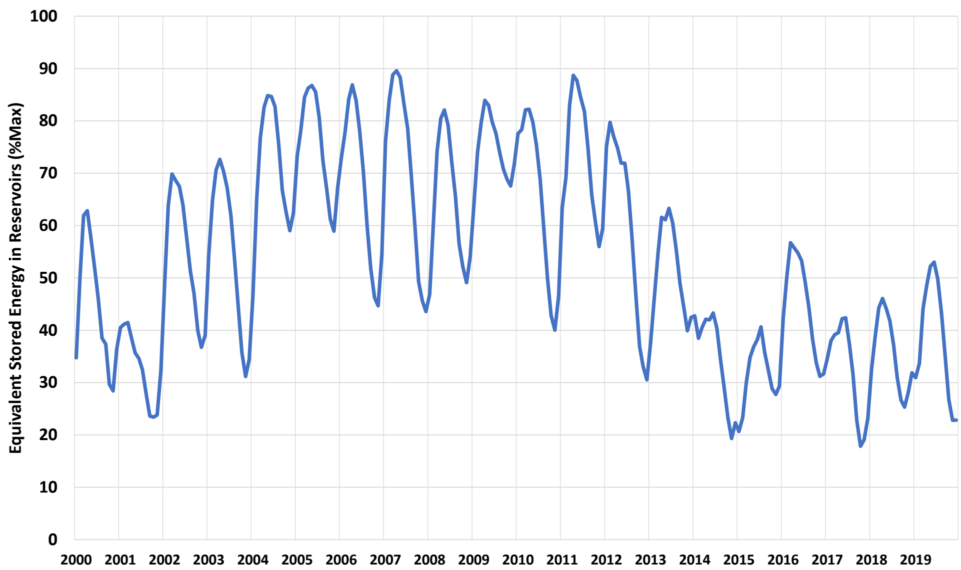

Figure 1.1: Percentage of maximum hydro energy storage in NIS (2000-2019)

Despite the observed increase in thermal generation, the models used to assess the optimal generation mix were not able to provide the proper economic signs regarding the marginal costs. In other words, the thermal generation indicated by NEWAVE and DECOMP has been lower than that perceived as necessary by ONS and other power industry entities. Thereby, as shown in

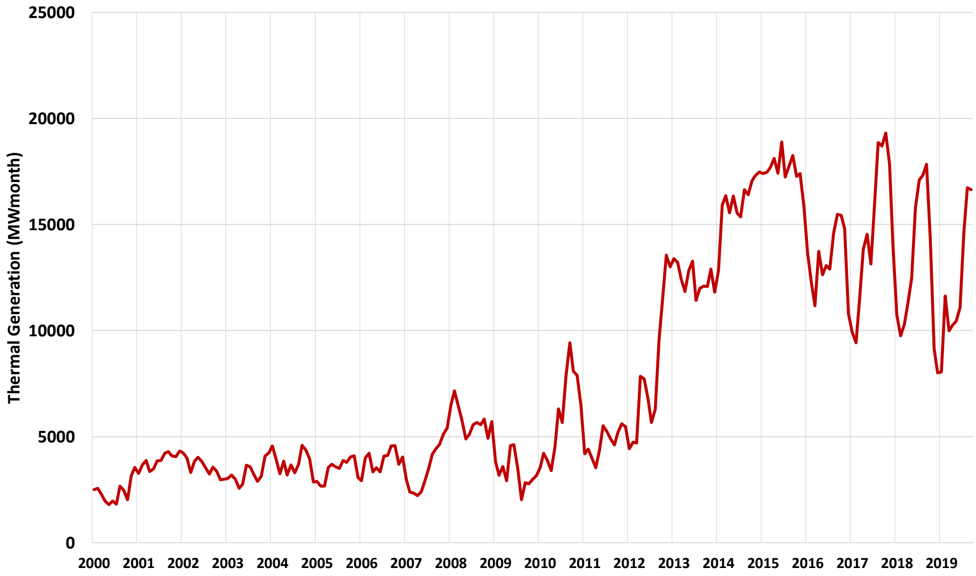

Figure 1.2: Thermal generation in NIS (2000-2019)

Fig. 1.3, an important share of the thermal dispatch over the last years was commanded by CMSE to guarantee the adequate power supply conditions [11].

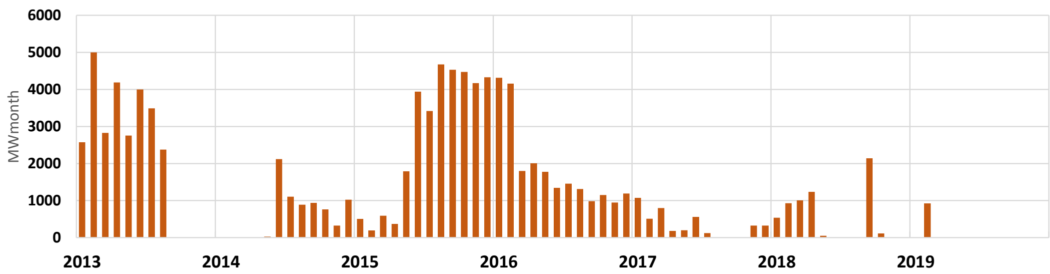

Figure 1.3: Out-of-merit thermal generation in NIS (2013-2019)

The plotted thermal generation in Fig. 1.3 corresponds to R$[1] 14.5 billion spent with security of power supply from 2013 to 2019, in Brazil [11]. Yet, the observed out-of-merit dispatch relied mainly on tacit risk perception from the government entities' experts.

Considering no change in market and regulatory framework, solid metrics must be defined for the reservoirs operation monitoring, in order to evaluate the dispatch models performance and the need of government intervention with additional thermal generation, since this implies on larger energy costs to all consumers and unpredictable regulatory instability to different market players. To the best of the author's knowledge, there is no academic work that proposes a methodology to compute reservoirs minimum required levels with regard to reliability of power supply.

[1] According to [12], US$ 1.00 corresponds to R$ 5.48 in November 15th, 2020.

Although ONS proposed a new method to assess the need for additional thermal dispatch (CREF, described in Section 3.4.6), at the end of 2019, it fails as a reference for the security of energy supply since it considers very specific assumptions of rivers' inflows and thermal generation. Besides, based on its iterative 'trial and error' process, it can result in sub-optimal results of minimum storage levels.

The objective of this work is to propose a new method to evaluate the security of power supply in systems with predominance of hydroelectricity, such as NIS. This method is intended to be an evolution to the CREF method, and it is based on the development of an optimization model that computes the minimum secure levels for hydroelectric plants operation in each month, from a recursive simulation of historical inflow series from 1931 to 2018. In addition, based on the simulation results, reference curves were suggested for the continuous monitoring of the security of power supply regarding the reservoirs operation.

Unlike the dispatch models used by ONS, the model proposed on this dissertation does not provide the optimal dispatch scheduling but intends to fill the gap of security monitoring tools for hydrothermal power systems, assessing the minimum required energy storage for each subsystem from a recursive simulation of historical inflows. Its fundamental principle is to be a subsidy mechanism to Brazilian government entities decisions on unorthodox thermal generation dispatch. Furthermore, the monitoring of reference curves defined by a mathematical model is expected to represent a more robust criterion for additional out-of-merit thermal dispatch commands by CMSE.

This thesis is organized as follows. First, important concepts about the National Interconnected System are presented in Section 2. Next, Section 3 provides a more detailed explanation of the optimization models used for planning the operation, as well as the evolution of the risk-aversion metrics employed in these models and outside them. Section 4 explains the proposed methodology, detailing the modeling of the system constraints and the optimization process. Section 5 provides simulation results and the proposed reference curves. Finally, the conclusion is given in Section 6. At the end of the dissertation, the Appendix A presents the article on this same research topic published in the Electric Power Systems Research journal (ISSN: 0378-7796).

2
The National Interconnected System

The National Interconnected System (NIS) is a large power generation (162.1 GW of installed capacity [13]) and transmission system divided in four main subsystems: South (S), Southeast/Midwest (SE/MW), Northeast (NE) and North (N). The interconnection of electrical systems through the transmission grid provides energy transfer between subsystems, allowing synergistic gains through hydrological regimes' diversity. Besides, the integration of generation and transmission resources enables safe and cost-effective market service. The following sections will present more details about the electric power generation matrix and the power transmission network of the Brazilian electrical system.

2.1
Power Generation Mix

The Brazilian power generation matrix is predominantly hydroelectric, with 108.3 GW of hydropower installed capacity in December 2019 [13]. Currently, according to [14], Brazil is the second largest hydropower producer in the world, only behind China. However, despite still having a high hydroelectric potential to be explored, there are no large hydroelectric plants to be implemented in Brazil by 2024. The tightening of environmental laws has hampered the expansion of this resource across the country, which has prioritized wind, solar and thermal generation using natural gas. Fig. 2.1 illustrates the evolution of the Brazilian electricity matrix from 2019 to 2024.

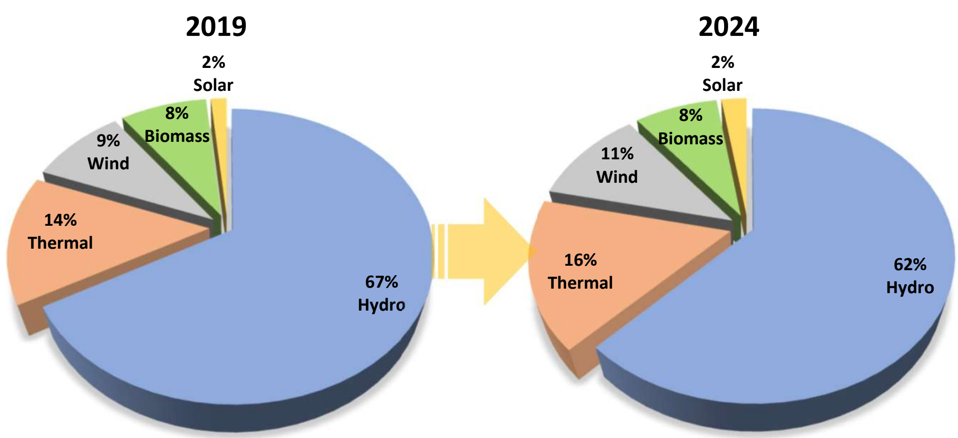

Figure 2.1: NIS' installed capacity mix (%) – 2019-2024

2.1.1 Hydroelectric Generation

The hydroelectric plants of the National Interconnected System are distributed in sixteen river basins in different regions of the country [15]. Fig. 2.2 shows an excerpt of the schematic hydropower plants diagram for Paranaíba and Grande River basins [16], two of the most important basins in terms of energy production. In this diagram, each power plant is represented either as a triangle (for impoundment power plants) or as a circle (for run-of-river power plants). Throughout the rivers' cascade, there is a large number of hydro plants from different generation companies (GENCOs).

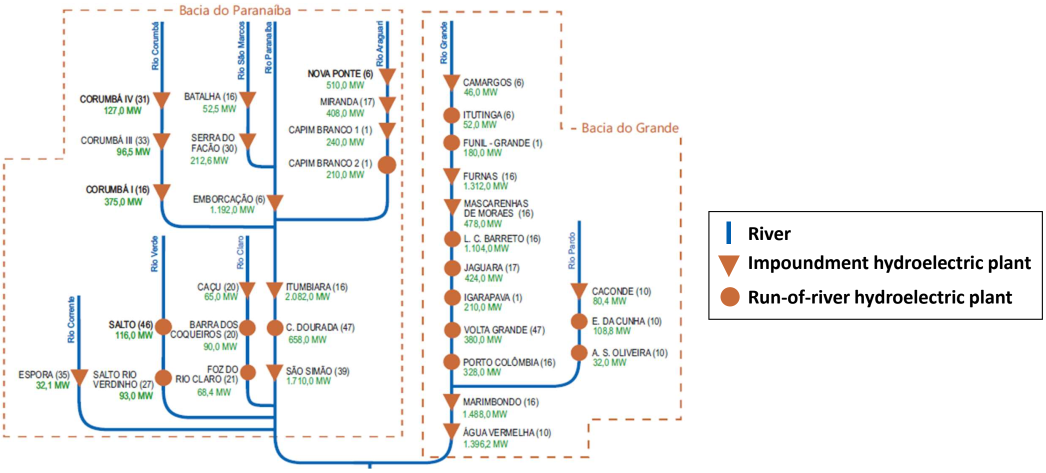

Figure 2.2: Excerpt from NIS' schematic hydropower plants diagram

In terms of stored hydropower capacity, SE/MW is considered the most relevant subsystem summing up more than 203 GW of stored capacity, about 70% of NIS total stored capacity [3]. The stored energy capacity is distributed among the subsystems as follows:

- **Southeast/Midwest:** 70%
- **Northeast:** 18%
- **South:** 7%
- **North:** 5%

Considering the large area Brazil occupies in South America, the river basins from different regions are subject to distinct climate phenomena and hydrological regimes. From an energy production perspective, the observed streamflow in different river basins can be evaluated by the Affluent Natural Energy (ANE). ANE is the energy obtained when the natural flow of an affluent is turbined in downstream plants from an observation point, considering equivalent productivity of 65% of useful storage volume of reservoirs [17]. Fig. 2.3 presents ANE's seasonality and monthly mean for each subsystem [3]. Apart from the South, in general, all subsystems have well defined wet and dry seasons. Therefore, from a global perspective, NIS' wet season goes from December to April, while its dry season usually goes from May to November.

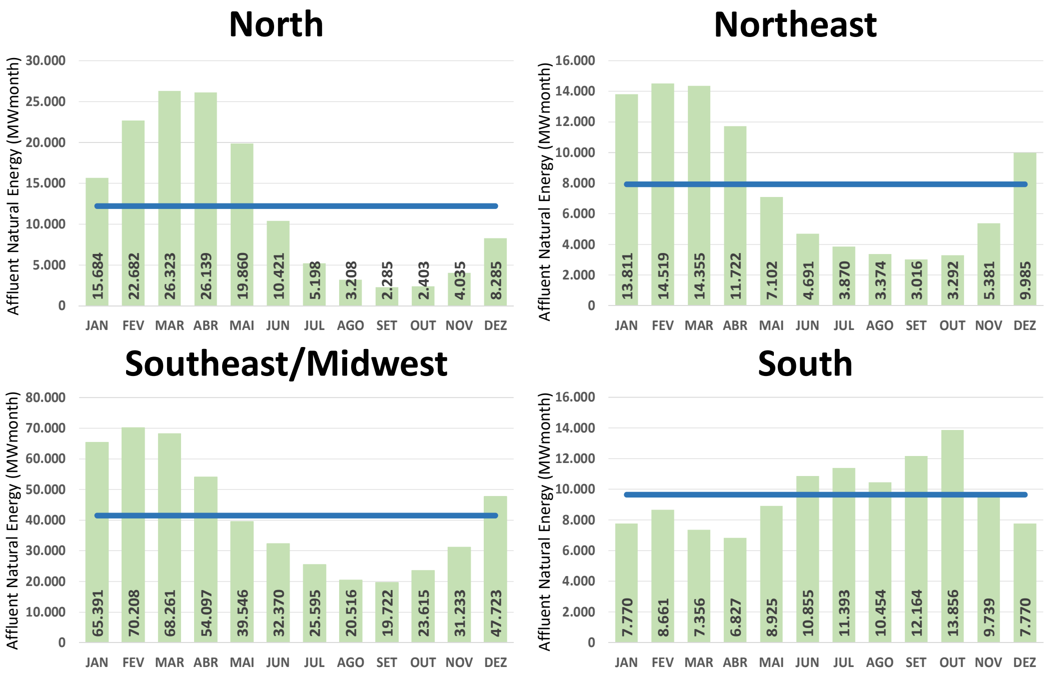

Figure 2.3: Monthly natural affluent energy per subsystem (MWmonth)

The coordination of the reservoirs operation represents a challenge, since decision-making in relation to the power production of different GENCOs must also take into account the interests of other economic activities, such as fishing, irrigation, water supply, sanitation, tourism, among others. For instance, the Brazilian National Water Agency (ANA - *Agência Nacional de Águas*) has been restricting the outflow from important power plants reservoirs in the Northeast region, due to a persistent drought that is affecting several economical activities and communities in areas close to the São Francisco River [18].

These critical hydrological conditions, also commented in Section 1, have been decreasing the share of hydroelectric generation in the supply of power demand, as displayed in Fig. 2.4. Hydropower, which accounted for more than 90% of all electrical energy generated in NIS, has given rise to thermal, wind and solar energy [3]. The tightening of environmental laws has influenced the expansion of this energy source, especially with regard to the construction of large regularization reservoirs. As a consequence, hydroelectric plants have played an increasingly important role as an operational reserve for intermittent energy sources, such as wind and solar.

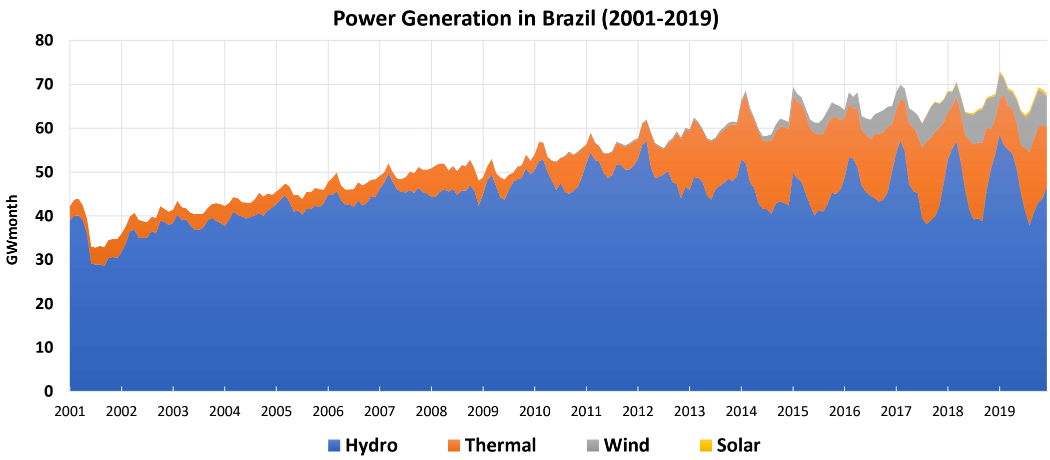

Figure 2.4: Power Generation in NIS from 2001 to 2019

2.1.2 Thermoelectric Generation

The thermal plants are essential resources for meeting NIS' demand, especially under critical hydrological conditions. In terms of technology, natural gas has the largest share of Brazilian thermoelectric plants, having an expected growth of almost 4 GW from 2019 to 2024, according to [13]. In addition of being less expensive, natural gas is also less polluting than other fossil fuels.

Fig. 2.5 presents a scatter chart comparing the cumulative thermal generation availability and the variable cost per unit (VCU) of thermal power plants in NIS [19]. VCU is the amount (expressed in R$/MWh) necessary to cover all operating costs from a given thermoelectric plant. Between R$

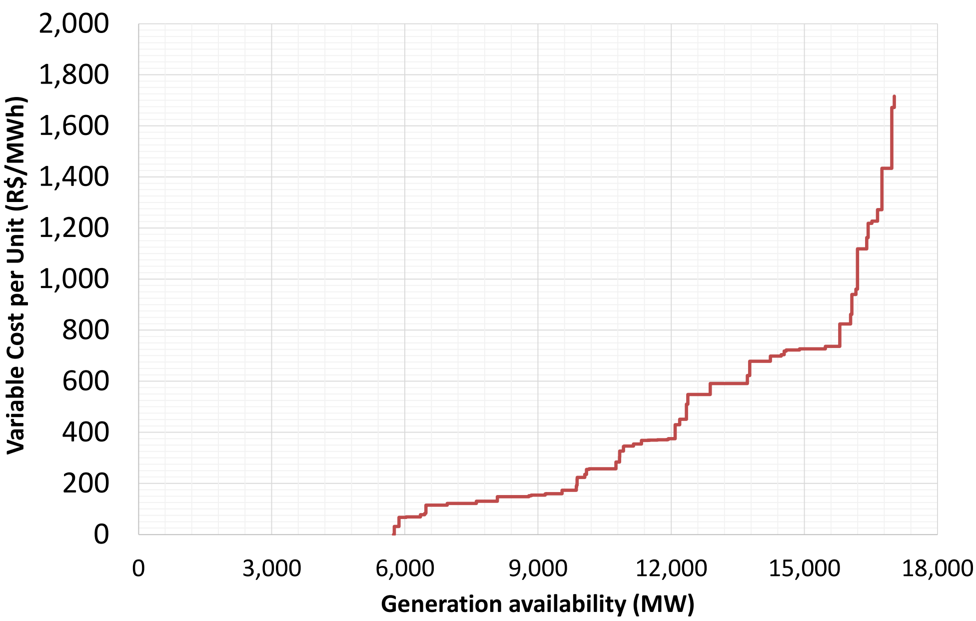

Figure 2.5: Thermal Generation Availability vs Variable Cost per Unit - November 2019 (adapted from [19])

100.00/MWh and R$ 250.00/MWh there is an important increase in thermal generation availability with little variation on units cost of dispatch. The opposite occurs for VCUs higher than R$ 800.00/MWh, and the dispatch of such expensive plants implies in a high volatility of marginal costs.

2.1.3 Wind and Solar Power

Renewable energy sources, such as wind and solar, have had great development over the last few years in Brazil. While installed wind capacity is expected to grow by more than 4 GW by 2024, the estimated growth for solar energy is almost 1.4 GW, considering this same period [13]. Along with natural gas thermal plants, wind and solar are the energy sources with the greatest expansion expected in Brazil until 2024.

Fig. 2.6 and Fig. 2.7 show the distribution of wind and solar power installed capacity per Brazilian state [20]. Wind energy is more representative in the Northeast subsystem, where trade winds operate with permanent east-to-west winds. The geographical position of the Northeast region of Brazil provides capacity factors up to 80% on an hourly basis, some of the highest found in the world. The lower latitudes of the Northeast region are also responsible for the high insulation pattern in this region during the whole year. As a consequence, the higher solar energy potential is also located in the Northeast region, along with the higher amounts of solar power installed capacity.

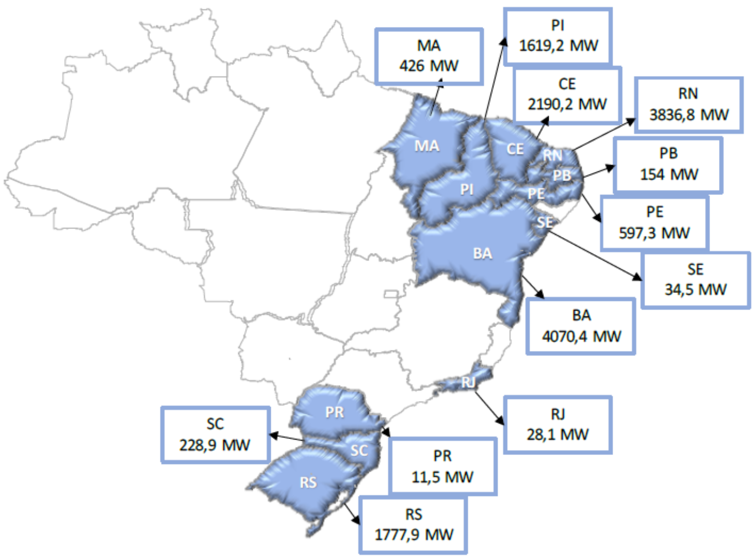

Figure 2.6: Wind power installed capacity in Brazil per state – 2019 [20]

These renewable energy sources are responsible for serving a large part of the energy load of the Northeast subsystem, especially from August to

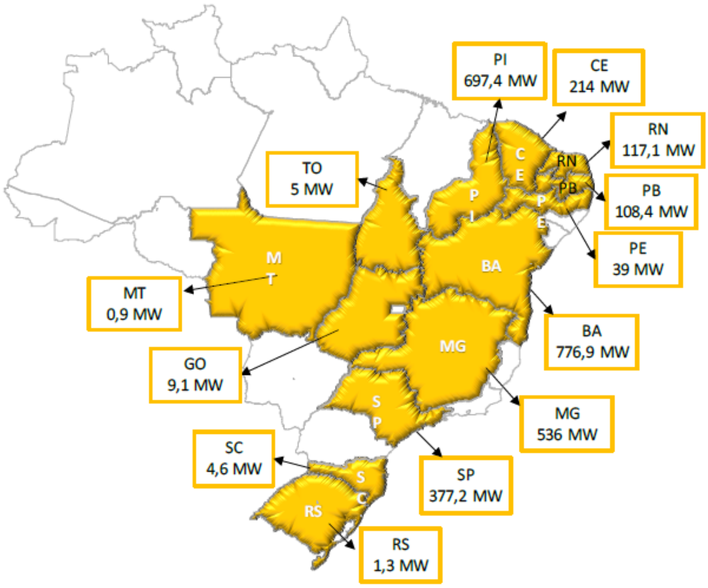

Figure 2.7: Solar power installed capacity in Brazil per state – 2019 [20]

October, when the wind flows at a constantly higher speed [20]. Fig. 2.8 shows the Northeast's energy supply from January to July 2020 [21]. The black line represents demand and the difference between demand and the sum of generation corresponds to energy transfers between the subsystems. Thus, when the demand is greater than the sum of generation, it means that the Northeast subsystem imported the rest of the necessary generation from other subsystems. As of mid-June, the opposite situation is observed, in which the sum of generation was greater than demand, which means that in this period the Northeast exported energy to other subsystems. NIS' power demand and power transmission system will be discussed in the next sections.

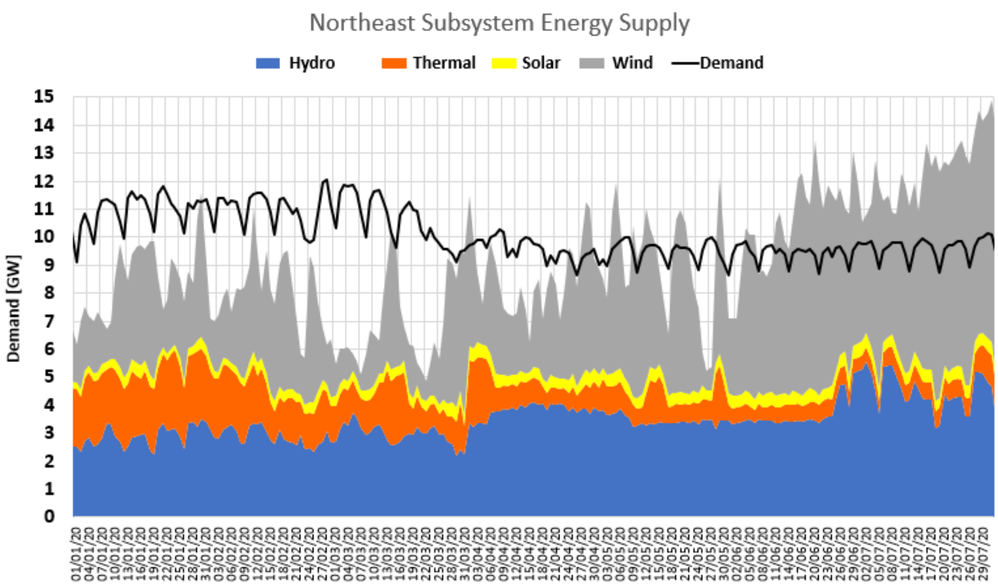

Figure 2.8: Power supply in Northeast subsystem (adapted from [21])

2.2 Power Demand

2020 has been an atypical year in terms of demand for electricity. The effects of the COVID-19 pandemic had strong economic impacts in Brazil with projections of considerable Gross Domestic Product (GDP) retraction, as shown in Fig. 2.9. As remarked in [22], *'the first half of 2020 was marked by the rise of uncertainty and continuous revisions in economic projections, with no clear perspective about the depth and length of the installed health, social and economic crises'*.

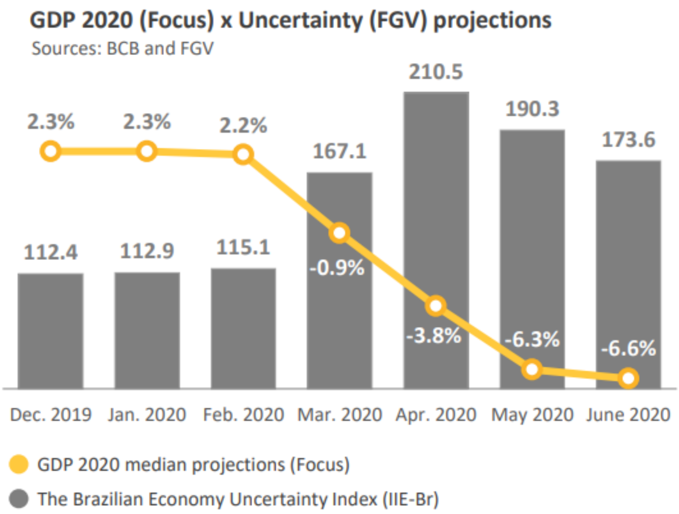

Figure 2.9: GDP and uncertainty projections - Brazil/2020 [22]

Despite this, from 2022 onwards, a more stable economic environment is expected, which should provide greater confidence for agents with significant impacts on consumption and investment, with emphasis on the infrastructure sector [23]. As a result, demand for electricity is expected to grow by 16.5% between 2020 and 2024, as shown in Fig. 2.10.

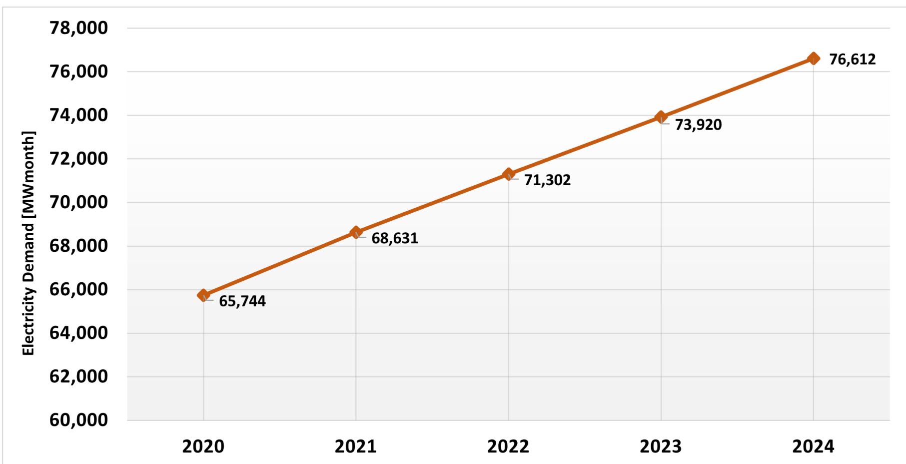

Figure 2.10: Electricity demand projection of NIS – 2020-2024

2.3 Power Transmission System

The continental extent of Brazil, sometimes compared to Europe, represents a challenge in energy supply, especially with regard to isolated areas, such as communities in the Amazon rainforest. The NIS power transmission system is robust and is responsible for serving more than 99% of all electricity consumption in Brazil [24].

Fig. 2.11 presents existing (continuous) and future (dashed) transmission lines of NIS power transmission system. In [25], the transmission network is expected to extend from 141,756 km to 181,528 km in length between 2019 and 2024.

Figure 2.11: Existing and future transmission lines in NIS (2024) [26]

Two important high-voltage direct current (HVDC) transmission systems inaugurated in recent years stand out. The transmission lines that carry the energy produced by the Belo Monte hydroelectric plant were the last major transmission project, inaugurated between 2018 and 2019, with lines of over 2,000 km in length and a capacity of up to 8,000 MW. Inaugurated in 2013, the HVDC bipoles of the Madeira transmission system, send up to 6,300 MW from the Santo Antônio and Jirau hydroelectric plants, in northern Brazil, to the state of São Paulo. Both these enterprises were considered a challenge, particularly concerning the hardening of environmental laws on the last years.

In relation to the expansion for the coming years, the largest transmission works are planned for the Northeast subsystem, and for its connection with the Southeast/Midwest subsystem. This expansion is expected to increase the reliability of the Northeast region's energy supply, especially with regard to the integration of a large amount of wind and solar plants, with an intermittent generation profile. We can also highlight future works to increase reliability in the connection between the Southeast/Midwest and South subsystems, and works that will connect the electrical system of the state of Roraima, in the extreme north of the country, with the rest of the NIS.

Finally, Fig. 2.12 shows the main interconnections between subsystems considered in NEWAVE model. The optimization models used for the optimal dispatch scheduling in NIS will be discussed in the next section.

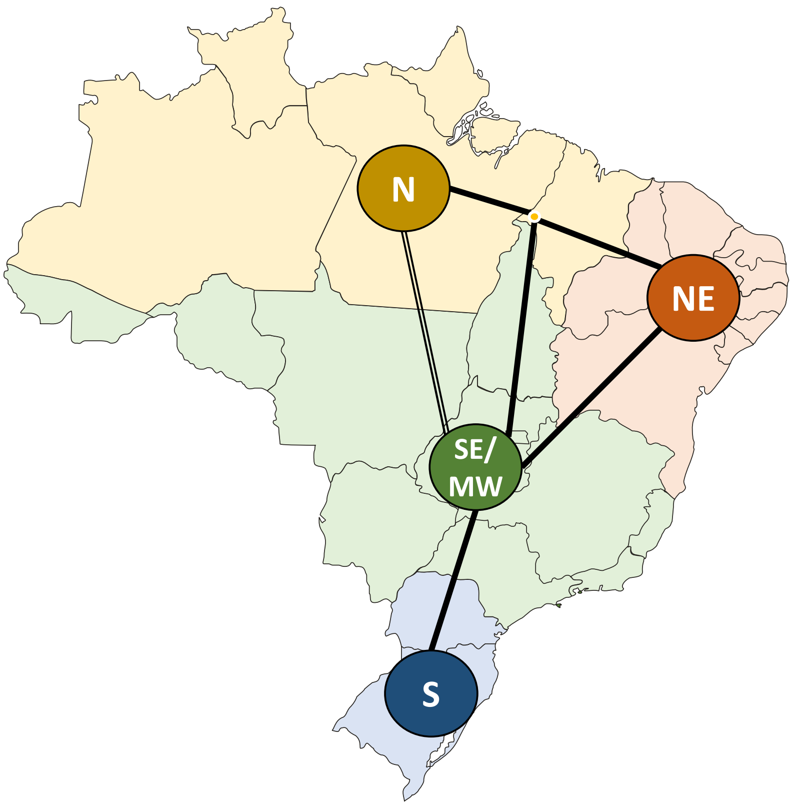

Figure 2.12: Main interconnections between NIS' subsystems

3
Security of Power Supply in NIS

World installed capacity of hydroelectric energy reached 1,308 GW in 2019, with emphasis on Brazil, which was the country with the largest increase in installed hydropower capacity during the year (4.92 GW) [27]. Although China is the country with the largest hydroelectric installed capacity, as noted in Fig. 3.1, the diversity of its electric energy matrix, primarily thermal, means that severe hydrological conditions do not represent a risk to the security of energy supply.

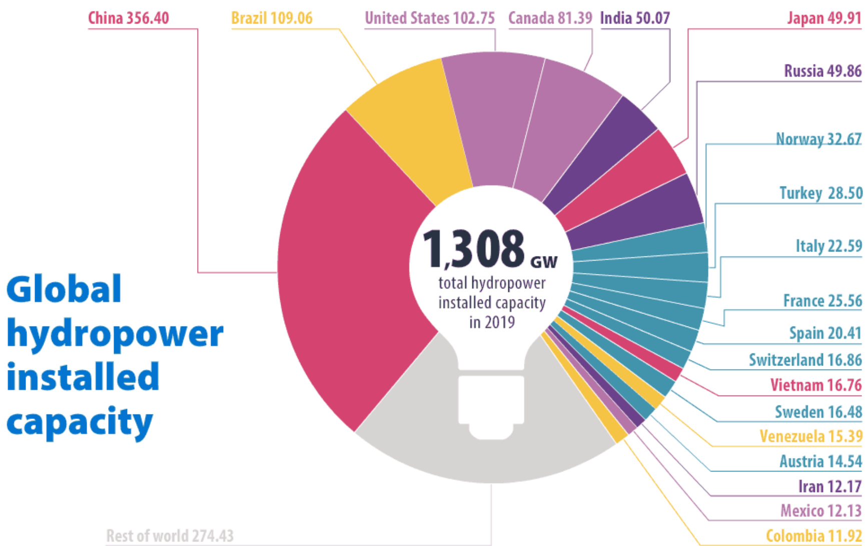

Figure 3.1: World hydropower installed capacity in 2019 [27]

On the other hand, countries like Brazil, Canada and Norway have hydroelectricity as the main energy resource. In Brazil, for instance, hydroelectricity accounted for 70% of all electrical energy produced in 2019 [3]. In this sense, intense droughts can affect the supply/demand balance, emptying reservoirs and raising energy prices. In the matter of security of power supply of hydrothermal systems, the existing literature investigates mainly regulatory framework/market design improvements, such as in [28], [29], and [30], and environmental/climate changes concerns regarding future energy mix and reservoirs management. From the regulatory point of view, [31] shows that a secure power system's operation should include a close coordination strategy between the mid and short-terms problems. On the other hand, [32] analyzes the effects of market deregulation over system security and management of reservoirs in Norway, and [33] addresses issues of long-term security of power supply and spillage control with a renewable electricity system in New Zealand.

The climate change is subject for studies on optimal hydroelectric plants operation in Canada [34] and Switzerland [35]. Still on the environmental perspective, [36] analyzes possible impacts of climate change on hydroelectricity generation in Brazil, and [37] describes how Brazil has invested in hydroelectric and thermal plants with high greenhouse gas emissions in order to achieve a secure operation.

The recent energy crisis that led to depletion of reservoirs in Brazil is discussed in [38] and [39]. While [38] analyzes possible operation planning failures, suggesting the use of more detailed dispatch scheduling models, [39] shows that the diversification in the electricity generation mix could be a strategy to improve the power supply reliability in Brazil.

In this context, the security of NIS' energy supply is intrinsically linked to its main attributes as a power system: hydro dominated, characterized by large reservoirs with multi-annual regulation capacity, arranged in complex cascades over several river basins [40]. Thus, the scheduling of generating units must be executed with a future vision of the availability of energy resources. Wrong decisions can lead to undue depletion of reservoirs and the need for extraordinary measures to ensure the electricity supply. For instance, Fig. 3.2 illustrates the so-called hydrothermal systems' 'operator's dilemma'.

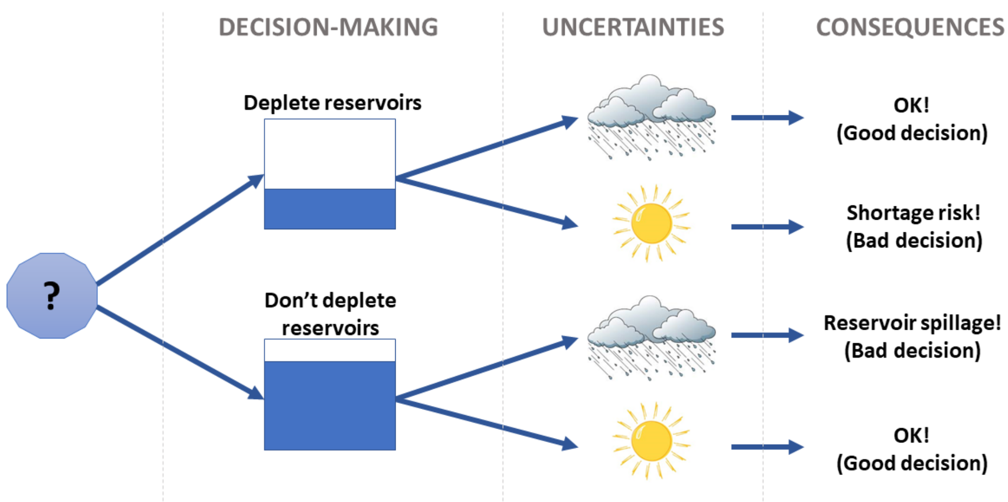

Figure 3.2: Hydrothermal systems' operator's dilemma

The operator's dilemma demonstrates decision making under uncertainty by an operator of a hydrothermal system. To meet demand, the operator must take one of the following actions:

- Meet the demand with energy generated mostly by hydroelectric plants, emptying the reservoirs, or
- Store water in reservoirs, using more expensive thermal generation.

However, actions taken in the present can have a profound impact on the future. The operator must make his decision under uncertain weather conditions. Thus, if he chooses to empty the reservoirs at present and there is a strong drought in the future, the security of the energy service could be compromised, requiring a high amount of thermal energy generation in the future, with risk of energy shortage and need of rationing measures. In the same way, if he chooses to store water in the reservoirs and there is a very rainy wet season, it may be necessary to spill water from the reservoirs, which represents an energy waste.

In the case of the National Interconnected System, the operator's decision-making can be divided in long, mid and short-term operation planning problems Next sections will bring further details of how the operation planning is carried out in Brazil.

3.1 Long-Term Operation Planning

In Brazil, the Energy Research Office (EPE - *Empresa de Pesquisa Energética*) supports the Ministry of Mines and Energy (MME) guidelines with studies and research on energy planning in electricity, biofuels, oil and its derivatives [41]. Through the Ten-Year Energy Expansion Plan (PDE - *Plano Decenal de Expansão de Energia*), EPE indicates, from a governmental point of view, the expansion of the energy sector in the period of ten years, with an integrated view of different energy sources [42].

EPE's long-term vision on the generation and transmission expansion planning is essential to anticipate actions, allowing the system to absorb and adapt to new technologies, maintaining a safe, economical and sustainable service. This is the 'first level' of planning in which supply risk is assessed in Brazilian power system. The indication of the generation matrix and transmission network expansions presupposes the fulfillment of the supply guarantee criterion.

The concept of the supply guarantee criterion originates from the dimensioning of reservoirs for human water supply, later used in the economic dimensioning of hydroelectric plants and their cascade production. Until 2019, the supply guarantee criteria were composed by 5% limited deficit risk in any subsystem, and the equality between the Marginal Operating Cost (CMO - *Custo Marginal de Operação*) and the Marginal Expansion Cost (CME - *Custo Marginal de Expansão*) [43]. However, significant changes have been taking place in the electric energy matrix of the NIS, making it necessary to redefine the supply criteria, now separated into two dimensions:

– **Energy**: CVaR(non-supplied energy) and CVaR(CMO)

– **Power**: CVaR(non-supplied power) and LOLP

Accordingly, these criteria must ensure that investments in expansion are done at the right time and in the right way. Whenever necessary (when economic optimization is not sufficient to induce investment), they should signal for the contracting of an additional offer that helps to meet the system requirements.

In addition, during the operation planning, ONS must use the supply guarantee criteria to monitor and evaluate the adequacy of the conditions to meet the system's electricity demand. These criteria, in turn, serve as a reference for carrying out analyzes that may assist the CMSE in making decisions regarding the need for additional thermal dispatch to that indicated by the optimization models. Next sections will address the 'second level' of NIS' operation planning, detailing the optimization models used for the optimal generation scheduling.

3.2 Mid-Term Operation Planning

As outlined earlier, the operator of a hydrothermal system must plan the use of energy resources well in advance, in view of the possible impact of climatic uncertainties. Considering the offer contracted by the generation and transmission auctions, the next step in planning the operation makes use of a chain of optimization models to calculate the 'water value', and optimal dispatch of generating units.

The NEWAVE model is the optimization model with the longest horizon used in planning the energy operation of the National Interconnected System. It was implemented in 2000, and according to [40], its objective is to minimize the expected value of the total operation cost during the planning period (5 years on a monthly basis in official ONS simulations). The main assumptions are the initial state of the system, the fuel costs of the thermoelectric plants (VCUs), the schedules for expanding the generation units and transmission net, the expected load growth and the deficit penalties. Some simplifications permit the NEWAVE model to be able to simulate the 5-year operation ahead, with different ANE scenarios in a reasonable computational time. Hydroelectric plants are aggregated in equivalent energy reservoirs (EER) and the water inflows uncertainties are modeled by a periodic autoregressive model of order p (PAR(p)). A Monte Carlo simulation is used to iteratively build multivariate functions of expected future cost.

The total operation cost assessed in the mid-term operation planning is the sum between the present and future costs. Fig. 3.3 [44] represents the future and immediate cost functions and their relation to the decision-making in the operator's dilemma problem.

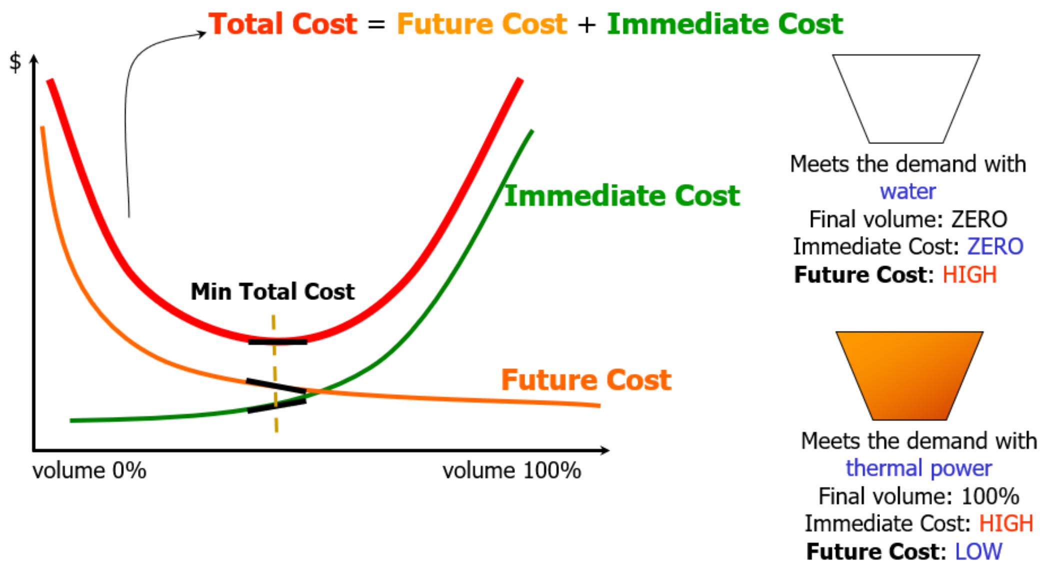

Figure 3.3: Total cost of operation minimization (adapted from [44])

The total cost is represented as a cost per stored volume function. The immediate cost grows in the same direction as the volume stored in the reservoirs, since the greater the volume at the end of a given stage, it means that the load at this stage was mostly served by thermoelectric generation. The derivative of this curve represents the generation cost of thermal plants or the deficit cost [44]. On the other hand, the future cost is higher the smaller the storage at the end of a given stage, because the demand for future stages will be met primarily with thermal power. In this case, the derivative of the future cost function (FCF, also related as cost-to-go function) in relation to the stored volume represents the water value. The total cost is the minimum when the derivatives of the immediate cost and cost-to-go functions are opposite.

To calculate the minimum cost, the immediate and future costs must be known. The immediate cost is known, as it will be a consequence of the decisions that the operator makes at the present stage. However, the future cost depends on future water inflows that are unknown.

The PAR(p) model, implemented in NEWAVE model, is used to generate synthetic series of flows in the form of affluent natural energy. The FCF can be calculated as the expected cost of future scenario costs and dynamic programming algorithms can be used to calculate sequential decision problems, such as the operation of hydrothermal systems in subsequent stages. However, to build the FCF, it is necessary to discretize the state variables for each future scenario generated. This leads to the so-called 'curse of dimensionality'. Assuming a system with 10 reservoirs discretized into 100 states, for instance, there would be a total of 1^{20} state variables.

In this context, the SDDP algorithm [1] proposes to solve multistage stochastic optimizations problems by approximating the stochastic dynamic programing FCF by piecewise linear functions. In this algorithm, the piecewise linear functions are obtained from the dual solution of the optimization problem at each stage through a Benders decomposition framework.

The SDDP algorithm is implemented in NEWAVE and DECOMP models, which are used together on mid-term operation planning of NIS. The NEWAVE model provides the expected cost-to-go function for the DECOMP based on a fully stochastic assessment of future inflows, simplifying the operation over the 5-year horizon. The DECOMP model, on the other hand, makes a much more detailed simulation of the operation over a 2-month horizon. Fig. 3.4 [45] shows the coupling between NEWAVE and DECOMP models.

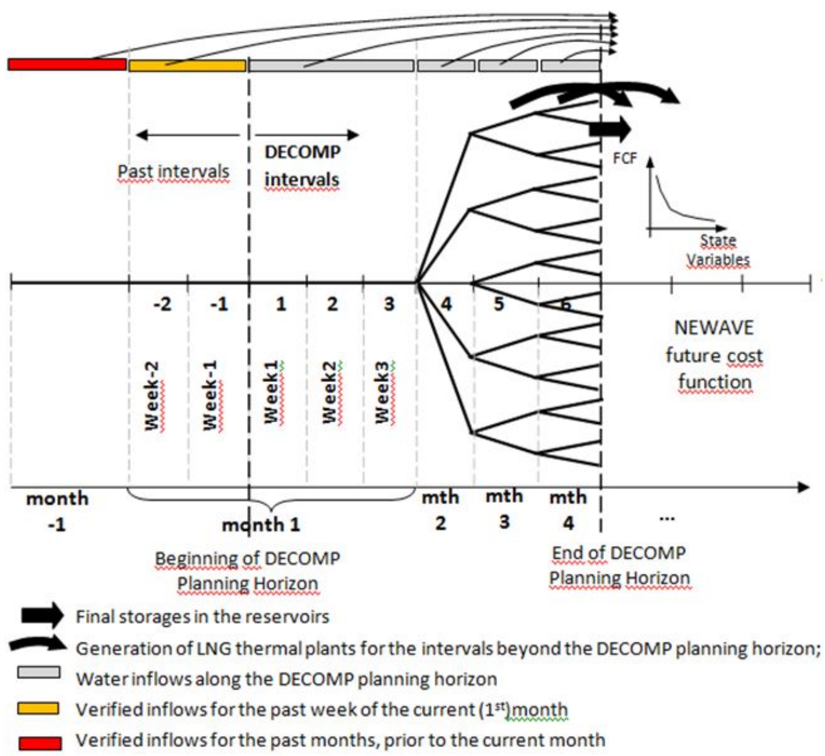

Figure 3.4: DECOMP's scenario tree and coupling with NEWAVE's FCF [45]

The first month of DECOMP model is discretized into weekly time steps separated by 3 distinct load levels (light, medium and heavy) with deterministic inflows calculated based on precipitation forecasts (using ECMWF [46], GEFS [47] and ETA models [48]), application of rainfall-runoff models (SMAP/ONS [49]) and statistical models of inflows forecasting (PREVIVAZ [50]). For the second month on, the inflows uncertainties are represented through a monthly scenario tree. DECOMP couples with NEWAVE cost-to-go function in the end of the second month, guaranteeing the minimum total operation cost, considering future uncertainties assessed previously by NEWAVE. In addition, unlike NEWAVE, all hydroelectric plants are represented individually in DECOMP, with an important emphasis on the better detailing of the water balance equations and the power production function of each plant.

With participation of all power sector agents, ONS prepares NEWAVE's FCF on a monthly basis during the Monthly Dispatch Scheduling (PMO - *Programa Mensal da Operação Energética*), updating information on the generation and transmission expansion schedules, current storage status of the reservoirs and energy load forecasts. During the PMO, regularly weekly reviews are performed incorporating updated information (reservoirs levels, power plants availability, maintenance schedules, weather conditions, load forecasts, inflows estimates, etc) on the DECOMP model.

Until the end of 2019, DECOMP established main policies for thermal generation and interregional exchanges, providing guidelines to be followed by the Daily Dispatch Scheduling (PDP - *Programa Diário de Produção*) and by the real time operation. The next section will discuss about the newcomer DESSEM model, and how the short-term operation planning at SIN is carried out.

3.3 Short-Term Operation Planning

The DESSEM model [5] has been in development for more than 10 years, but only in 2019 it was approved to be implemented in the end of the optimization models chain by the Ministry of Mines and Energy through Ordinance No 301, published on July 31st, 2019. Its implementation aimed to optimize the daily operation of energy systems in Brazil, considering both aspects related to the electrical network and the operation of hydroelectric, thermoelectric, wind and solar power plants.

Until the end of 2019, the dispatch scheduling was based on the thermal generation blocks per load level indicated by the DECOMP model. The energy transformation of the Brazilian electricity matrix required a refinement in the assessment of marginal operating costs considering the operation of renewable sources with an intermittent profile. In addition, technological advances in computational power allowed the modeling of a power system as robust as NIS, considering ramp and thermal unit commitment constraints, and important details of the operation of the reservoirs cascade in a multi-stage problem.

DESSEM model was developed for the daily scheduling of generating units. It computes the generation dispatch for each half an hour of the next day taking into account detailed hydraulics constraints and the representation of the transmission network through a D.C. power flow model [4]. DESSEM applies deterministic mixed integer programming (MIP) to the multi-stage problem minimizing the total operating costs using DECOMP's FCF to assess the hydro plants operating costs in the each period. The greater detail of the operation modeled by DESSEM allows the dispatch schedule to be optimized taking into account a much more detailed set of system constraints when compared to the optimal generation policy resulting from DECOMP. Fig. 3.5 shows the comparison between DECOMP and DESSEM guidelines on thermal generation dispatch for the first week of November 2020 [51].

Figure 3.5: DECOMP x DESSEM thermal generation guidelines (in MW) [51]

The energy guidelines resulting from DESSEM may require adjustments in view of specific operating conditions not envisaged during the simulations. In this way, an electrical validation of the generation and exchange schedules is carried out through power flow simulations, and it may be necessary to readjust dispatch schedules from DESSEM. The daily operation scheduling is the process in which these adjustments are done for DESSEM guidelines, resulting in a more feasible schedule for the next day.

To give an overview, Fig. 3.6 shows the chain of optimization models used for the energy operation planning in NIS, discussed in the last sections.

Long-term operation guidelines (FCF) assessed by NEWAVE are coupled at the end of DECOMP's horizon. In the same way, the future cost calculated by DECOMP is coupled at the end of DESSEM's horizon, ensuring the optimal dispatch considering the water value assessment. The Electrical Energy Research Center (CEPEL - *Centro de Pesquisas de Energia Elétrica*) is responsible for developing and maintaining in the state of the art the chain of optimization models (NEWAVE, DECOMP and DESSEM), along with auxiliary applications (such as PREVIVAZ and GEVAZP) used to carry out the PMO activities.

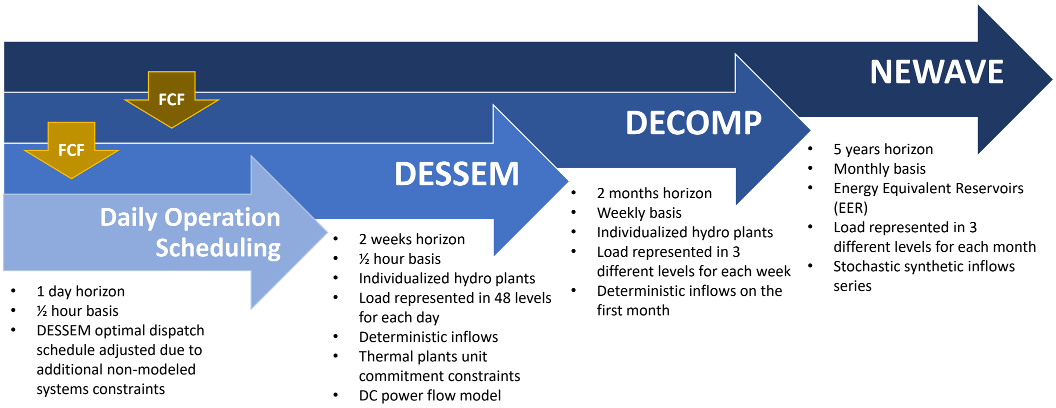

Figure 3.6: Dispatch scheduling optimization models chain

3.4 Evolution of Risk-Aversion Procedures in NIS

The optimization models used in NIS' operation planning are, by design, risk-neutral. In economics, an agent is said to be risk-neutral if the expected value of its utility function is linear. The utility function models decision maker's preferences over choices with uncertain outcomes [52]. In the case of the optimization models used in NIS' operation planning, the objective function minimizes the expected value of the total operation cost. Thus, as the decision making is made under the expected value of the operational costs resulted from different inflows scenarios, the maximization of the utility function is linear and equivalent to the minimization of the total cost of operation.

Risk-neutral planning may lead to unacceptable points for the power system operation, with a possible consequence of energy deficit. Between the years of 2001 and 2002, Brazilian consumers faced energy shortage because of low inflows and delays of expansion plans [6]. After that episode, the Brazilian government created the CMSE, with the objective of permanently monitoring the power supply conditions. Besides, through a government resolution [7], the Brazilian government instituted the Risk-Aversion Curves. This resolution stated that until the end of 2002, there would be adopted a mechanism to represent risk of energy rationing, external to the optimization models, based on a biannual security curve of the equivalent reservoirs storage, per subsystem. Fig. 3.7 presents the first risk-aversion curve elaborated to the Southeast/Midwest subsystem, by ONS [53]. The biannual security curves, later known as CAR, were implemented for the analysis of the energy service conditions and price formation.

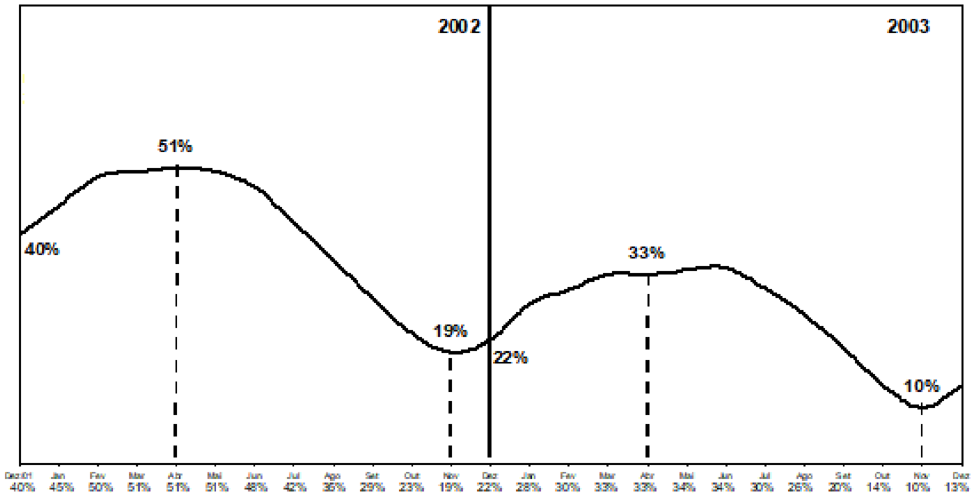

Figure 3.7: Southeast/Midwest CAR (2002-2003) [53]

3.4.1 Risk-Aversion Curves (CAR) – 2002-2013

From 2002 to the beginning of 2013, ONS prepared the biannual risk-aversion curves, with the objective of ensuring the minimum storage requirement for each subsystem at the end of November of the second year [54]. CAR was calculated recursively for each NIS subsystem. Particularly for the North subsystem, CAR was not a measure of risk aversion, but an operating policy to maximize the export of energy surpluses.

Energy balances were carried out for each subsystem during the calculation of the CAR. The recursion started at the end of November of the second year, which was also end of NIS dry season. While SE/MW and NE subsystems started from 10% of minimum stored energy, South subsystem's level at the end of November was 13%. Typically, some of the most critical biennia in the affluent energy history were used to calculate the stored energy requirements. All thermal power availability was used for the energy balance equations, and the estimated load was the same considered in mid-term operation planning studies. One of CAR's main criticisms concerns the way of defining the energy exchanges between subsystems. They were calculated with no respect to energy policies defined in operation planning models, only aiming to equally distribute the surplus energy from one subsystem to the rest of the National Interconnected System. Fig. 3.8 shows the recursive methodology for assessing storage requisites.

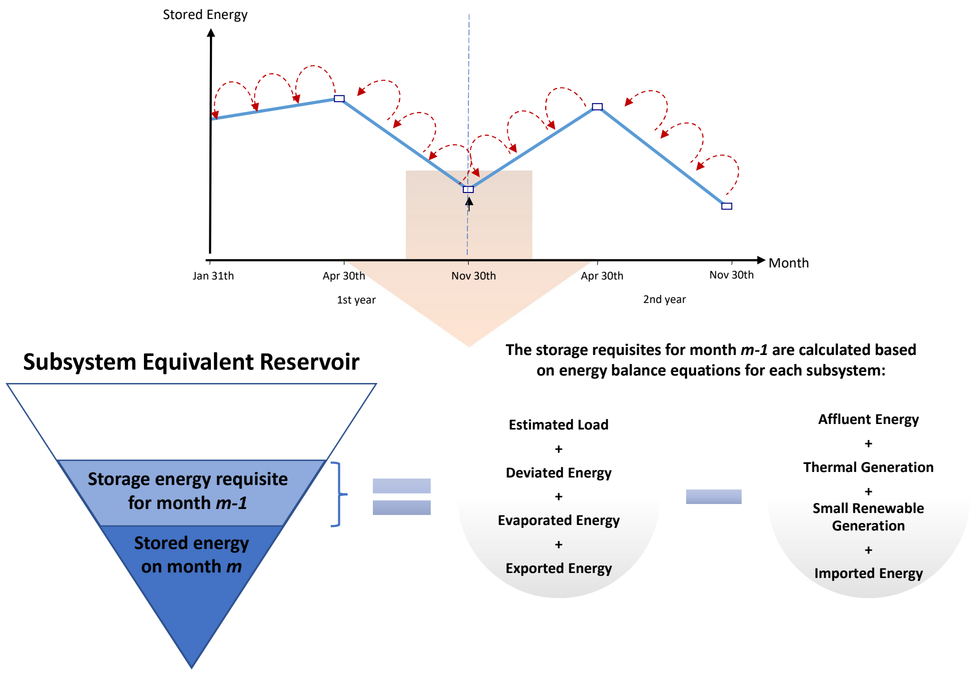

Figure 3.8: CAR methodology (adapted from [55])

The resulting levels from the CAR methodology were used in NEWAVE model as input data. If during the optimization process, the subsystems' levels situated below the CAR resulting levels, there would be applied a penalty[2] to the objective function, equal to the amount of violation of the CAR levels. Fig. 3.9 presents CAR resulting curves for SE/MW subsystem from 2002 to 2012 [54].

CAR resulting levels were as high as the worse were the systemic conditions for meeting energy requirements. The constant need for additional thermal dispatch to merit has led government entities to push for the consideration of more robust risk-aversion methodologies.

CAR was in effect with biannual horizon until March 2013, when the Brazilian government instituted that a new risk aversion methodology internalized to the optimization models should be developed and tested until July 31, 2013 [56]. During this period, for the purposes of planning the operation, the government also instituted that the CAR would be considered with a 5-

[2]Initially implemented with a 'fixed penalty' that could cause a marked increase in marginal operating costs in several situations, although it was mathematically consistent. As of 2004, an adjustable penalty was implemented throughout the SDDP iterations, reducing the cumulative effect on marginal operating costs. This new penalty was called a 'creative penalty'.

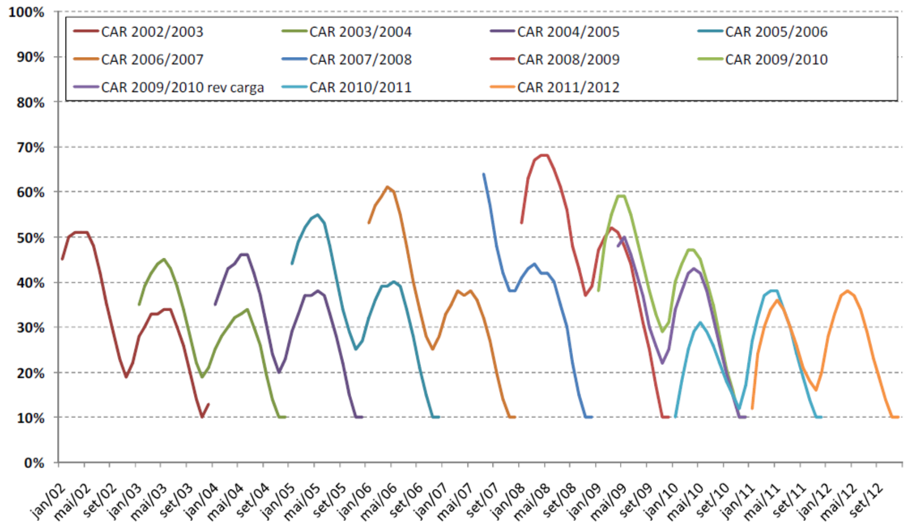

Figure 3.9: SE/MW curves resulted from CAR methodology [54]

year horizon (CAR5), using the same methodology defined for the biannual CAR. The CAR5 considered, in each year and for each subsystem, the first year of the curves elaborated with the same methodology as the biannual CAR, as observed in Fig. 3.10 [55]. The last two years of the CAR5 were a regular biannual CAR starting on the 4th year. The five-year horizon CAR was in effect until the end of August 2013, when the conditional value-at-risk (CVaR) methodology was implemented in NEWAVE and DECOMP models.

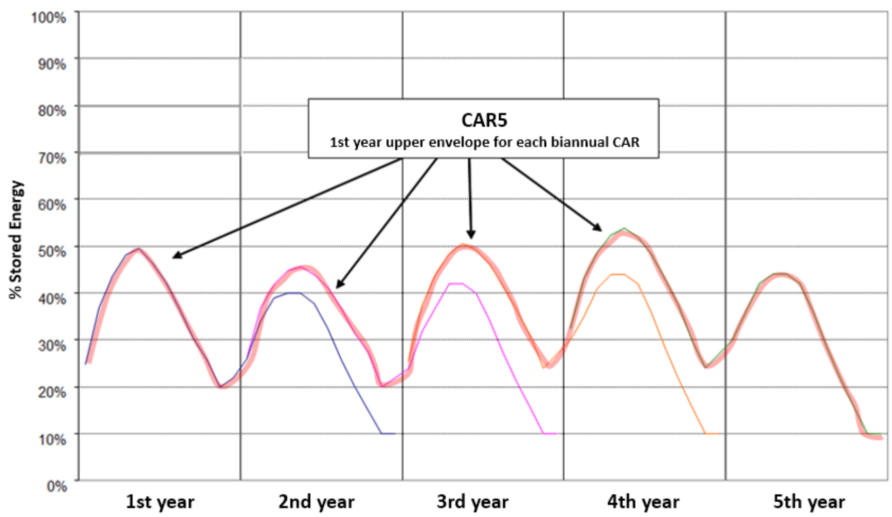

Figure 3.10: CAR5 example (adapted from [55])

3.4.2
Short-Term Operating Procedures (POCP) – 2009-2013

Despite its objective, the inclusion of penalties for invasion of CAR in the NEWAVE model was not sufficient to anticipate necessary decisions regarding dispatch of thermal generation in order to avoid future violation of CAR itself.

The same can be said for any other target level that was established with more distant horizons than the one envisaged monthly in the PMO (up to 2 months ahead) as, for instance, the end of the next dry season.

For this reason, ONS formulated a methodological alternative of an energy security mechanism called Short-term Operating Procedures (POCP - *Procedimentos Operativos de Curto-Prazo*), which was approved in February 2009, by a government resolution [57]. The objective of the POCP was to ensure that, at the end of each dry period, there would be enough water in the reservoirs to meet demand in the following year, even if one of the most severe droughts observed in history occurred again.

The POCP methodology is illustrated in Fig. 3.11 and, according to [58], it had the following steps:

1. At the beginning of each year, target levels were set for the end of November (end of the dry season) of the same year. The target levels were defined with premises similar to the ones employed during the calculation of the CAR curves, with small differences regarding the affluent inflow series.

2. At the beginning of each month, the possibility of reaching (or exceed) the target levels at the end of November was checked, assuming that:

   (a) from the current month until the end of November, it would happen the fifth worst sequence of inflows observed in history;

   (b) all thermal plants were activated at the most, from the month following the current month until the end of November; and

   (c) the thermal decision for the current month was the same as for the 'traditional' procedure, that was, without target levels.

3. If the result of step 2 was negative, that is, it was not possible to reach the target levels, the amount of additional thermal generation in the current month was determined to allow reaching these levels or, if this was still not possible, bring reservoirs levels to the end of November as close as possible to the targets.

During its term, POCP received criticism from different authors. [58] showed that the implementation of POCP from 2009 to 2012 was able to reduce the risk of violation of the target levels by a maximum of 5%. In addition, the authors demonstrated that the economic value of avoiding a deficit was greater than the deficit cost itself, representing a bad cost-benefit procedure.

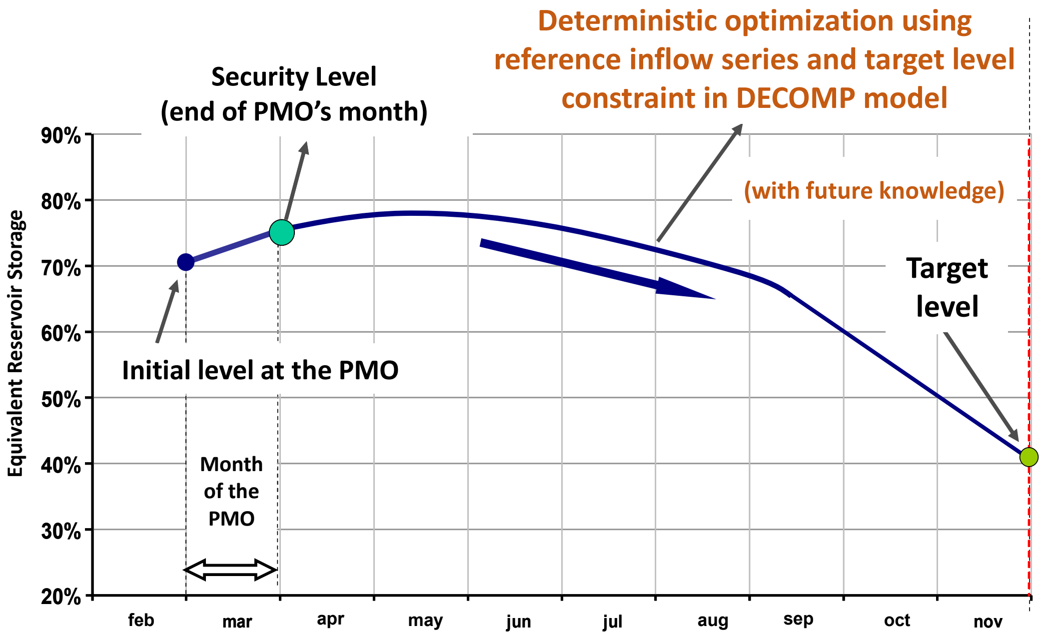

Figure 3.11: POCP methodology (adapted from [55])

In a different analysis, [59] showed that the application of POCP had a net effect of reducing hydroelectric generation, since the possibility of using the reservoirs' capacity of regulation was reduced, avoiding the risk of eventual non-recovery of the reservoirs in the rainy season. However, this procedure could generate a much higher volume of spills during the wet period, limiting the chance of financial recovery of hydroelectric generators that had their generation reduced during the dry period due to the anticipated dispatch of thermoelectric plants.

The Short-term Operating Procedures were in effect until the end of August 2013, being revoked together with the CAR methodology.

3.4.3 Risk-Aversion Surface (SAR)

As stated previously, in March 2013, the Brazilian government instituted that a new risk aversion methodology, internalized to the optimization models, should be developed and tested until July 31, 2013 [56]. The first methodology evaluated by the Permanent Commission for Analysis of Methodologies and Computer Programs for the Electric Sector (CPAMP - *Comissão Permanente para Análise de Metodologias e Programas Computacionais do Setor Elétrico*) was the Risk-Aversion Surface (SAR - *Superfície de Aversão a Risco*), firstly proposed in [60], later implemented by CEPEL [61][62].

SAR was a more accurate way of establishing minimum secure levels for stored energy in each subsystem than CAR or POCP methods, since it considered the interconnected operation between subsystems and could be internalized throughout the problem solving process, in the operation planning models [63]. In general terms, SAR was an extension, for the multivariate case, of the restrictions on minimum energy storage in the subsystems. Fig. 3.12 shows an example of the SAR methodology for SE/MW and NE subsystems.

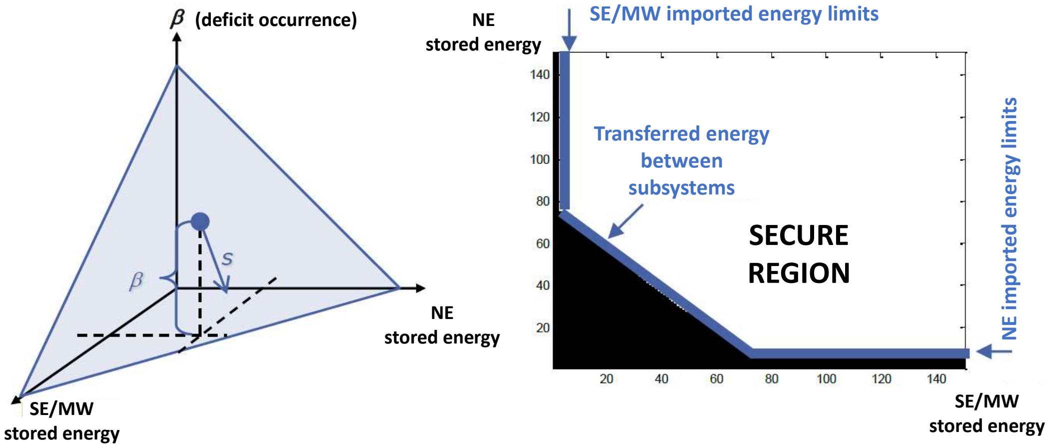

Figure 3.12: SAR methodology (adapted from [63])

According to [63], the β variable indicates the level of deficit occurrence in the future (for a series or a set of pre-established hydrological series) as a function not only of the individual levels of stored energy of each subsystem (vertical and horizontal lines in the figure on the right), but also as a function of the total energy of the subsystem (sloped line). The sloping constraint acts on the range of stored energy values for which the interchange between the subsystems is not at the limit, while the vertical and horizontal lines represent the individual minimum storage requirements of each subsystem, due to the energy import limit. If more than two subsystems are considered, the SAR could contain plans involving one, two or more subsystems in its constraint.

In its original design, SAR was built during the SDDP convergence process, solving an additional optimization subproblem for a critical series (SAR subproblem), using the storage values obtained by the NEWAVE subproblem solution as input. If it was not possible to meet the target level or the subproblem had a deficit, restrictions were added to the NEWAVE problem in order to increase storage levels [64]. However, for the same affluence series, the violation of SAR restrictions could result in several periods, producing an unwanted cumulative penalty effect.

With that in mind, [64] proposed in 2016 an alternative to penalize SAR in order to avoid the cumulative effect of penalties for not complying with SAR restrictions. In this methodology, the non-compliance with SAR restrictions is penalized only in the period prior to the period of the target level and only the greatest violation between all periods is penalized. However, as explained in the next section, the preference for the CVaR methodology limited the application of SAR only to tests and academic studies.

3.4.4 Conditional Value-at-Risk (CVaR) – 2013-Present

In risk management, a widely used measure is value-at-risk (VaR). VaR is the assessment of the potential worst loss at a specified confidence interval (α level of confidence) that an investor would be exposed to within a considered time horizon. VaR can be translated as the amount in which the losses will not exceed $(1-\alpha)\%$ of the scenarios [65]. On the other hand, the conditional value-at-risk (CVaR), is a measure of risk that indicates the average loss that exceeds the VaR, quantifying, on average, how large is the loss to which one is subject in a given portfolio. CVaR is considered a coherent risk measure [66] and is more pessimistic than VaR.

Between 2010 and 2013, different studies proposed to apply CVaR as a risk measure in the context of the SDDP. While [67] and [68] proposed the use of artificial variables, a direct approach proposed in [69] proved to be simpler and more efficient in solving problems related to the planning of the operation. This approach was also subsequently applied on [70] and [71]. This methodology aims to give greater importance to critical hydrological scenarios through the application of a convex combination in the objective function of the optimization models, as represented in Fig. 3.13. In a simplified way, it considers two key parameters (α and λ) and can be described as follows [63]:

- The objective function, in addition to minimizing the expected value of the total cost of operation with a given weight $(1-\lambda)$, also considers an additional parcel referring to the cost of the most critical hydrological scenarios, with a weight λ.
- The set of most critical hydrological scenarios is identified by the parameter α, related to the level of risk-aversion. It indicates the percentage of scenarios that will be considered with additional cost in the objective function.

The determination of the parameters λ and α is associated with the greater or lesser degree of risk aversion. The operating policy is more risk averse the more the value of λ approaches 1 and the more the percentage of α approaches zero. According to [63], in the multi-stage case, the level α does not correspond to the usual interpretation of the $\alpha\%$ critical scenarios from the first to the last year of the planning horizon. At each stage, this parameter corresponds to the $\alpha\%$ most critical scenarios for the stage itself. Therefore,

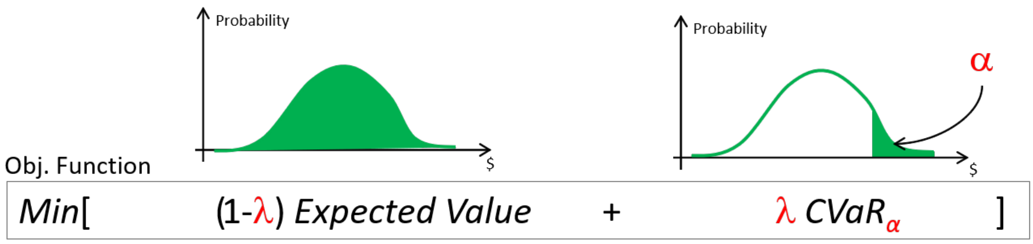

Figure 3.13: SDDP simplified objective function considering CVaR parameters (adapted from [55])

in the case of pure CVaR ($\lambda = 1$), the application of factor α in a multi-stage context of T periods leads to a protection level of α^T. Fig. 3.14 illustrates an example with T = 4 and α = 25%.

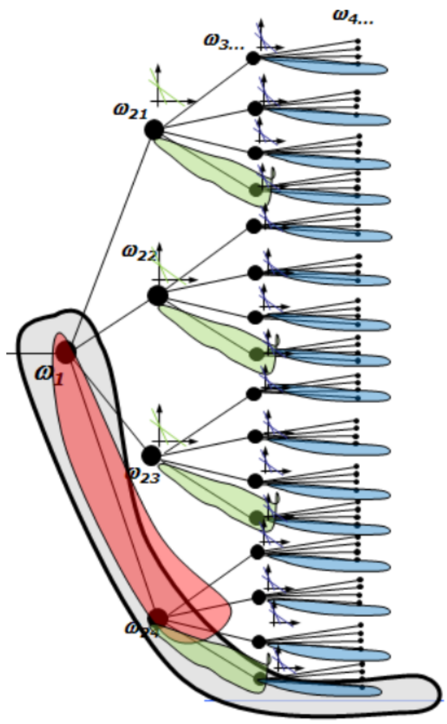

Figure 3.14: Cumulative aspect of α in CVaR modeling [63]

Under the same regulatory context in which studies with the SAR methodology were performed [56], the application of CVaR was tested in the operation planning models, considering different pairs of α and λ parameters. Together with the level of risk aversion that was being sought, the results of the simulations regarding the energy stored in the subsystems, unsupplied energy (deficit risks), thermal generation, spills and marginal operating costs were analyzed. As much as the operator was as risk-averse as possible, minimizing the cost of service was still an important requirement for choosing a risk-aversion methodology that would be incorporated into the models.

Thus, the CVaR risk-aversion mechanism with α = 50% and λ = 25%

parameters was selected to be adopted from September 2013 on, as it presented the best compromise between increased security and with lesser impacts on system costs. Fig. 3.14 shows the comparison between the SE/MW stored energy results with the CAR methodology (red) and the $\alpha = 50\%$ and $\lambda = 25\%$ implemented CVaR (blue) [63].

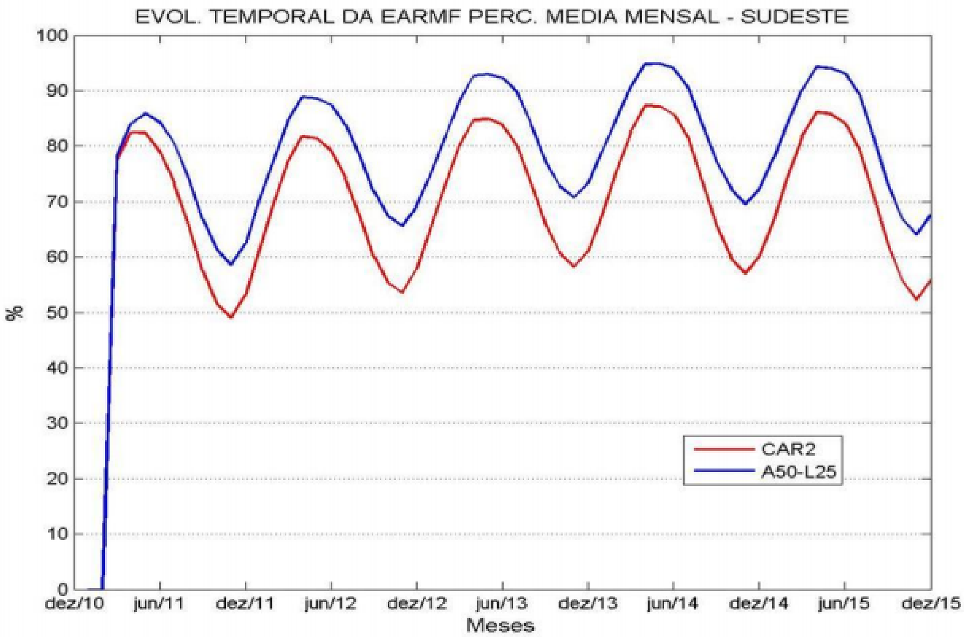

Figure 3.15: CAR x CVaR methodologies (SE/MW stored energy) [63]

CVaR has been in effect in the NEWAVE and DECOMP models since then, undergoing a change in parameterization in 2020 [72]. A new CVaR parameterization was necessary in the face of changes in the system configuration, methodological improvements in energy models and the inclusion of additional security mechanisms (VminOP, which will be discussed in the next section), among other relevant issues that affected the system's supply x demand relationship. The λ parameter was recalibrated to 35%, and there was no need to change the α parameter, which continued 50%.

3.4.5 Minimum Operating Volumes (VminOp) – 2020-Present

The unfavorable hydrological conditions experienced in 2018 dry season, led the CMSE to adopt heterodox measures to the optimization models for the dispatch of thermoelectric plants, in September and October 2018, aiming at guaranteeing reservoir levels at the headwaters of the main river basins of the NIS. This additional thermal dispatch, already illustrated in Fig. 1.3, was motivated by simulations presented by ONS of important reservoirs storage estimates for the end of 2018 in the Southeast/Midwest subsystem.

In view of the above, the CMSE had been highlighting its concern with the inclusion of safety mechanisms in the medium-term energy operation planning models, in addition to the risk aversion mechanisms already present in the models (CVaR), so that the probability of the occurrence of stored energy levels as low as those seen in recent years was reduced and, thus, the chance of adopting heterodox measures was mitigated [73].

At the end of 2018, the adoption of minimum level restrictions was proposed for each equivalent energy reservoir [74]. This mechanism was named Minimum Operating Volumes (VminOp - *Volumes Mínimos Operativos*). The violation of the VminOp levels is penalized in the objective function of the NEWAVE model, so that its cost-to-go function can assess properly the water value, increasing its value as the storage levels approach the critical levels. Through the cost-to-go function, DECOMP and DESSEM models can evaluate the consequences of reaching critical levels, enabling storage gains.

VminOp has been officially in effect in NEWAVE model since January 2020. The implemented version penalizes NEWAVE's objective function with the maximum violation of VminOp levels at the end of NIS' dry season (November), for each year. The maximum violation of VminOp levels can occur at any month, however, the cost of this violation will only be penalized in the objective function in November. Usually, as exemplified in Fig. 1.1, the lowest stored levels in NIS occur during November. The minimum levels per subsystem are detailed below:

– **Southeast/Midwest:** 10.0% of maximum storage capacity. According to ONS, below this level there may be loss of controllability of the reservoirs. Furthermore, this is the storage level below which ONS submits proposals for the adoption of operational measures to rationalize the demand.

– **South:** 30.0% of maximum storage capacity. According to [75], this was determined considering the safety levels of South subsystem's basins, weighted by their share in the subsystem's storable energy.

– **Northeast:** 22.5% of maximum storage capacity. The minimum operating volume for the Northeast subsystem is associated with the minimum levels for the Três Marias, Sobradinho and Itaparica reservoirs, defined based on the Brazilian National Water Agency (ANA) Resolution No. 2081/2017 [18].

– **North:** 10.7% of maximum storage capacity. The minimum operating volume for the North subsystem is associated with the 60.5 meters quota of Tucuruí power plant's reservoir. Below this quota, there is the complete shutdown of 3600 MW of Tucuruí's second powerhouse. The objective of linking the minimum operating volume to this quota is to make the mid-term operation planning model seek full generation of Tucuruí power plant, contributing to systemic power gains.

The VminOp risk-aversion mechanism was expected to improve the dispatch models' response, increasing thermal generation under critical hydrological conditions. Fig. 3.16 shows the weekly marginal operating costs for the official NEWAVE-DECOMP simulations and the shadow simulations considering the VminOp mechanism [73].

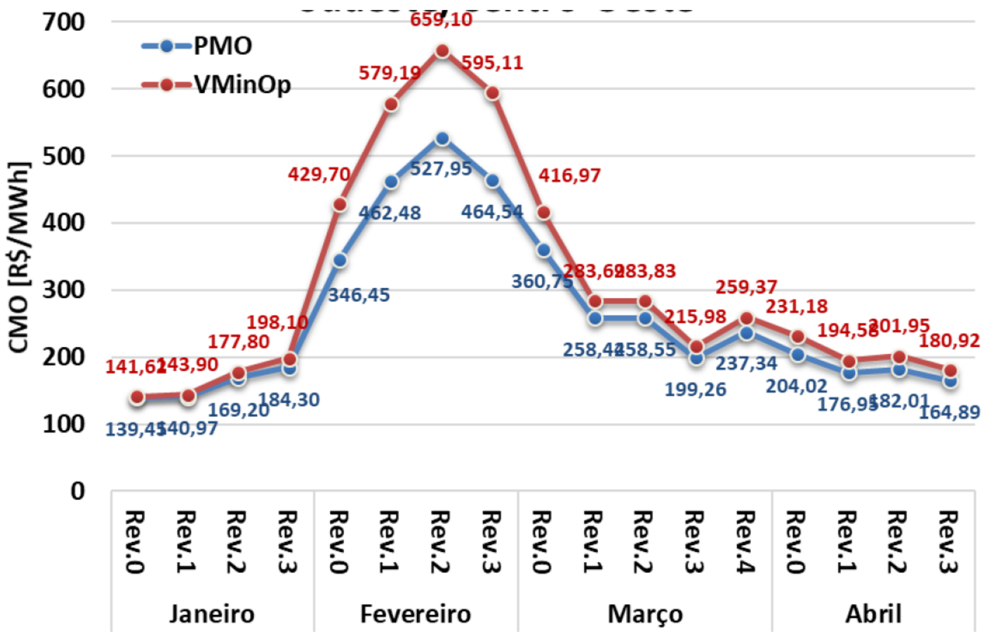

Figure 3.16: Official (PMO) x VminOp – SE/MW CMOs [73]

The very dry hydrological conditions observed in January 2019, one of the months with the highest affluent natural energy in NIS, raised the concern of power sector entities. In view of that, during the revisions (weeks) 2 and 3 of February 2019, CMSE deliberated the dispatch of additional[3] thermal generation up to a VCU limit of 588.75 R$/MWh in the SE/MW and South subsystems, after suggestion by ONS. The shadow simulations considering the VminOp methodology resulted in more thermal generation than the indicated by CMSE for the same weeks in February. These results showed that the new risk-aversion mechanism was adherent to CMSE's risk perception, giving even more certainty for the need of its implementation in 2020.

[3]Additional to the thermal dispatch indicated by the operation planning models (NEWAVE and DECOMP).

3.4.6
Referential Storage Curve (CREF) – 2020-Present

Besides the implementation of risk-aversion mechanisms (such as CVaR and VminOp) on the operation planning models, during the last years there has been a constant need for out-of-merit thermal generation in NIS. The unorthodox thermal dispatch, based mainly on the power sector entities' risk perception, has always caused discomfort due to the lack of objective criteria and reproducible metrics, since these actions result in additional costs to the system operation, impacting the whole society.

To this end, at the 220th CMSE's meeting in 2019, the Brazilian Ministry of Mines and Energy asked ONS to present a new methodology to subsidy out-of-merit thermal dispatch. Throughout the rest of the year, there were several technical CMSE meetings where proposals for this new methodology were refined, resulting in the work proposed by ONS in December 2019 [76], the Referential Storage Curve (CREF - *Curva Referencial de Armazenamento*) methodology.

CREF is a biannual recursive curve whose premise is to fully meet NIS' energy demand, given a hydrological scenario and a previously dispatched amount of thermoelectric generation. As it is a recursive curve, it is drawn on backwards direction, aiming to determine the lowest levels that ensure 10% of storage in the SE/MW subsystem, at the end of November of the second year.

The CREF methodology resembles in some aspects the extinct CAR methodology, specially regarding the biannual horizon, the recursive direction to assess the minimum level in each month, and the target levels at the end of November of the second year. Differently from the CAR methodology, the CREF curve in effect for 2020 considers thermal dispatch up to a VCU limit of 256 R$/MWh, being, in this regard, less risk-averse than CAR. Besides, CREF's hydrological scenario is the average inflow of the 5 most critical years between 1999 and 2019, while CAR usually considered the most or the 2nd most critical series in the inflows history since 1931. An important evolution from the CAR methodology, however, concerns the use of a optimization model to build the reference curves: the DECOMP model.

DECOMP was simulated in a monthly basis following the steps illustrated in the flowchart in Fig. 3.17 [76]. Since DECOMP does not simulate the system's operation in the backward direction, the simulations were executed iteratively, using constraints to set target levels at the end of each stage. Firstly, the month of November 2021 was simulated considering end-of-November target levels of 10%, 30% and 22.5% for SE/MW, S and NE

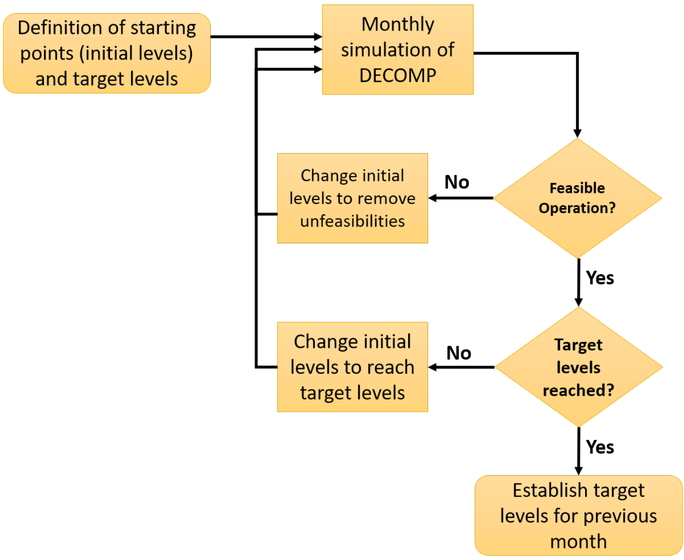

Figure 3.17: CREF calculation flowchart (adapted from [76])

subsystems, respectively. These were the same levels defined in the VminOp methodology, and these levels were also used as starting points for the initial levels in the first iteration. After the first simulation of November 2021, the iterations for calculating the initial levels (beginning-of-November levels) proceeded as follows:

- If the operation resulted in a deficit, or failure to meet the storage targets of any subsystem, a new simulation was carried out with an uniform increase in the starting level of the hydroelectric plants of the SE/MW subsystem.
- If the operation resulted in unfeasibilities due to the compliance with hydraulic or electrical constraints, a new simulation was carried out raising the starting levels from the hydroelectric plants related to the resulting unfeasibilities.
- After the removal of unfeasibilities, it was possible that the viable operation reached levels above the established target levels (end of the month). In this way, a new simulation was carried out by uniformly modifying the starting levels so that the target level was exactly reached.
- Finally, the initial levels resulting from the iterative process were used as target levels in the recursive simulation to be carried out for the previous month, following on the same steps described above and limited to a minimum storage of 10%.

The referential storage curve proposed for SE/MW subsystem is presented in Fig. 3.18 [76] and, according to ONS, it must be updated annually at the end of each year's dry season. The CREF represents the subsystem's minimum required levels for each month to bear an average of critical hydrological series from the recent years, considering a thermal dispatch up to 256 R$/MWh of thermal plants' VCU. As stated above, none of these premises are as critical as the ones considered in the CAR methodology. In this sense, the CREF methodology provides protection to a not so critical hydrological series (in view of all historical inflows) considering there is still an important thermal generation block that could be dispatched with VCUs greater than 256 R$/MWh, as observed in Fig. 2.5.

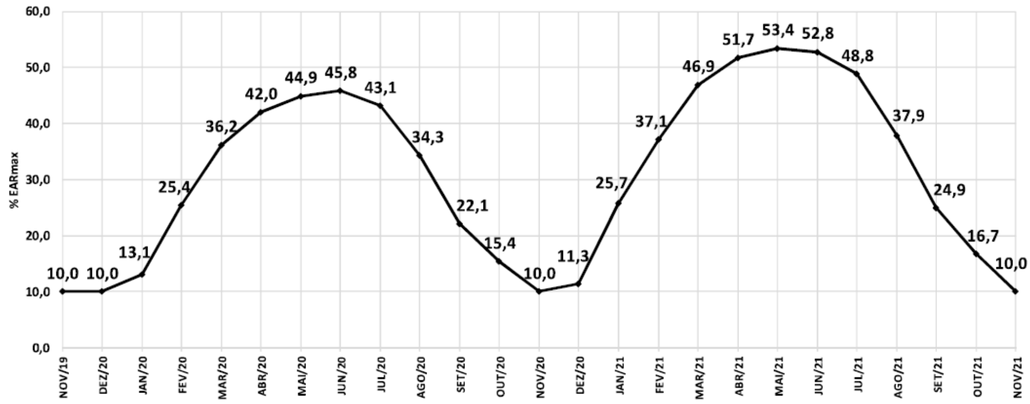

Figure 3.18: Referential Storage Curve for 2020 - SE/MW subsystem [76]

The biannual characteristic of the reference curve does not seem to be very important as it was while the CAR methodology was in effect. Whether due to the evolution of the electric power matrix with an increase in supply greater than that of demand, or due to the use of an optimization model to build the CREF, the fact that the curve reaches the minimum volume in November of the 1st year shows that it could have an annual horizon. Still, the CREF is limited to supporting CMSE's decision making on out-of-merit thermal dispatch with no defined procedure in case the observed levels situate below the referential curve.

3.5 Final Remarks

There has been a long path in risk-aversion procedures evolution since CAR was firstly proposed in 2002. The operation planning models used to support the optimal dispatch of energy resources are risk neutral and, considering the characteristics of Brazilian electric energy matrix, so dependent on hydroelectric generation, it was a matter of time until such methodologies became necessary. The recent developments (VminOp and CREF), however, indicate that, even after such evolution in risk-aversion procedures, CMSE and other power sector agents aren't quite satisfied with the level of risk resulted from the operation planning models guidelines.

Inconsistencies between planning and operation policies in Brazilian power system have already been identified in literature. According to [77], simplifications in the long-term planning, may give rise to time-inconsistent policies, as planned decisions may not be reproduced in the actual implementation of the decision process. Besides, modeling simplifications by neglecting Kirchhoff's voltage law and $n-1$ security criteria have been proven to increase energy spot prices and cause unnecessary reservoirs depletion over the time. Until power sector authorities address these inconsistencies with a major improvement in the operation planning models' chain and regulatory framework, the Brazilian government must be equipped with the best tools to assess the security of energy supply.

The newly proposed CREF methodology fails as a reference for energy supply security because it considers very specific assumptions of affluence (occurring more critical series in the 88-year history than the chosen synthetic series) and thermal generation, since there is still an relevant set of plants with VCU above 256 R$/MWh. In addition, despite using an optimization model to define the optimal energy exchanges between subsystems, the CREF methodology can result in a sub-optimal curve since DECOMP cannot simulate the operation in the backward direction, and it is necessary to carry out an iterative 'trial and error' process to reach the established target levels at the end of each month.

In this context, this work aims to propose a new methodology to assess the security of supply of the National Interconnected System. The proposed model intends to represent an evolution to the CREF methodology, and will be better detailed in Section 4.

4
Methodology

The models currently used by ONS to support the optimal dispatch scheduling of generation units consider physical inputs and constraints with the objective of minimizing the total cost of meeting the demand. The energy stored in hydro plants reservoirs is not explicitly represented in the objective function of these models, but is included in the problem's set of constraints, having strong influence on the optimal energy mix defined for each period of time. Low storage leads to higher cost scenarios, thanks to the need for complementary thermal generation. If the subsystem's storage is completely depleted and the other resources availability is not enough to meet the load, a high sum must be paid as a penalty for each MW of deficit.

Unlike the dispatch models used by ONS, the model proposed on this dissertation does not provide the optimal dispatch scheduling but intends to fill the gap of security monitoring tools for hydrothermal power systems, assessing the minimum required energy storage for each subsystem from a recursive simulation of historical inflows. The proposed model is expected to be considered an evolution to the CREF methodology. It is going to be referred as Backward Hydrothermal Simulation (BHS) model.

The BHS model was developed in Julia programming language [78]. Along with JuMP [79], Julia's features are well-suited for high-performance numerical analysis and optimization. The problem is divided in monthly stages, which are solved separately. The stages are coupled by initial and final reservoir volumes of each period. For instance, on the first stage, from given end-of-November levels for each hydroelectric plant, the model finds the minimum stored volumes that respect all system constraints for the beginning of November. The resulting levels from the first stage are then set as end-of-October levels, starting points for the next stage. The coupled optimization process is carried out through the beginning of January. Fig. 4.1 presents a simplified flowchart of the simulation process.

The proposed model seeks the minimum stored energy for each month of the year and, as a recursive model, the simulation process starts at the end of November. The simulation is carried out this way, since the lowest hydro energy storage of each year usually occurs at the end of NIS' dry season

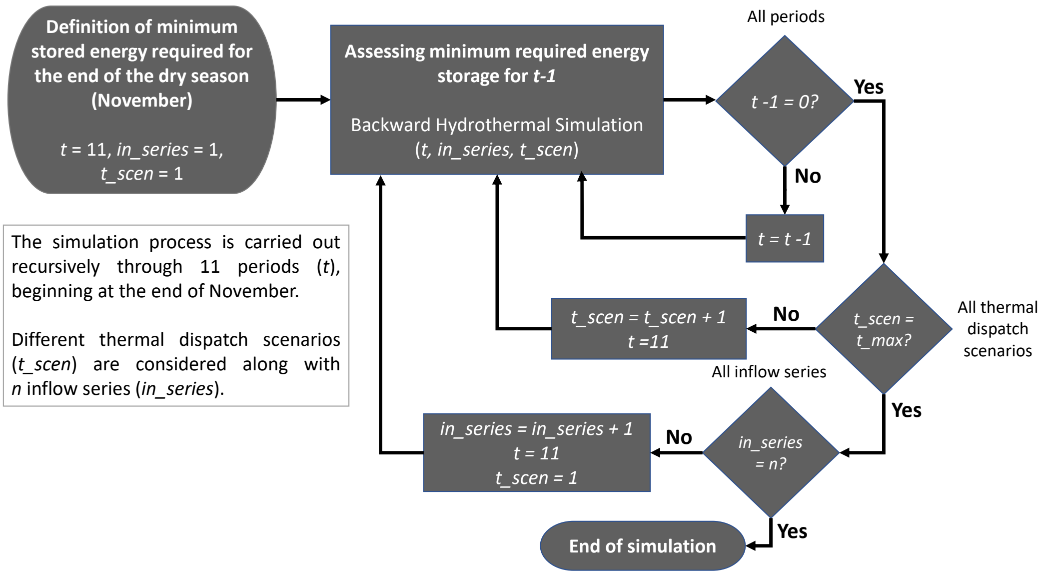

Figure 4.1: Simulation process flowchart

(late November), as previously observed in Fig. 1.1. By doing so, it is possible to find what is the minimum stored energy for each month that assures the secure operation of the system through the entire simulation period. This methodology is applicable to any year of the history of affluent flows. Fig. 4.2 illustrates how the recursive simulation process is performed.

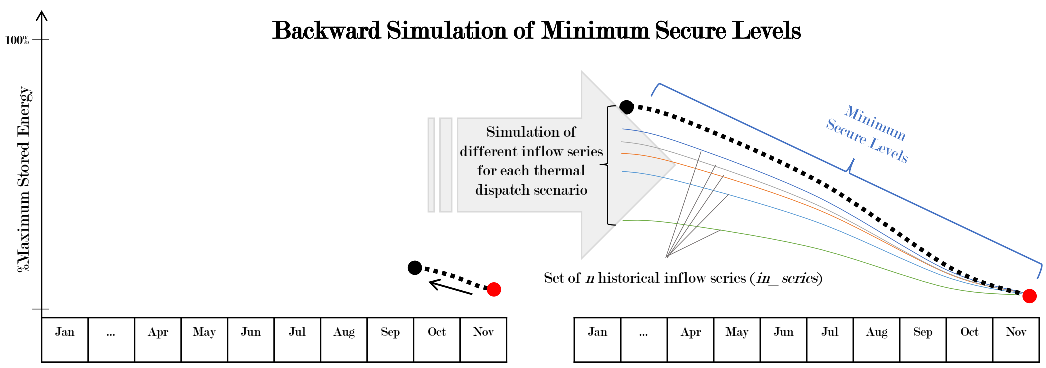

Figure 4.2: Backward Simulation of Minimum Secure Levels

The end-of-November levels (starting points for the BHS model) were defined accordingly to the minimum operating volumes (VminOp) implementation in NEWAVE model, presented in Section 3.4.5. The minimum levels per subsystem are detailed below:

– **Southeast/Midwest:** 10.0% of maximum storage capacity. According to ONS, below this level there may be loss of controllability of the reservoirs. Furthermore, this is the storage level below which ONS submits proposals for the adoption of operational measures to rationalize the demand.

- **South:** 30.0% of maximum storage capacity. According to [75], this was determined considering the safety levels of South subsystem's basins, weighted by their share in the subsystem's storable energy.
- **Northeast:** 22.5% of maximum storage capacity. The minimum operating volume for the Northeast subsystem is associated with the minimum levels for the Três Marias, Sobradinho and Itaparica reservoirs, defined based on the Brazilian National Water Agency (ANA) Resolution No. 2081/2017 [18].
- **North:** 10.7% of maximum storage capacity. The minimum operating volume for the North subsystem is associated with the 60.5 meters quota of Tucuruí power plant's reservoir. Below this quota, there is the complete shutdown of 3600 MW of Tucuruí's second powerhouse. The objective of linking the minimum operating volume to this quota is to make the mid-term operation planning model seek full generation of Tucuruí power plant, contributing to systemic power gains.

These end-of-November levels correspond to an equivalent of 14.4% of NIS' maximum energy storage.

4.1 Modeling of System Components

The BHS model solves a nonlinear programming problem, considering a detailed modeling of the water balance constraints and the hydro power production function. This ensures a proper representation of head variation in cascaded reservoirs, as stated by [80].

With the intent of finding the minimum stored energy for beginning of each stage, the problem's objective function is given by:

$$\min_{f,s,u,z} \quad \left\{ \sum_{h \in H^I} E_h^{ini} + \pi \cdot \sum_{c \in C} z_c \right\} \tag{4-1}$$

The expression (4-1) minimizes the sum of the initial stored energy E^{ini} per power plant h and the penalized slack z per constraint c. Because of the problem complexity as a nonlinear and non-convex optimization problem, slacks had to be added in some constraints in order to ensure the problem's feasibility.

The problem's constraints can be divided in two main groups: demand meeting and water balance constraints. Sections 4.1.1 and 4.1.2 detail the main premises assumed for each group of constraints.

4.1.1 Demand Meeting Constraints

Expression (4-2) shows the demand meeting constraint for each subsystem:

$$\sum_{h \in H_i} g_h + \sum_{j=1}^{N^{sys}} (f_{j,i} - f_{i,j}) = D_i^{net} \qquad \forall\, i \in [1, N^{sys}] \mid i \neq j \tag{4-2}$$

Each hydroelectric plant generation g_h is calculated by the energy production function in expression (4-3), considering maximum and minimum generation limits defined in equation (4-4). The hydro production function multiplies the production coefficient ρ_h, the turbined inflow u_h, and the net head x_h. The production coefficient ρ_h is a constant resulting from the multiplication of the efficiency of the turbine/generator set, the specific mass of water and the gravity factor, converting potential energy of stored water into kinetic energy used to rotate turbines coupled to electric generators.

$$g_h = \rho_h \cdot u_h \cdot x_h \qquad \forall\, h \in H \tag{4-3}$$

$$\underline{G}_h \leq g_h \leq \overline{G}_h \qquad \forall\, h \in H \tag{4-4}$$

The transferred energy f between different subsystems is limited by power transmission limits defined by ONS, in expression (4-5). Moreover, additional constraints were considered to represent the maximum limits of the sum of different interchange lines and generating units. For instance, the maximum energy the Northeast subsystem can receive from other subsystems is lesser than the sum of the individual transmission lines limits to which it is connected. These specific operation constraints are described as linear combinations, as observed in expression (4-6).

$$\underline{F}_{i,j} \leq f_{i,j} \leq \overline{F}_{i,j} \qquad \forall\, i \in [1, N^{sys}] \mid i \neq j \tag{4-5}$$

$$LB_c \leq \sum_{h \in NH_c} g_h + \sum_{i,j \in NT_c} f_{i,j} \leq UB_c \qquad \forall\, c \in I^{sum} \tag{4-6}$$

Thermal, wind, solar, biomass and small hydropower plants are not individually simulated on the BHS model. The thermal dispatch of different units is aggregated in an equivalent thermal power plant which generation corresponds to the total availability of units with equal or lower VCUs to a predefined marginal cost. By doing so, it is possible to calculate minimum secure levels for different thermal dispatch scenarios. The complementary generation of the wind, solar, small hydro and biomass plants corresponds to the estimate generation used in NEWAVE model [81]. Thus, the net demand from each subsystem is calculated by subtracting the thermal dispatch and complementary generation of small plants from the total load estimate, as shown in expression (4-7).

$$D_i^{net} = D_i - NS_i - \sum_{w \in W_i^{mc}} gt_w \qquad \forall\, i \in [1, N^{sys}] \tag{4-7}$$

4.1.2 Water Balance Constraints

The water balance constraints, represented in equation (4-8), express the coupling of water outflow in reservoirs through successive stages. The stored water at the end of each stage is equal to the initial storage plus the sum of lateral and upstream inflows (calculated in expression (4-9)), minus the sum of outflow volumes (turbined and spilled flows, represented in expression (4-10), and reservoir evaporation, irrigation and diverted flows). Since the reservoir volumes are given in hm^3, the inflows had to be converted from m^3/s with the use of outflow-volume monthly conversion factors δ. All variables in water balance constraints are subject to operational lower and upper bounds. Moreover, slacks were added in some of these constraints to make the problem feasible under critical inflow series simulation[4].

$$V_h^f = V_h^{ini} - v_h^{evap} + \delta \cdot (q_h^{in} - q_h^{out} - q_h^{irrig} - q_h^d) + z_c \qquad \forall\, h \in H \tag{4-8}$$

$$q_h^{in} = q_h^l + \sum_{m \in H_h^{up}} (u_m + s_m) + \sum_{m \in H_h^d} q_m^d \qquad \forall\, h \in H \tag{4-9}$$

$$q_h^{out} = u_h + s_h \qquad \forall\, h \in H \tag{4-10}$$

The evaporated volume of the plants' reservoirs is calculated by multiplying the reservoir area by a previously calculated monthly evaporation constant k^{evap}, as represented in expression (4-11). The reservoir area is calculated through a predetermined 'level x area' 4th degree polynomial function $A(l^{up})$. The reservoir level l^{up} is resultant from another 4th degree function, referred as 'volume x level' polynomial, expressed in (4-12).

$$v_h^{evap} = A_h(l_h^{up}) \cdot \frac{k_h^{evap}}{1000} \qquad \forall\, h \in H \tag{4-11}$$

$$l_h^{up} = L_h^{up}\left(\frac{V_h^f + V_h^{ini}}{2}\right) \qquad \forall\, h \in H \tag{4-12}$$

[4]The added slacks were penalized in the objective function to avoid infeasible hydraulic operation of power plants. The solution to address infeasibilities implemented in the BHS model is different from the one implemented in the CREF. In the CREF methodology, all infeasible constraints are relaxed between each iterative simulation of the DECOMP model.

The tailwater level of each plant is calculated according to the turbined outflow by a 4th degree polynomial ‘outflow x tailwater level’. For plants which spillage flow has no influence on the tailwater level, only the turbined outflow u is considered during the calculation of the downstream level. The reservoir net head is then calculated by subtracting the tailwater level and the hydraulic losses from the forebay reservoir level, as shown in equation (4-14). For the monthly definition of the forebay level, the average between the initial and final reservoirs’ volumes was considered for each power plant.

$$l_h^{down} = L_h^{down}(q_h^{out}) \qquad \forall\, h \in H \tag{4-13}$$

$$x_h = l_h^{up} - l_h^{down} - loss_h \qquad \forall\, h \in H \tag{4-14}$$

The equations described above implicate that the greater the outflow, the higher will be the tailwater level, decreasing the net height of fall and consequently also decreasing the plant’s production factor calculated in equation (4-3). The stored energy in a reservoir is calculated by weighting the plant’s useful storage by the productivity of the plants located downstream in the cascade, as expressed in (4-15). The calculated energy must be multiplied by 1/2.6352 to convert the potential energy from joule (J) to MWmonth. The plants’ useful storage is the difference between the stored volume and the minimum operational storage. Lastly, the equivalent net head is calculated in expression (4-16) by the integral of the volume x level function minus hydraulic losses and the tailwater level.

$$E_h^{ini} = \frac{1}{2.6352} \cdot (V_h^{ini} - V_h^{min}) \cdot \sum_{m \in H_h^{down}} \rho_m \cdot x_m^{equiv} \qquad \forall\, h \in H \tag{4-15}$$

$$x_h^{equiv} = \frac{1}{V_h^{ini} - V_h^{min}} \cdot \int_{V_h^{min}}^{V_h^{ini}} L_h^{up}(V_h).dV_h - l_h^{down} - loss_h \qquad \forall\, h \in H \tag{4-16}$$

4.2 Optimization Process Details

In spite of not finding a global optimal solution thanks to the non-convexity of the $L_h^{up}(V_h)$, $L_h^{down}(q_h^{out})$ and $A_h(l_h^{up})$ polynomial functions, the higher detailed modeling of system’s components was preferable over linearizing key equations, such as the water balance constraints. As stated previously, this type of modeling ensures a proper representation of head variation in cascaded reservoirs. On the other hand, the solving complexity increased, especially under nonlinear optimization, and a large amount of time was necessary to simulate all historic inflows, as described in Section 5.

Different methods can be found in the literature for solving nonlinear and non-convex programming problems. For instance, in [82] the improved harmony search algorithm was used to solve a nonlinear and non-convex hydrothermal generation scheduling problem. The implemented algorithm takes advantage from the use of few parameters and ease of application in optimization problems. On the other hand, heuristic optimization methods have been employed with promising results in the most diverse types of applications. In [83], real-coded genetic algorithm based on improved Mühlenbein mutation was implemented for solving the optimal generation scheduling of hydrothermal systems, obtaining better solutions with respect to other optimization methods. However, the development of a solver for nonlinear optimization problems was not the focus of this work. Therefore, wide access solver packages, such as Ipopt [84] and Juniper [85], were used together to carry out the nonlinear optimization in Julia programming environment.

While Ipopt is a well-established package for large-scale nonlinear optimization, Juniper is a solver for Mixed Integer Nonlinear Programs (MINLP). Besides the suitability for solving the proposed problem, both solvers were chosen due to the ease of access, as they are free and have open source codes. Ipopt implements a nonlinear primal-dual interior point optimization with line search filters used for fast computation of search directions resulting from special sparse structures from the mathematical formulation. Aside from [84], the algorithm and mathematical details from Ipopt can also be found in [86] and [87].

Although there are not any discrete variables on this specific problem, Juniper suits well since its heuristics are specialized for non-convex problems, which get solved locally optimal. Non-convex generic functions require global optimization algorithms for linear problems, with a proof of optimality. However, their limited scalability prevents application to larger real-world problems featuring thousands of variables and constraints, such as the problem presented in this dissertation. On this matter, Juniper plays an important role facilitating the algorithm convergence process, thanks to the employed heuristics of nonlinear branch-and-bound (NLBB) and feasibility pump [85].

5
Results

The proposed methodology was applied for the year of 2019, considering NEWAVE and DECOMP official system's data available in December/2018 [88]. There were solved a total of 1936 nonlinear optimization problems. Each problem had 4039 variables, 3438 linear constraints and 760 nonlinear constraints, and the whole simulation process took about 30h using an Intel Core i7-4500U CPU @ 1.80GHz-2.40GHz, with 8GB RAM. The algorithms and data input used for the completion of this dissertation can be found in `https://data.mendeley.com/datasets/f7s9mrbzhj/1`.

The 88 historic inflow series (1931 to 2018) were simulated for 164 hydroelectric plants and 4 interconnected subsystems, from the end of November to the beginning of January (considering the backward direction), in light of two different thermal dispatch scenarios:

– **Scenario I**: Thermal power availability up to 250.00 R$/MWh VCU, summing up about 10.5 GW of total thermal dispatch.

– **Scenario II**: All thermal power availability, summing up about 16.5 GW of total thermal dispatch.

Considering that the marginal operating costs of SE/MW were on average 429.22 R$/MWh [3] during the last 5 years, the chosen scenarios can be interpreted as a lower and an upper bound in terms of thermal dispatch.

Fig. 5.1 shows the results of minimum required stored energy per subsystem for scenario I. Each line represents a different historical inflow series. The most critical inflow series simulated required a higher amount of stored energy in the beginning of each stage to meet the load respecting all existing constraints. As each subsystem has different patterns in precipitation throughout the year, monitoring the NIS equivalent stored energy is important for a global overview of the system's operation security. Fig. 5.2 shows the equivalent stored energy for the National Interconnected System in each historic inflow series.

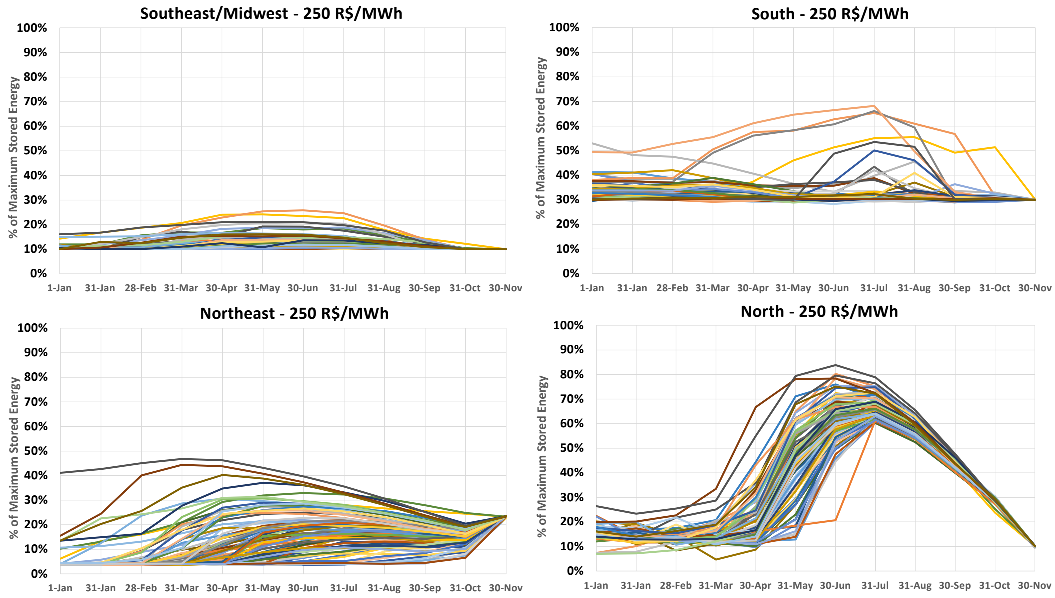

Figure 5.1: Simulation results per subsystem in scenario I (250 R$/MWh VCU thermal dispatch)

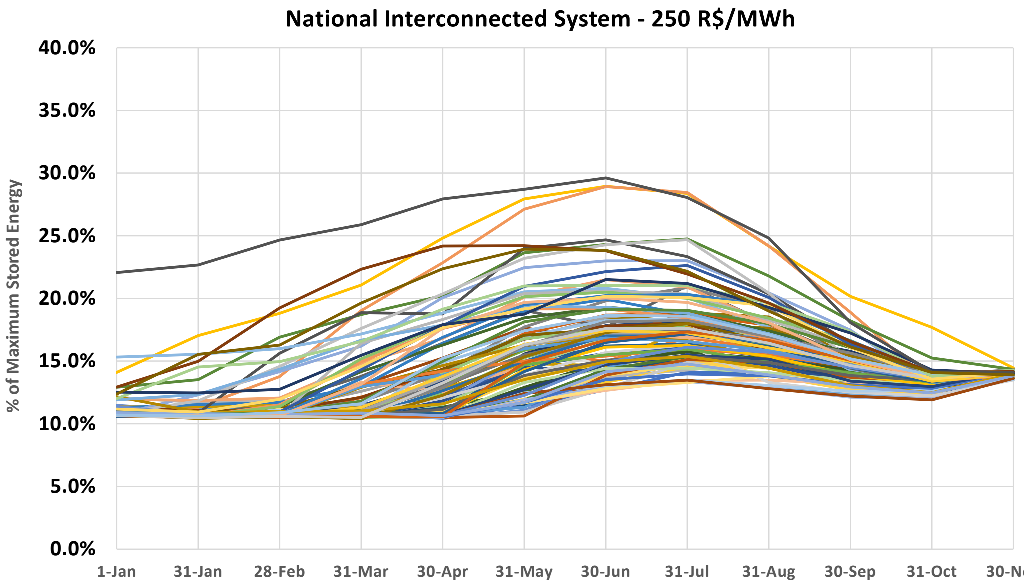

Figure 5.2: Simulation results for NIS in scenario I (250 R$/MWh VCU thermal dispatch)

The same procedure was applied for the thermal dispatch scenario II. Lower stored energy was necessary on this scenario as a result of a lower net demand to meet. In terms of system's secure operation, these are the most important curves, as all resources are being used to meet the demand. Thus, reaching levels below the resulted curves may jeopardize the reliability of the system's operation. Fig. 5.3 shows the achieved results per subsystem, and Fig. 5.4 presents the equivalent stored energy results for NIS.

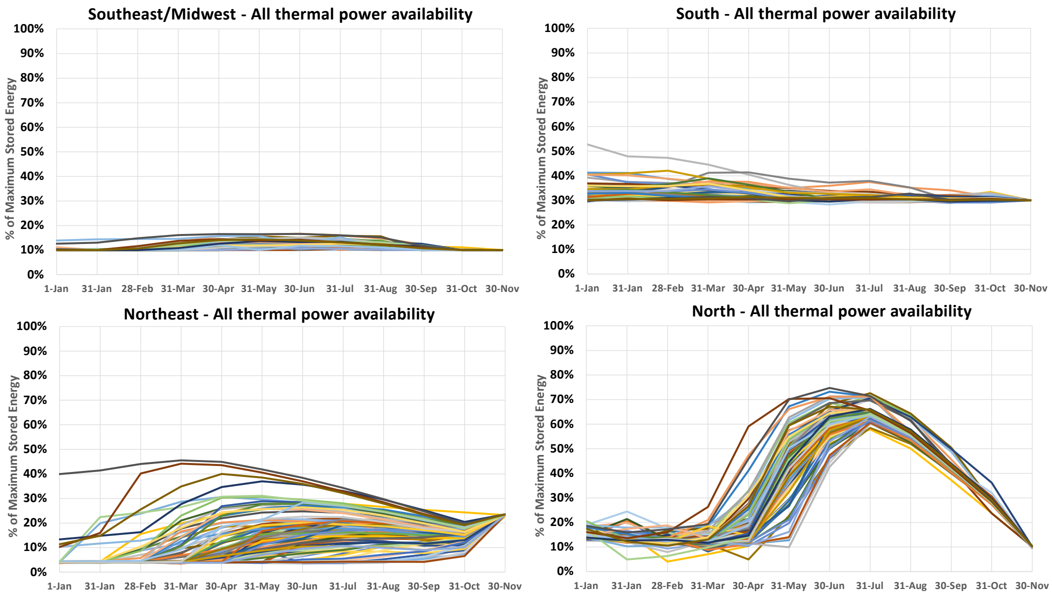

Figure 5.3: Simulation results per subsystem in scenario II (all thermal availability)

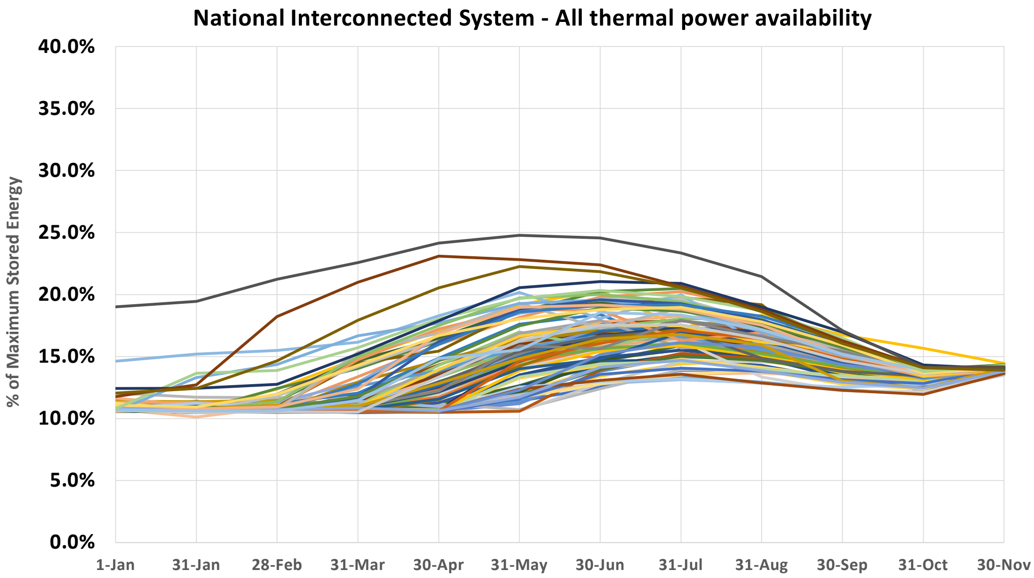

Figure 5.4: Simulation results for NIS in Scenario II (all thermal availability)

The historical series which resulted in the five higher required levels for each month were: 1934, 1936, 1944, 1945, 1951, 1954, 1964, 1971, 1986, 2001, 2007, 2014, 2015, 2016, 2017 and 2018. It is worth observing that the simulation of series from 2014-2018 resulted in higher amounts of required stored energy, which corroborates with the recent risk perception from the power industry entities.

Considering that the subsystems are interconnected and able to exchange power through transmission lines, following up NIS' equivalent stored energy is a simple and effective way for secure monitoring the whole system's supply conditions. Based on the results for both thermal dispatch scenarios, two reference curves (Fig. 5.5) were set based on historical series minimum secure levels:

– **Attention Curve**: Average of NIS' five higher levels for each month on scenario I.

– **Critical Curve**: Average of NIS' five higher levels for each month on scenario II.

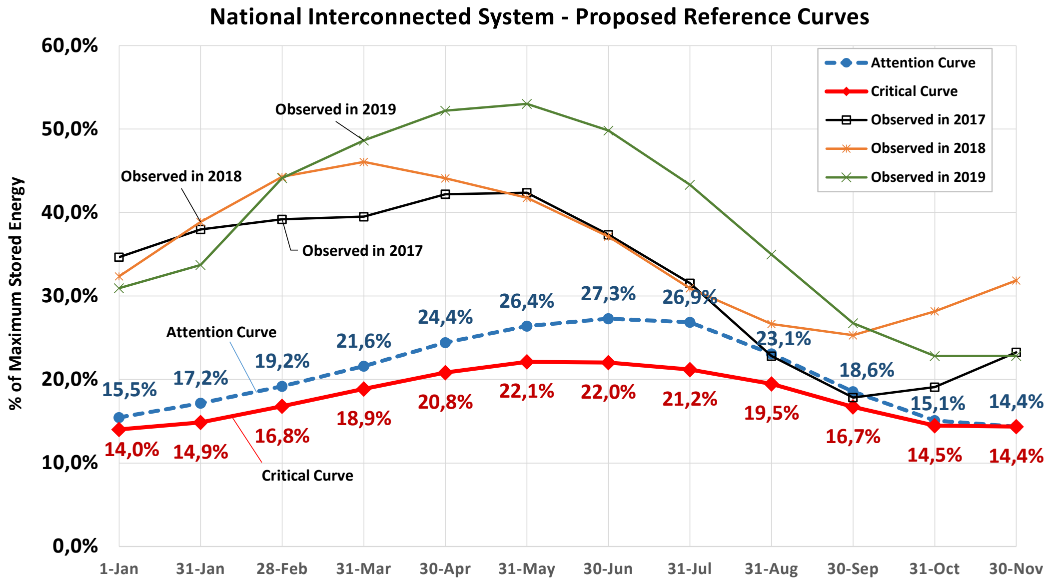

Figure 5.5: Proposed curves for secure monitoring of NIS' stored energy

As stated previously, the proposed curves would be effective for 2019 as they were built using data from December 2018. To give a better view of the levels resulting from the simulated curves, the 2017, 2018 and 2019 observed levels were also plotted in Fig. 5.5. As both attention and critical curves situate below the observed levels for 2019, additional out-of-merit thermal generation would not have been recommended to ensure the security of power supply. However, if the reservoirs operation in 2019 had resulted in levels such as those observed in 2017, additional thermal dispatch might have been recommended for September and October, considering the proposed reference curves were being used to support decisions on additional thermal dispatch.

The average of the five higher required levels is a conservative criterion for the definition of the reference curves. However, depending on the level of risk aversion from the power sector entities, more severe criteria may be employed to define the reference curves. For instance, if it is preferable to prevent from the worst simulated scenarios, the curves' upper wrap of the historical simulation may be used to set the reference curves, even though it will protect from a critical scenario very unlikely to occur. On the other hand, the end-of-November input levels can be raised to higher and more practical values if the system operator wishes to guarantee a higher degree of power supply reliability. Even though the SE/MW's minimum operating levels were defined as 10% on the VminOp risk-aversion procedure, historically this subsystem has never reached levels below 15%.

Ideally, the proposed reference curves should be calculated at least once a year since future load estimates and anticipation or delay of new power plants and transmission lines may affect the demand/supply balance over the months.

6
Conclusions

This dissertation proposed a new method to evaluate the security of power supply in systems with predominance of hydroelectricity. An optimization model, referred as BHS model, was developed and carried out the recursive simulation of 88 historical inflows series, from 1931 to 2018, using NIS' available data for the year of 2019. The simulation process provided minimum levels for each month that guarantee the security of power supply until the end of the dry season, in November. The developed model has proven to be robust and brought innovation by representing in detail the water balance nonlinear constraints in a recursive simulation process. Moreover, the BHS model represents and evolution to the current CREF risk-aversion procedure, proposed by ONS at the end of 2019. Table 6.1 shows the comparison between the CAR and CREF methodologies and the proposed BHS model.

Table 6.1: Comparison between CAR, CREF and BHS model

	Risk-aversion Curves (CAR)	Referential Storage Curve (CREF)	Backward Hydrothermal Simulation Model (BHS)
Hydroelectric plants representation	Aggregated in subsystems	Individualized	Individualized
Thermal dispatch scenario	All thermoelectric plants dispatched	Dispatch up to 256 R$/MWh VCU	2 different scenarios (250 R$/MWh VCU and all thermal power availability)
Inflow series	Usually, the 1st or 2nd worst affluent series for each subsystem	Average inflow of the 5 most critical series from 1999 to 2019	All historical inflow series from 1931 to 2018
Energy exchange between subsystems	Defined through system operation's heuristics	Calculated through trial-and-error process in DECOMP model	Optimized through each simulation of the BHS model
Water balance equations representation	Linear	Linear	Non-linear
Horizon	Biannual	Biannual	Annual

Furthermore, two reference curves were suggested for continuous monitoring of NIS' equivalent stored energy. Reaching the attention curve indicates that the hydroelectric plants operation must be followed up closely, and further actions might be necessary to ensure the security of the system. On the other hand, the critical curve indicates a higher alert in terms of secure dispatch of generating units. In this case, it might be reasonable to consider additional out-of-merit thermal dispatch, in view of the risks involved when visiting levels below this curve.

The comparison between the reference curves and the inflows normal behavior from Fig. 2.3 suggests a good representation of the affluent energy seasonality by the BHS model, as the storage requisites are well correlated to the inflows behavior. On top of that, if the reservoirs operation in 2019 had resulted in levels such as those observed in 2017, additional thermal dispatch might have been recommended for September and October, considering the proposed reference curves were being used to support decisions on unorthodox thermal dispatch. Moreover, from a top-down approach, the BHS model can yet be used to monitor the secure operation of subsystems and individualized reservoirs.

Assessing the operation marginal costs is a big challenge in power systems with strong dependency of renewable energy resources, such as the National Interconnected System. The system operator must be constantly evaluating the trade-off between the security of supply and the economical dispatch. Any out-of-merit thermal dispatch command must be accountable, as it implies on larger costs to all consumers. For instance, from 2013 to 2019, R$ 14.5 billion was spent on out-of-merit thermal generation for security of power supply purposes in Brazil [11], based mainly on tacit risk perception from the government entities.

Thus, the model proposed here is relevant, as it fills the existing gap of security monitoring tools for hydrothermal power systems, providing important insights on reservoirs' storage conditions and resources availability from the simulation of historical inflows. Furthermore, the monitoring of reference curves defined by a mathematical model is expected to represent a more robust criterion for additional out-of-merit thermal generation commands by government entities. This work was also published as an article on the Electrical Power Systems Research journal (ISSN: 0378-7796)[5], which can be found attached in Appendix A.

As future studies on this matter, it is suggested to evaluate:

- If the performance gains by linearizing the nonlinear and non-convex water balance equations justify the loss of precision in the results;
- How does the model perform in simulations that start from higher levels at the end of November;

[5]https://doi.org/10.1016/j.epsr.2020.106523

- Whether the extension of the simulation horizon can be beneficial to increase the security of supply of the system (biannual horizon);
- The application of the methodology for increasing storage by operating ranges employed in the SUISHI model, during the BHS simulation process; and
- The minimum storage requisites of different wind and solar power scenarios.

Acknowledgments

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

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A
Published Paper - Electric Power Systems Research

The following paper was published on Electrical Power Systems Research journal (ISSN: 0378-7796).

The algorithms and data input used for the completion of this dissertation can be found in `https://data.mendeley.com/datasets/f7s9mrbzhj/1`.

Electric Power Systems Research 188 (2020) 106523

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Security of power supply in hydrothermal systems: Assessing minimum storage requisites for hydroelectric plants

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ARTICLE INFO

Keywords:
Hydrothermal power systems
Out-of-merit dispatch
Backward simulation
Security of power supply

ABSTRACT

Unfavorable hydrological conditions experienced from 2014 to 2019 led to the depletion of main reservoir systems in Brazil, causing an increase of thermal energy dispatch. However, an important share of the observed thermal generation was out of economic merit, commanded by government entities which risk perception relies mainly on experts' tacit knowledge. Despite the common sense that storage in reservoirs is intrinsically linked to system security, the metrics employed so far failed to compute the system's real needs in terms of required stored energy in hydroelectric plants. This work proposes a new method to evaluate the security of power supply in systems with predominance of hydroelectricity, by the development of an optimization model that assesses the minimum secure levels for hydroelectric plants operation in each month, from a nonlinear-backward simulation of 88 historical streamflow series (1931–2018). In addition, based on the simulation results, two reference curves were suggested for the continuous monitoring of the reservoirs operation, with the purpose of subsidizing Brazilian government entities decisions on unorthodox thermal generation dispatch. The monitoring of the proposed reference curves is expected to represent a more robust criterion for decisions on out-of-merit thermal generation in Brazilian power system.

1. Introduction

The medium and long term operation planning of hydrothermal power systems generally rely on state-of-the-art optimization techniques, such as stochastic dual dynamic programming (SDDP) [1] or sampling stochastic dynamic programming (SSDP) [2], to ensure reliable power supply at minimum cost. Considering the predominance of hydropower generation in the Brazilian electricity matrix (approximately 72% in 2018 [3]), the mid-term operation planning's main concerns are related to the availability of energy resources during persistent droughts. In Brazil, the National System Operator (ONS) is the organization responsible for operating the power plants and transmission grid.

The thermal generation dispatched by ONS follows cost-based guidelines provided by NEWAVE (Strategic Model for Hydrothermal Generation by Equivalent Subsystems) and DECOMP (Medium-Term Operation and Planning Software) optimization models [4], taking into account the future cost of present time decisions. While NEWAVE finds the optimal operation policy through a stochastic simulation of 2000 synthetic inflow series in a five-year horizon, DECOMP is a more detailed model that provides the optimal present-time dispatch, considering the possibilities assessed by NEWAVE's future cost function. Thus, according to the current system's conditions and estimates for load, power plants inflows and resources availability, NEWAVE and DECOMP minimize the total operation costs, defining the optimal resources dispatch per load level in each week.

Between the years of 2001 and 2002, Brazilian consumers faced energy shortage because of low inflows and delays of expansion plans [5]. After that episode, the Brazilian government created the Power Sector Monitoring Committee (CMSE), with the objective of permanently monitoring the power supply conditions. Besides, additional risk-aversion procedures, such as the Risk-Aversion Curves (CAR)[6] and the conditional value-at-risk (CVaR) [7,8], were implemented in NEWAVE and DECOMP models during the units dispatch optimization, in order to avoid load curtailment and anticipate necessary thermal generation.

However, even with the application of such risk-aversion procedures, unfavorable hydrological conditions experienced during the last 6 years have led to the exhaustion of the main reservoir systems in Brazil [9]. Fig. 1a shows the percentage of stored hydropower in the Brazilian interconnected power system, referred as National Interconnected System (NIS), from 2000 to 2019 [3]. By the end of 2018, Brazilian reservoirs reached levels below 20% of stored energy, the lowest ever recorded. As a consequence, larger amounts of thermoelectric generation have had to be dispatched [3], as seen expressed in megawatt-month (MWmonth) in Fig. 1b.

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https://doi.org/10.1016/j.epsr.2020.106523
Received 24 March 2020; Received in revised form 22 June 2020; Accepted 7 July 2020
Available online 28 July 2020
0378-7796/

Notation

δ	Outflow-volume monthly conversion factor
π	Objective function penalty for constraints violation
ρ_h	Production coefficient in MWh/m^4 per hydroelectric plant h
$A_h(l_h^{up})$	Level x Area polynomial. Calculates area in km^2 for a given level in m
C	Set of problem's constraints
D_i	Total demand of subsystem i
D_i^{net}	Net demand of subsystem i
E_h^{ini}	Initial stored energy in MWmonth for hydroelectric plant h
$\overline{F}_{i,j}$	Maximum energy transfer limit from subsystem i to subsystem j
$f_{i,j}$	Energy transfer from subsystem i to subsystem j
$\underline{F}_{i,j}$	Minimum energy transfer limit from subsystem i to subsystem j
$f_{j,i}$	Energy transfer from subsystem j to subsystem i
$\underline{G}_h$	Minimum generation limit in MWmonth by hydroelectric plant h
$\overline{G}_h$	Maximum generation limit in MWmonth by hydroelectric plant h
g_h	Energy generated in MWmonth by hydroelectric plant h
gt_w	Available generation in MWmonth for thermoelectric plant w
	Set of hydroelectric plants
	Set of plants that divert flow to plant h
own	Set of plants downstream on the same cascade of plant h
	Set of impoundment hydroelectric plants
	Set of run-of-river hydroelectric plants
p	Set of plants immediately upstream of plant h
	Set of hydroelectric plants from subsystem i
n	Set of interchange/generation sum constraint c
ap	Monthly reservoir evaporation rate in mm/month for hydroelectric plant h
vn	Tailwater level in m for hydroelectric plant h
$L_h^{down}(q_h^{out})$	Outflow x Tailwater Level polynomial. Calculates tailwater level in m for a given outflow in m^3/s
l_h^{up}	Forebay reservoir level in m for hydroelectric plant h
$L_h^{up}(V_h)$	Volume x Level polynomial. Calculates level in m for a given volume in hm^3
LB_c	Lower bound for interchange/generation sum constraint c
$loss_h$	Hydraulic losses in m or % from penstock ducts for hydroelectric plant h
N^{sys}	Number of subsystems
NH_c	Set of hydroelectric plants from generation sum constraint c
NS_i	Not-individually simulated plants generation estimative from subsystem i
NT_c	Set of transmission lines from interchange sum constraint c
q_h^d	Deviated inflow in m^3/s for hydroelectric plant h
q_h^{in}	Total upstream outflow in m^3/s for hydroelectric plant h
q_h^{irrig}	Irrigation in m^3/s for hydroelectric plant h
q_h^l	Lateral inflow in m^3/s for hydroelectric plant h
q_h^{out}	Total outflow in m^3/s for hydroelectric plant h
s_h	Spillage outflow in m^3/s for hydroelectric plant h
u_h	Turbined outflow in m^3/s for hydroelectric plant h
UB_c	Upper bound for interchange/generation sum constraint c
v_h^{evap}	Evaporated volume in hm^3 for hydroelectric plant h
V_h^f	Stored volume in hm^3 for hydroelectric plant h at the end of the stage
V_h^{ini}	Stored volume in hm^3 for hydroelectric plant h at the beginning of the stage
V_h^{min}	Minimum reservoir volume in hm^3 for hydroelectric plant h
W_i^{mc}	Set of thermoelectric plants from subsystem i with VCU equal or lower to a marginal cost mc
x_h^{equiv}	Equivalent net head in meters for hydroelectric plant h
x_h	Net head in meters for hydroelectric plant h
z_c	Total violation of constraint c

Despite the observed thermal generation increase, the models used to assess the optimal generation mix were not able to provide the proper economic signs regarding the marginal costs. In other words, the thermal generation indicated by NEWAVE and DECOMP was lower than that perceived as necessary by ONS and other power industry entities. Thereby, as shown in Fig. 2, an important share of the thermal dispatch over the last years was commanded by CMSE to guarantee the adequate power supply conditions.

The plotted thermal generation in Fig. 2 corresponds to R$[1] 14.5 billion spent with security of power supply from 2013 to 2019, in Brazil [11]. Yet, the observed out-of-merit dispatch relied mainly on tacit risk perception from the government entities' experts.

Inconsistencies between planning and operation policies in Brazilian power system have already been identified. According to [12], simplifications in the long-term planning, may give rise to time-inconsistent policies, as planned decisions may not be reproduced in the actual implementation of the decision process. Besides, modeling simplifications by neglecting Kirchhoff's voltage law and n-1 security criteria have been proven to increase energy spot prices and cause unnecessary reservoirs depletion over the time.

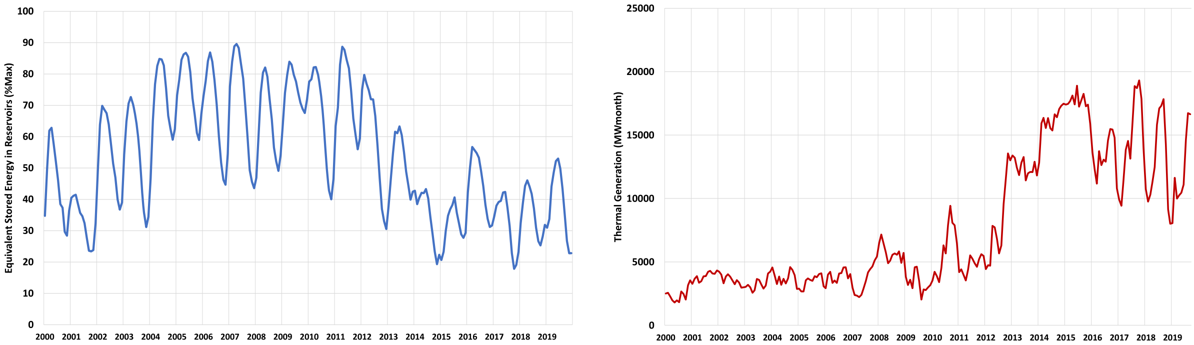
In the matter of security of power supply of hydrothermal systems, the existing literature investigates mainly regulatory framework/ market design improvements. From the regulatory point of view, [13] shows that a secure power system's operation should include a close coordination strategy between mid-term and short-terms problems. The recent energy crisis that led to depletion of reservoirs in Brazil is discussed in [14] and [15]. While [14] analyzes possible operation planning failures, suggesting the use of more detailed dispatch scheduling models, [15] shows that the diversification in the electricity generation mix could be a strategy to improve the power supply reliability in Brazil.

The reservoirs operation is also concern in other hydrothermal power systems. In [16], the effects of market deregulation are analyzed over system security and management of reservoirs in Norway. The climate change is subject for studies on optimal hydroelectric plants operation in Canada [17] and Switzerland [18]. Finally, [19] addresses issues of long-term security of power supply and spillage control with a renewable electricity system in New Zealand.

Considering no change in market and regulatory framework, solid metrics must be defined for the reservoirs operation monitoring, in order to evaluate the dispatch models performance and the need of government intervention with additional thermal generation, since this implies on larger energy costs to all consumers and unpredictable regulatory instability to different market players. To the best of the authors knowledge, there is no work that proposes a methodology to compute reservoirs' minimum required levels with regard to power supply reliability.

The objective of this work is to propose a new method to evaluate the security of power supply in systems with predominance of hydroelectricity, such as NIS. This method is based on the development of an optimization model that computes the minimum secure levels for hydroelectric plants operation in each month, from a recursive simulation

[1] According to [10], US$ 1.00 corresponds to R$ 4.74 in March 13th, 2020.



(a) Percentage of maximum hydro energy storage in NIS (2000-2019)

(b) Thermal generation in NIS (2000-2019)

Fig. 1. Reservoirs' storage x thermal generation from 2000 to 2019 in NIS.

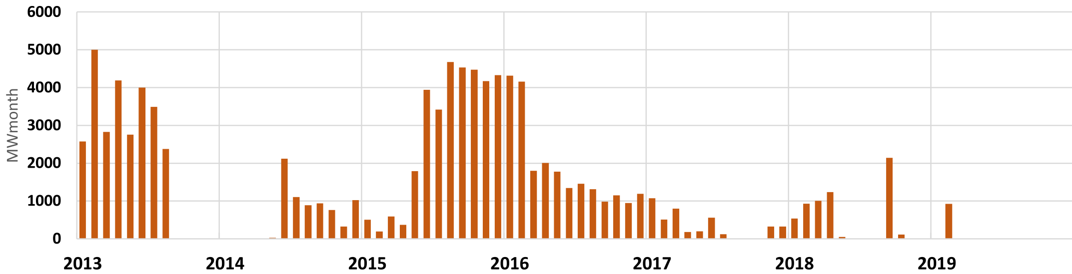


Fig. 2. Out-of-merit thermal generation in NIS (2013–2019).

of historical inflow series from 1931 to 2018. In addition, based on the simulation results, reference curves were suggested for the continuous monitoring of the security of power supply regarding the reservoirs operation.

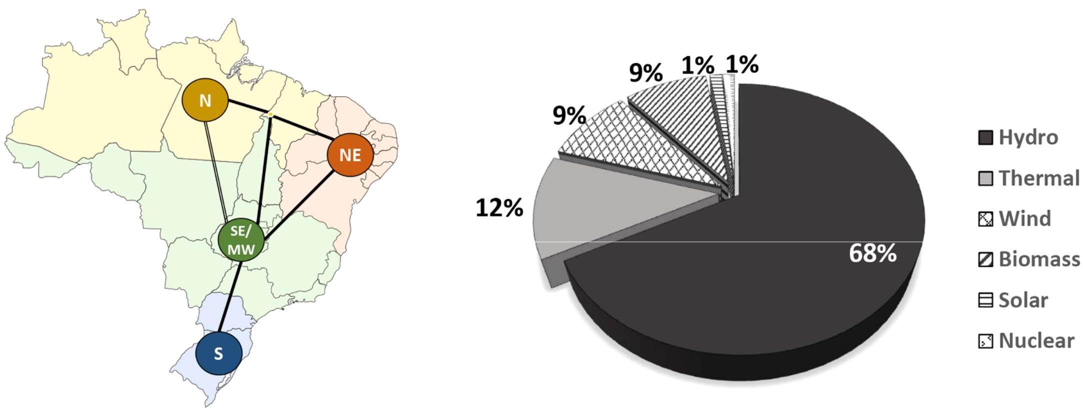
Unlike the dispatch models used by ONS, the model proposed on this paper does not provide the optimal dispatch scheduling but intends to fill the gap of security monitoring tools for hydrothermal power systems, assessing the minimum required energy storage for each subsystem from a recursive simulation of historical inflows. Its fundamental principle is to be a subsidy mechanism to Brazilian government entities decisions on unorthodox thermal generation dispatch. Furthermore, the monitoring of reference curves defined by a mathematical model is expected to represent a more robust criterion for additional out-of-merit thermal dispatch commands by CMSE.

This paper is organized as follows. First, important concepts about the National Interconnected System are presented in Section 2. Next, Section 3 explains the proposed methodology, details the modeling of the system constraints and the optimization process. Section 4 provides simulation results and the proposed reference curves. Finally, the conclusion is given in Section 5.

2. The National Interconnected System (NIS)

NIS is a large power generation (162.9 GW of installed capacity [20]) and transmission system divided in four subsystems: South (S), Southeast/Midwest (SE/MW), Northeast (NE) and North (N). The interconnection of electrical systems through the transmission grid provides energy transfer between subsystems, allowing synergistic gains through hydrological regimes' diversity. Besides, the integration of generation and transmission resources enables safe and cost-effective market service. Fig. 3a shows the main interconnections between subsystems considered in NEWAVE model.

There is a predominance of hydroelectric plants distributed in sixteen river basins in different regions of the country [21]. In recent years, the construction of wind and solar farms increased the share and importance of these energy sources, as observed in Fig. 3b.



(a) Main interconnections between NIS' subsystems

(b) NIS' installed capacity mix (%) - Apr/2019

Fig. 3. Main subsystems interconnections and installed capacity mix.

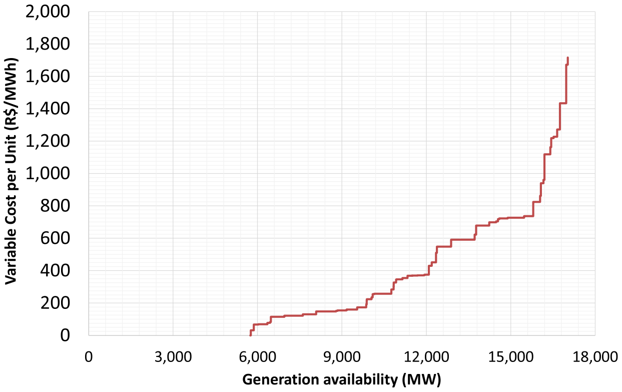


Fig. 4. Thermal Generation Availability vs Variable Cost per Unit - November, 2019.

As stated previously, the thermal plants are essential resources for meeting NIS' demand, specially under critical hydrological conditions.

Fig. 4 presents a scatter chart comparing the cumulative thermal generation availability and the variable cost per unit (VCU) of thermal power plants in NIS [22]. Between R$ 100.00/MWh and R$ 250.00/MWh there is an important increase in thermal generation availability with little variation on units cost of dispatch. The opposite occurs for VCUs higher than R$ 800.00/MWh, and the dispatch of such expensive plants implies in a high volatility of spot prices.

Considering the large area Brazil occupies in South America, the river basins from different regions are subject to distinct climate phenomena and hydrological regimes. From an energy production perspective, the observed streamflow in different river basins can be evaluated by the affluent natural energy (ANE). ANE is the energy obtained when the natural flow of an affluent is turbined in downstream plants from an observation point, considering equivalent productivity of 65% of useful storage volume of reservoirs [23]. Fig. 5 presents ANE's seasonality and monthly mean for each subsystem [3].

Apart from the South, in general, all subsystems have well defined wet and dry seasons. Therefore, from a global perspective, the NIS' wet season goes from December to April, while the dry season usually goes from May to November. In terms of stored hydropower capacity, SE/MW is considered the most relevant subsystem, with approximately 70% of NIS' maximum stored capacity [24].

3. Methodology

The models currently used by ONS to support the optimal dispatch scheduling of generation units consider physical inputs and constraints with the objective of minimizing the total cost of meeting the demand. The energy stored in hydro plants reservoirs is not explicitly represented in the objective function of these models, but are included in the problem's set of constraints, having strong influence on the optimal energy mix defined for each period of time. Low storage leads to higher cost scenarios, thanks to the need for complementary thermal generation. If the subsystem's storage is completely depleted and the other resources availability is not enough to meet the load, a high sum must be paid for each MW of deficit.

Unlike the dispatch models used by ONS, the model proposed on this paper does not provide the optimal dispatch scheduling but intends to fill the gap of security monitoring tools for hydrothermal power systems, assessing the minimum required energy storage for each subsystem from a recursive simulation of historical inflows. The proposed model is going to be referred as Backward Hydrothermal Simulation (BHS) model.

The BHS model was developed in Julia programming language [25]. Along with JuMP [26], Julia's features are well-suited for high-performance numerical analysis and optimization. The problem is divided in monthly stages, which are solved separately. The stages are coupled by initial and final reservoir volumes of each period. For instance, on the first stage, from given end-of-November levels for each

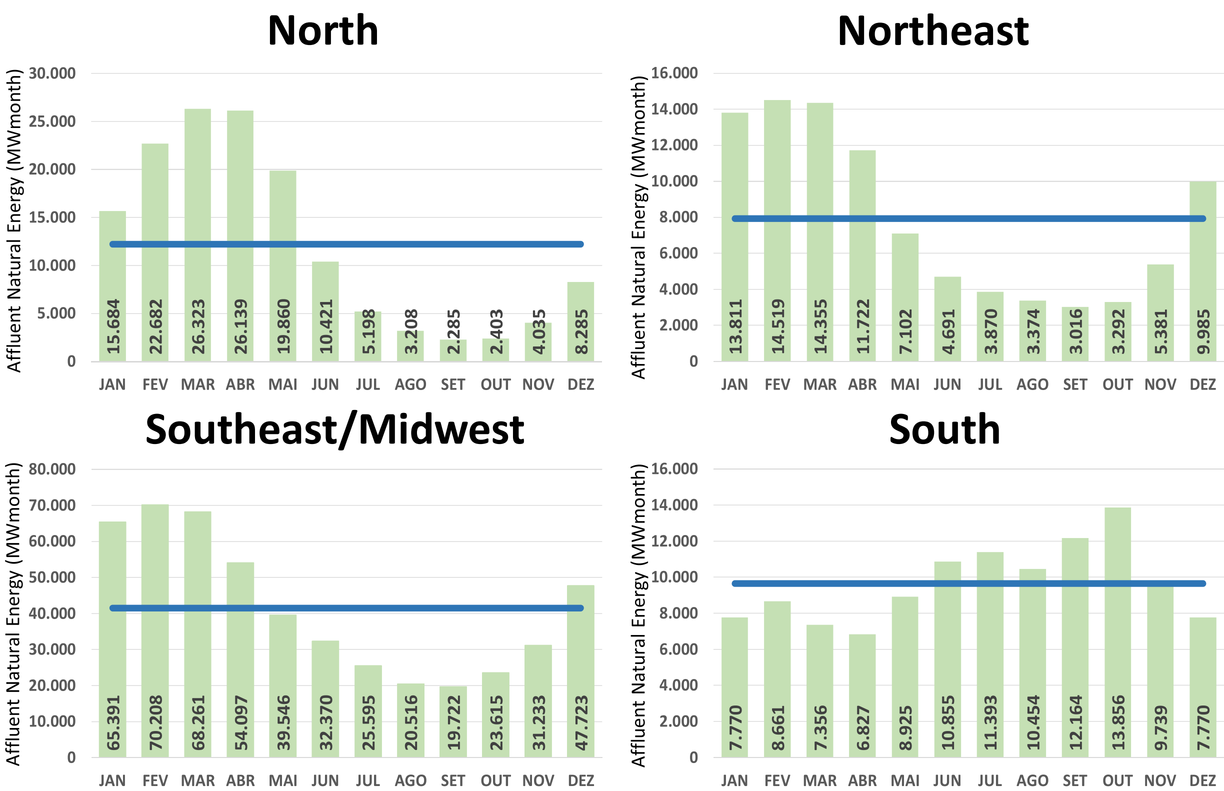


Fig. 5. Monthly natural affluent energy per subsystem (MWmonth).

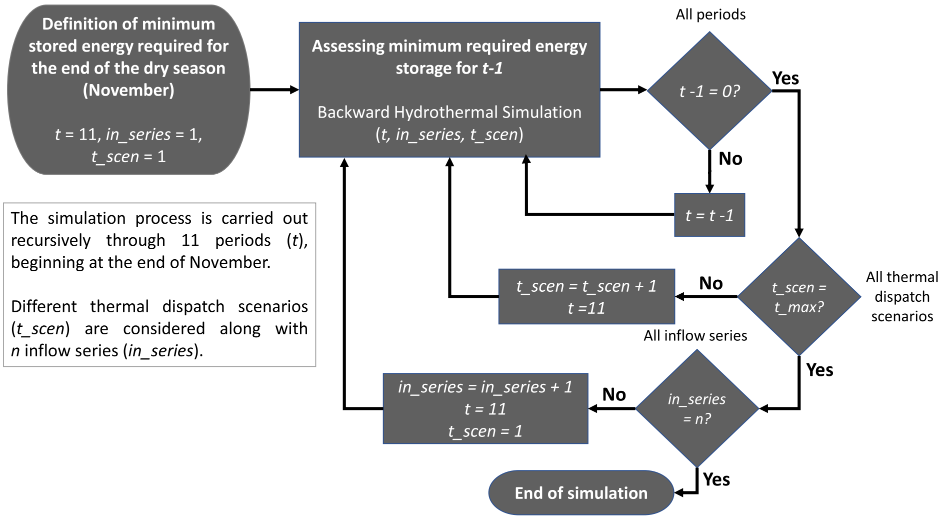


Fig. 6. Simulation process flowchart.

hydroelectric plant, the model finds the minimum stored volumes that respect all system constraints for the beginning of November. The resulted levels from the first stage are then set as end-of-October levels, starting points for the next stage. The coupled optimization process is carried out through the beginning of January. Fig. 6 presents a simplified flowchart of the simulation process.

The proposed model seeks the minimum stored energy for each month of the year and, as a recursive model, the simulation process starts at the end of November. The simulation is carried out this way, since the lowest hydro energy storage of each year usually occurs at the end of NIS' dry season (late November), as previously observed in Fi[illegible]a. By doing this, it is possible to find what is the minimum stored energy for each month that assures the secure operation of the system through the entire simulation period. Fig. 7 illustrates how the recursive simulation process is performed.

The end-of-November levels (starting points for the BHS model) were defined accordingly to the minimum operating volume (VminOp[2]) implementation in NEWAVE model [27]. The minimum levels per subsystem are detailed below:

- **Southeast/Midwest:** 10.0% of maximum storage capacity. According to ONS, below this level there may be loss of controllability of the reservoirs. Furthermore, this is the storage level below which ONS submits proposals for the adoption of operational measures to rationalize the demand.
- **South:** 30.0% of maximum storage capacity. According to [28], this was determined considering the safety levels of South subsystem's basins, weighted by their share in the subsystem's storable energy.
- **Northeast:** 22.5% of maximum storage capacity. The minimum operating volume for the Northeast subsystem is associated with the minimum levels for the Três Marias, Sobradinho and Itaparica reservoirs, defined based on the Brazilian National Water Agency (ANA) Resolution No. 2,081/2017 [29].
- **North:** 10.7% of maximum storage capacity. The minimum operating volume for the North subsystem is associated with the 60.5 m quota of Tucuruí power plant's reservoir. Below this quota, there is the complete shutdown of 3600 MW of Tucuruí's second powerhouse. The objective of linking the minimum operating volume to this quota is to make the mid-term operation planning model seek full generation of Tucuruí power plant, contributing to systemic power gains.

[2] VminOp is an additional risk aversion measure implemented in NEWAVE model from 2020 onwards. It consists of additional penalties to the objective function for the violation of a given minimum stored energy per subsystem. This implemented measure is expected to improve the dispatch models' response, increasing thermal generation under critical hydrological conditions. Besides, it is another evidence of the government entities' concerns on reservoirs depletion and the need of tools for monitoring the security of power supply, such as the BHS model.

These end-of-November levels correspond to an equivalent of 14.4% of NIS' maximum energy storage.

3.1. Modeling of system components

The BHS model solves a nonlinear programming problem, considering a detailed modeling of the water balance constraints and the hydro power production function. This ensures a proper representation of head variation in cascaded reservoirs, as stated by [30].

With the intent of finding the minimum stored energy for beginning of each stage, the problem's objective function is given by:

$$\min_{f,s,u,z}\left\{\sum_{h\in H^I} E_h^{ini} + \pi\cdot\sum_{c\in C} z_c\right\} \tag{1}$$

The expression (1) minimizes the sum of the initial stored energy E^{ini} per power plant h and the penalized slack z per constraint c. Because of the problem complexity as a nonlinear and non-convex optimization problem, slacks had to be added in some constraints in order to ensure the problem's feasibility.

The problem's constraints can be divided in two main groups: demand meeting and water balance constraints. Sections 3.1.1 and 3.1.2 detail the main premises assumed for each group of constraints.

3.1.1. Demand meeting constraints

Expression (2) shows the demand meeting constraint for each subsystem.

$$\sum_{h\in H_i} g_h + \sum_{j=1}^{N^{sys}} (f_{j,i} - f_{i,j}) = D_i^{net}\ \forall\ i\in[1, N^{sys}]|i\neq j \tag{2}$$

Each hydroelectric plant generation g_h is calculated by the energy production function in expression (3), considering maximum and minimum generation limits defined in Eq. (4). The hydro production function multiplies the production coefficient ρ_h, the turbined inflow u_h, and the net head x_h. The production coefficient ρ_h is a constant resulting from the multiplication of the efficiency of the turbine/generator set, the specific mass of water and the gravity factor, converting potential

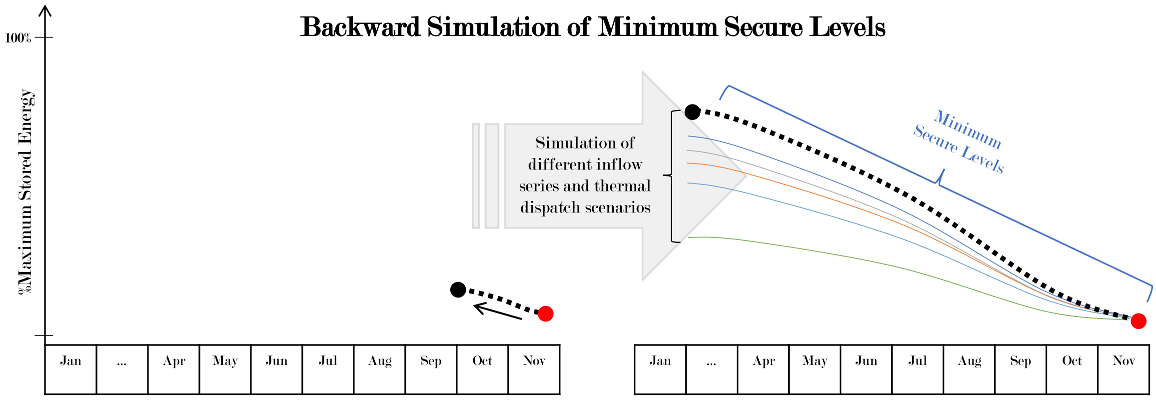


Fig. 7. Backward Simulation of Minimum Secure Levels.

energy of stored water into kinetic energy used to rotate turbines coupled to electric generators.

$$g_h = \rho_h \cdot u_h \cdot x_h \ \forall \ h \in H \tag{3}$$

$$\underline{G}_h \leq g_h \leq \overline{G}_h \ \forall \ h \in H \tag{4}$$

The transferred energy f between different subsystems is limited by power transmission limits defined by ONS, in expression (5). Moreover, additional constraints were considered to represent the maximum limits of the sum of different interchange lines and generating units. For instance, the maximum energy the Northeast subsystem can receive from other subsystems is lesser than the sum of the individual transmission line limits to which it is connected. These specific operation constraints are described as linear combinations, as observed in expression (6).

$$\underline{F}_{i,j} \leq f_{i,j} \leq \overline{F}_{i,j} \ \forall \ i \in [1, N^{sys}] | i \neq j \tag{5}$$

$$LB_c \leq \sum_{h \in NH_c} g_h + \sum_{i,j \in NT_c} f_{i,j} \leq UB_c \ \forall \ c \in I^{sum} \tag{6}$$

Thermal, wind, solar, biomass and small hydropower plants are not individually simulated on BHS model. The thermal dispatch of different units is aggregated in an equivalent thermal power plant which generation corresponds to total availability of units with equal or lower V[illegible] to a predefined marginal cost. By doing so, it is possible to calculate the minimum secure levels for different thermal dispatch scenarios. The complementary generation of the wind, solar, small hydro and biomass plants corresponds to the estimate generation used in NEWAVE model [31]. Thus, the net demand from each subsystem is calculated by subtracting the thermal dispatch and complementary generation of small plants from the total load estimate, as shown in expression (7).

$$D_i^{net} = D_i - NS_i - \sum_{w \in W_i^{mc}} gt_w \ \forall \ i \in [1, N^{sys}] \tag{7}$$

3.1.2. Water balance constraints

The water balance constraints, represented in Eq. (8), express the coupling of water outflow in reservoirs through successive stages. The stored water at the end of each stage is equal to the initial storage plus the sum of lateral and upstream inflows (calculated in expression (9)), minus the sum of outflow volumes (turbined and spilled flows, represented in expression (10), and reservoir evaporation, irrigation and diverted flows). Since the reservoir volumes are given in hm^3, the inflows had to be converted from m^3/s with the use of outflow-volume monthly conversion factors δ. All variables in water balance constraints are subject to operational lower and upper bounds. Moreover, slacks were added for some hydroelectric plants to make the problem feasible under critical inflow series simulation.

$$V_h^f = V_h^{ini} - v_h^{evap} + \delta \cdot (q_h^{in} - q_h^{out} - q_h^{irrig} - q_h^d) + z_c \ \forall \ \ h \in H \tag{8}$$

$$q_h^{in} = q_h^l + \sum_{m \in H_h^{up}} (u_m + s_m) + \sum_{m \in H_h^d} q_m^d \ \forall \ h \in H \tag{9}$$

$$q_h^{out} = u_h + s_h \ \forall \ h \in H \tag{10}$$

The evaporated volume of the plants' reservoirs is calculated by multiplying the reservoir area by a previously calculated monthly evaporation constant k^{evap}, as represented in expression (11). The reservoir area is calculated through a predetermined level x area fourth degree polynomial function $A(l^{up})$. The reservoir level l^{up} is resultant from fourth degree function, referred as volume x level polynomial, expressed in (12).

$$v_h^{evap} = A_h(l_h^{up}) \cdot \frac{k_h^{evap}}{1000} \ \forall \ h \in H \tag{11}$$

$$l_h^{up} = L_h^{up}\left(\frac{V_h^f - V_h^{ini}}{2}\right) \ \forall \ h \in H \tag{12}$$

The tailwater level of each plant is calculated according to the turbined outflow by a fourth degree polynomial outflow x tailwater level. For plants which spillage flow has no influence on the tailwater level, only the turbined outflow u is considered during the calculation of the downstream level. The reservoir net head is then calculated by subtracting the tailwater level and the hydraulic losses from the forebay reservoir level, as shown in Eq. (14). For the monthly definition of the forebay level, the average between the initial and final reservoirs' volumes was considered for each power plant.

$$l_h^{down} = L_h^{down}(q_h^{out}) \ \forall \ h \in H \tag{13}$$

$$x_h = l_h^{up} - l_h^{down} - loss_h \ \forall \ h \in H \tag{14}$$

The equations described above implicate that the greater the outflow, the higher will be the tailwater level, decreasing the net height of fall and consequently also decreasing the plant's production factor calculated in Eq. (3).

The stored energy in a reservoir is calculated by weighting the plant's useful storage by the productivity of the plants located downstream in the cascade, as expressed in (15). The calculated energy must be multiplied by 1/2.6352 to convert the potential energy from joule (J) to MWmonth. The plants' useful storage is the difference between the stored volume and the minimum operational storage. Lastly, the equivalent net head is calculated in expression (16) by the integral of the volume x level function minus hydraulic losses and the tailwater level.

$$E_h^{ini} = \frac{1}{2.6352} \cdot (V_h^{ini} - V_h^{min}) \cdot \sum_{m \in H_h^{down}} \rho_m \cdot x_m^{equiv} \quad \forall \ \ h \in H \tag{15}$$

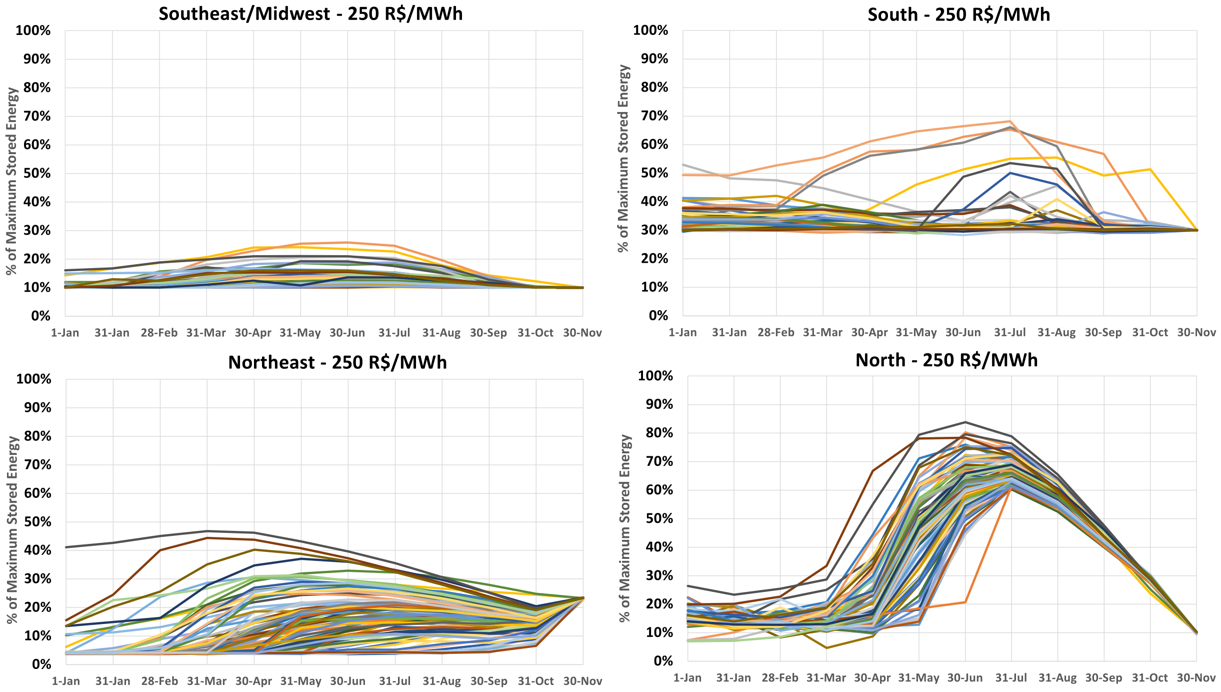


Fig. 8. Simulation results per subsystem in Scenario I (250 R$/MWh VCU thermal dispatch).

$$x_h = \frac{1}{V_h^{ini} - V_h^{min}} \cdot \int_{V_h^{min}}^{V_h^{ini}} L_h^{up}(V_h).\, dV_h - l_h^{down} - loss_h \quad \forall\ h \in H \tag{16}$$

3. Optimization process details

In spite of not finding a global optimal solution thanks to the non-convexity of the $L_h^{up}(V_h)$, $L_h^{down}(q_h^{out})$ and $A_h(l_h^{up})$ polynomial functions, the higher detailed modeling of system's components was preferable over linearizing key equations, such as the water balance constraints. As stated previously, this type of modeling ensures a proper representation of head variation in cascaded reservoirs. On the other hand, the solving complexity increased, specially under nonlinear optimization, and a large amount of time was necessary to simulate all historic inflows, as described in Section 4.

Different methods can be found in the literature for solving nonlinear and non-convex programming problems. For instance, in [32] the improved harmony search algorithm was used to solve a nonlinear and non-convex hydrothermal generation scheduling problem. The implemented algorithm takes advantage from the use of few parameters and ease of application in optimization problems. On the other hand, heuristic optimization methods have been employed with promising results in the most diverse types of applications. In [33], real-coded genetic algorithm based on improved Mühlenbein mutation was implemented for solving the optimal generation scheduling of hydrothermal systems, obtaining better solutions with respect to other optimization methods. However, the development of a solver for nonlinear optimization problems was not the focus of this work. Therefore, wide access solver packages, such as Ipopt [34] and Juniper [35], were used together to carry out the nonlinear optimization in Julia programming environment.

While Ipopt is a well-established package for large-scale nonlinear optimization, Juniper is a solver for Mixed Integer Nonlinear Programs (MINLP). Besides the suitability for solving the proposed problem, both solvers were chosen due to the ease of access, as they are free and their code is open source. Ipopt implements a nonlinear primal-dual interior point optimization with line search filters used for fast computation of search directions resulting from special sparse structures from the mathematical formulation. Aside from [34], the algorithm and mathematical details from Ipopt can also be found in [36] and [37].

Although there are not any discrete variables on this specific problem, Juniper suits well since its heuristics are specialized for non-convex problems, which get solved locally optimal. Non-convex generic functions require global optimization algorithms for linear problems, with a proof of optimality. However, their limited scalability prevents application to larger real-world problems featuring thousands of variables and constraints, such as the problem presented in this paper. On this matter, Juniper plays an important role facilitating the algorithm convergence process, thanks to the employed heuristics of nonlinear branch-and-bound (NLBB) and feasibility pump [35].

4. Results

The proposed methodology was applied for the year of 2019, considering NEWAVE and DECOMP official system's data available in December/2018 [24]. There were solved a total of 1936 nonlinear optimization problems. Each problem had 4039 variables, 3438 linear constraints and 760 nonlinear constraints, and the whole simulation process took about 45h using an Intel Core i7-4500U CPU @ 1.80GHz-2.40GHz, with 8GB RAM and 480GB SSD.

The 88 historic inflow series (1931 to 2018) were simulated for 164 hydroelectric plants and 4 interconnected subsystems, from the end of November to the beginning of January (considering the backward direction), in light of two different thermal dispatch scenarios[3]:

- **Scenario I:** Thermal power availability up to 250.00 R$/MWh VCU, summing up about 10.5 GW of total thermal dispatch.
- **Scenario II:** All thermal power availability, summing up about 16.5 GW of total thermal dispatch.

Fig. 8 shows the results of minimum required stored energy per subsystem for scenario I. Each line represents a different historical inflow series. The most critical inflow series simulated required a higher amount of stored energy in the beginning of each stage to meet the load

[3] Considering that the marginal operating costs of SE/MW were on average 429.22 R$/MWh [3] during the last 5 years, the chosen scenarios can be interpreted as a lower and an upper bound in terms of thermal dispatch.

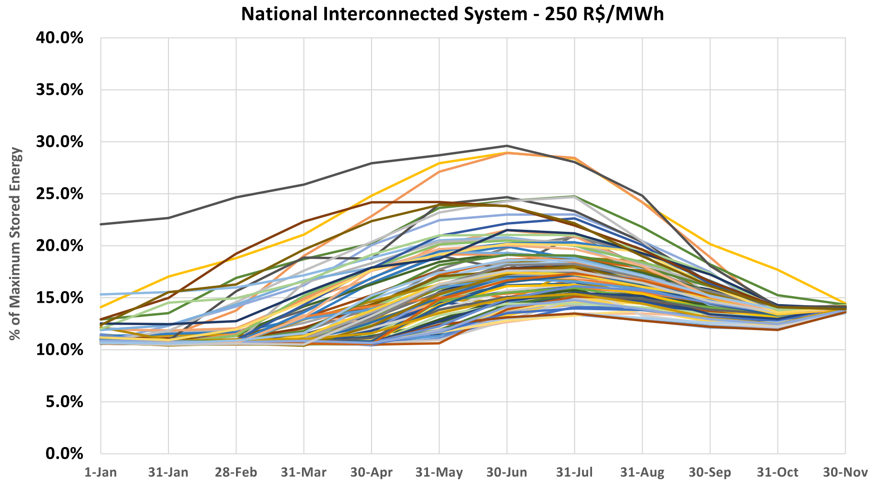


Fig. 9. Simulation results for NIS in Scenario I (250 R$/MWh VCU thermal dispatch).

respecting all existing constraints.

As each subsystem has different patterns in precipitation throughout the year, monitoring the NIS equivalent stored energy is important for a global overview of the system's operation security. Fig. 9 shows the equivalent stored energy for the National Interconnected System in each historic inflow series.

The same methodology was applied for the thermal dispatch scenario II. Fig. 10 shows the achieved results per subsystem, and Fig. 11 presents the equivalent stored energy results for NIS. Lower stored energy was necessary on this scenario as a result of a lower net demand to meet. In terms of system's secure operation, these are the most important curves, as all resources are being used to meet the demand. Thus reaching levels below the resulted curves may jeopardize the reliability of the system's operation.

Considering the subsystems are interconnected and able to exchange power through transmission lines, following up NIS' equivalent stored energy is a simple and effective way for secure monitoring the whole system's supply conditions. Based on the results for both thermal dispatch scenarios, two reference curves (Fig. 12) were set based on historical series minimum secure levels:

- **Attention Curve:** Average of NIS' five higher levels for each month on scenario I.
- **Critical Curve:** Average of NIS' five higher levels for each month on scenario II.

The historical series which resulted in the five higher required levels for each month were: 1934, 1936, 1944, 1945, 1951, 1954, 1964, 1971, 1986, 2001, 2007, 2014, 2015, 2016, 2017 and 2018. It is worth observing that the simulation of series from 2014 to 2018 resulted in higher amounts of required stored energy, which corroborates with the recent risk perception from the power industry entities.

As stated previously, the proposed curves are effective for 2019 as they were built using data from December 2018. To give a better view of the levels resulting from the simulated curves, the 2017, 2018 and 2019 observed levels were also plotted in Fig. 12. As both attention and

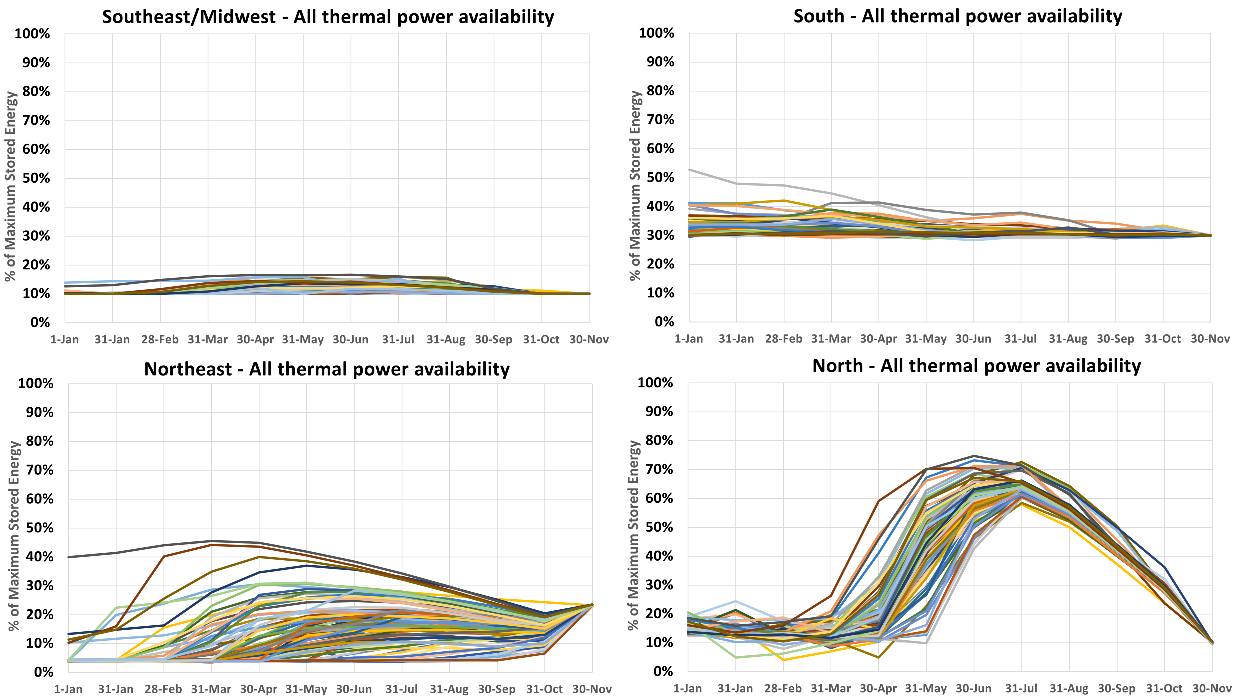


Fig. 10. Simulation results per subsystem in Scenario II (all thermal availability).

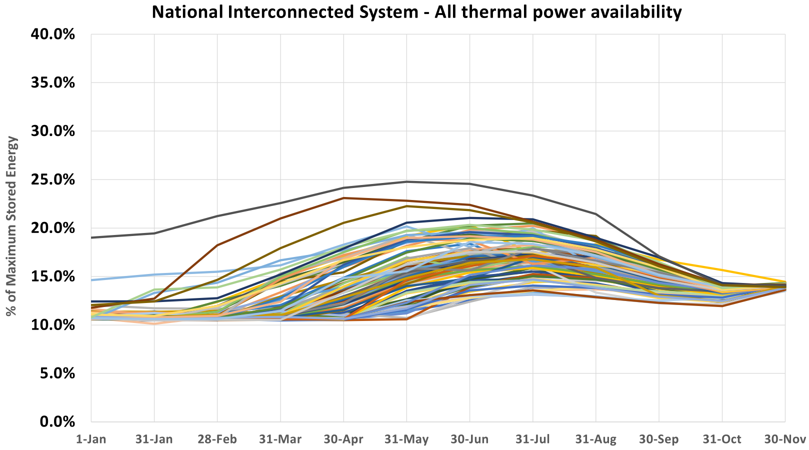


Fig. 11. Simulation results for NIS in Scenario II (all thermal availability).

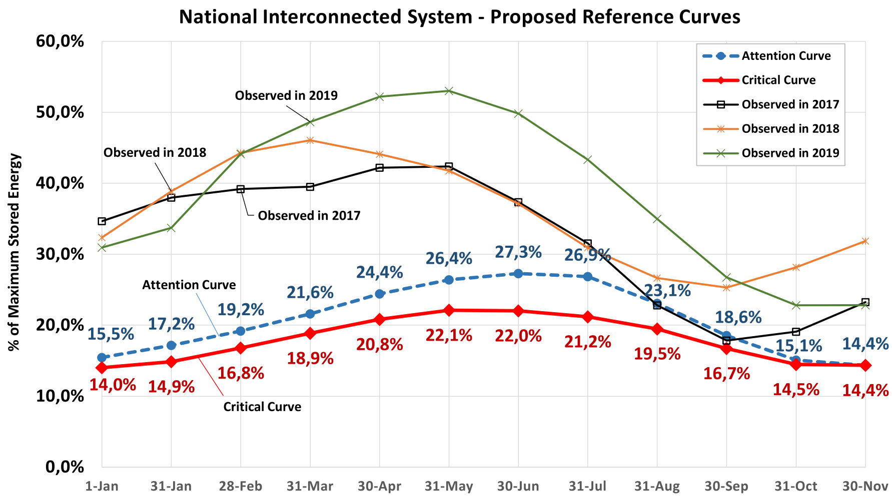


Fig. 12. Proposed curves for secure monitoring of NIS' stored energy.

critical curves situate below the observed levels for 2019, additional out-of-merit thermal generation would not have been recommended to ensure the security of power supply. However, if the reservoirs operation in 2019 had resulted in levels such as those observed in 2017, additional thermal dispatch might have been recommended for September and October, considering the proposed reference curves were being used to support decisions on additional thermal dispatch.

The average of the five higher required levels is a conservative criterion for the definition of the reference curves. However, depending on the risk aversion of the power sector entities, more severe criteria may be employed to define the reference curves. For instance, if it is preferable to prevent from the worst simulated scenarios, the curves' upper wrap of the historical simulation may be used to set the reference curves, even though it will protect from a critical scenario very unlikely to occur. On the other hand, the end-of-November input levels can be tweaked to higher values if the system operator is more risk averse and wishes to guarantee a higher degree of power supply reliability.

Ideally, the reference curves should be calculated at least once a year since future load estimates and anticipation or delay of new power plants and transmission lines may affect the demand/supply balance over the months.

5. Conclusions

This paper proposed a new method to evaluate the security of power supply in systems with predominance of hydroelectricity. An optimization model, referred as BHS model, was developed and carried out the recursive simulation of 88 historical inflows series, from 1931 to 2018, using NIS' available data for the year of 2019. The simulation process provided minimum levels for each month, that guarantee the security of power supply until the end of the dry season, in November. The developed model has proven to be robust and brought innovation by representing in detail the water balance nonlinear constraints in a recursive simulation process.

Besides, two reference curves were suggested for continuous monitoring of NIS' equivalent stored energy. Reaching the attention curve indicate the hydroelectric plants operation must be followed up closely, and further actions might be necessary to ensure the security of the system. On the other hand, the critical curve indicates a higher alert in terms of secure dispatching. In this case, it might be reasonable to consider an out-of-merit thermal dispatch command, since visiting levels below this curve may jeopardize the system's power supply.

The comparison between the reference curves and the inflows normal behavior from Fig. 5 suggests a good representation of the affluent energy seasonality by the BHS model, as the storage requisites are well correlated to the inflows behavior. On top of that, if the reservoirs operation in 2019 had resulted in levels such as those observed in 2017, additional thermal dispatch might have been recommended for September and October, considering the proposed reference curves were being used to support decisions on additional thermal dispatch. Moreover, from a top-down approach, the BHS model can yet be used to monitor the secure operation of subsystems and individualized reservoirs.

Assessing the operation marginal costs is a big challenge in power systems with strong dependency of renewable energy resources, such as the National Interconnected System. The system operator must be constantly evaluating the trade-off between the security of supply and the economical dispatch. Any out-of-merit thermal dispatch command must be accountable, as it implies on larger costs to all consumers. For instance, from 2013 to 2019, R$ 14.5 billion was spent on out-of-merit thermal generation for security of power supply purposes in Brazil [11], based mainly on tacit risk perception from the government entities.

Thus, the model proposed in this article is relevant, as it fills the existing gap of security monitoring tools for hydrothermal power systems, providing important insights on reservoirs' storage conditions and resources availability from the simulation of historical inflows. Furthermore, the monitoring of reference curves defined by a mathematical model is expected to represent a more robust criterion for additional out-of-merit thermal generation commands by government entities.

As future studies on this matter, it is suggested to evaluate if the performance gains by linearizing the nonlinear and non-convex water balance equations justify the loss of precision in the results. In addition, further methodology improvements regarding the reference curves definition and range of simulation are beneficial and pertinent.

CRediT authorship contribution statement

Gabriel Campos Godinho: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft. **Delberis Araújo Lima:** Conceptualization, Writing - review & editing, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowlgedgments

This study was financed in part by the Coordenao de Aperfeioamento de Pessoal de Nvel Superior - Brasil (CAPES) - Finance Code 001.

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