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PROGRAMA DE PÓS-GRADUAÇÃO EM RECURSOS HÍDRICOS E SANEAMENTO AMBIENTAL

ADA LIZ ARANCIBIA SAMANIEGO

PLANEJAMENTO DA EXPANSÃO DA CAPACIDADE DE SISTEMAS ELÉTRICOS SOB INCERTEZAS POLÍTICAS E CLIMÁTICAS. ESTUDO DE CASO SUBSISTEMA SUL DO BRASIL

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Tese submetida ao Programa de Pós-Graduação em Recursos Hídricos e Saneamento Ambiental da Universidade Federal do Rio Grande do Sul como requisito parcial para a obtenção do título de Doutor em Recursos Hídricos e Saneamento Ambiental.

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Este trabalho foi desenvolvido no Programa de Pós-Graduação em Engenharia de Recursos Hídricos e Saneamento Ambiental do Instituto de Pesquisas Hidráulicas da Universidade Federal do Rio Grande do Sul, sob a orientação do Prof. Dr. Guilherme Fernandes Marques, da Universidade Federal do Rio Grande do Sul e co-orientado pelo Prof. Dr. Carlos André Bulhões Mendes da Universidade Federal do Rio Grande do Sul.

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Dedico este trabajo a mis padres Esperanza y Adrián† .

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RESUMO

O planejamento da expansão da capacidade de sistemas elétricos visa garantir o fornecimento futuro de energia elétrica. A busca por esse objetivo deve ser feita tendo em vista critérios como custos, tecnologias disponíveis, confiabilidade e impactos ambientais. No presente trabalho, o foco são os objetivos de mínimos custos e mínimas emissões de gases de efeito estufa, da geração elétrica. No contexto global atual, esse planejamento representa um grande desafio. Sendo uma atividade de grande importância para o desenvolvimento dos países, envolve, além das incertezas próprias da atividade, também as incertezas das políticas energéticas, as quais dependem de outras agendas políticas da administração em turno. Além disso, uma vez que a geração de energia é baseada em muitos casos em recursos naturais sensíveis às condições climáticas, o processo de planejamento também deve lidar com a incerteza da mudança climática. Dessa forma, são necessários planos flexíveis capazes de antecipar possíveis mudanças (resultado das incertezas mencionadas) e evitar o desvio dos objetivos iniciais, que levariam em diferentes resultados. O primeiro passo é conhecer o impacto que possíveis mudanças podem gerar nas metas iniciais. Algumas metodologias e ferramentas exploradas nesta área, normalmente consideram apenas os efeitos da mudança climática, enquanto que outras mais gerais consideram as políticas de energia ou climáticas, mas não a possibilidade de mudança nessas políticas nem a sua combinação. Ou seja, são consideradas estáticas para o período de planejamento. O presente trabalho traz como contribuição original para a área a inclusão da incerteza inerente às políticas energéticas, combinada à incerteza climática, e a avaliação o desempenho dos caminhos possíveis, identificando os mais robustos. O objetivo deste trabalho é determinar o impacto e a influência das incertezas das políticas energéticas e das mudanças climática, de forma combinada, sobre os resultados finais no planejamento da expansão da capacidade de sistemas elétricos, em termos de custos e emissões de CO_2. Outros objetivos secundários incluem a identificação de políticas robustas com boa performance para qualquer cenário climático e desenvolvimento de uma abordagem de análises das mudanças climáticas e políticas. São aplicadas técnicas de otimização de expansão de capacidade para elaborar uma metodologia híbrida que combina programação dinâmica com programação linear multiobjectivo para a geração dos diferentes cenários de mudança da política energética, bem como os *trade-offs*. A metodologia é aplicada em uma região estudo de caso envolvendo a expansão de capacidade do subsistema elétrico sul do brasil. Resultados mostram que: (i) é possível determinar os impactos das mudanças de políticas energéticas para diferentes cenários de mudança climática a través dos trade-off de custos e emissões de CO_2; (ii) é possível identificar políticas energéticas robustas; (iii) é possível identificar a influência da mudança climática no desempenho (em termos de custos e emissões de CO_2) das políticas energéticas. Os resultados e métodos aqui produzidos são úteis para países em desenvolvimento e emergentes, como o Brasil, ao oferecer um marco metodológico capaz de auxiliar na programação de seus investimentos em expansão da geração de energia em ambientes com grandes incertezas, além de fornecer de uma ferramenta para o desenho de políticas energéticas e climáticas.
Palavras chave: planejamento de incremento da capacidade, sistemas elétricos, mudança climática, incertezas, políticas energéticas, programação dinâmica, programação linear multi-objetivo.

ABSTRACT

The planning of Power systems capacity expansion aims to guarantee the future supply of electrical energy. The pursuit of this objective should be made considering criteria such as costs, available technologies, reliability and environmental impacts. In the present work, the focus is the objectives of minimum costs and minimum emissions of greenhouse gases in the power generation. In the current global context, such planning is a major challenge. As an activity of great importance for the development of countries, it involves, in addition to the inherent uncertainties of the activity, energy policies uncertainties, which depend on other political agendas of the administration in turn. Also, since energy generation relies in many cases on climate-sensitive natural resources, the planning process must also deal with the climate change uncertainty. Hence, flexible plans are necessary to anticipate possible changes (that come up of the mentioned uncertainties) and avoid the deviation from the initial objectives, which would lead to different results. The first step is knowing the impact that possible changes can generate on the initial goals. Some methodologies and tools explored in this area consider only the effects of climate change, while others more general consider energy or climate policies, but not the possibility of change in these policies or their combination. That is, they are considered static for the planning period. The present work has as an original contribution to the area by the inclusion of the inherent uncertainty of energy policies, combined with the climatic uncertainty, and the evaluation of the possible paths, identifying the most robust ones. The objective of this work is to determine the impact and influence of energy policy and climate change uncertainties, combined, on the final results in the planning of the power systems capacity expansion regarding costs and CO_2 emissions. Other secondary objectives include identifying robust policies with good performance for any climate scenario and developing a climate change and policy analysis approach. Capacity-optimization techniques are applied to develop a hybrid methodology that combines dynamic programming with multi-objective linear programming to generate different scenarios for energy policy change, as well as trade-offs. The methodology is applied in a region case study involving the capacity expansion of the Brazilian southern power subsystem. Results show that: (i) it is possible to determine the impacts of energy policy changes for different scenarios of climate change through the trade-off of costs and CO_2 emissions; (ii) robust energy policies can be identified; (iii) it is possible to identify the influence of climate change on the performance (regarding costs and CO_2 emissions) of energy policies. The results and methods produced here are useful for developing and emerging countries, such as Brazil, by offering a methodological framework capable of assisting in scheduling their investments in expanding energy generation in environments with significant uncertainties, as well as providing a tool for the design of energy and climate policies.

Keywords: Planning capacity expansion, power systems, energy policy, climate change, uncertainties, dynamic programming, multi-objective linear programming.

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LISTA DE SIGLAS E ABREVIAÇÕES

ANN: Redes neurais artificiais (*Artificial Neural Networks*)

CDM: Mecanismo de desenvolvimento limpo (*Clean development mechanism*)

CNPq: Conselho Nacional de Desenvolvimento Científico e Tecnológico

COMFIT: Comunidade *Feed-in Tariff* (*Community Feed-in Tariff*)

DP: Programação dinâmica. (*Dynamic programming*)

ECG: Expansão de Capacidade de Geração

FIT: *Feed-in Tariff*

GA: Algoritmos genéticos (*Genetic algorithm*)

GAMS: General Algebraic Modeling System

IAEA: Agência Internacional de Energia Atômica *(International Atomic Energy Agency)*

IPCC: Painel Intergovernamental sobre Mudança do Clima *(Intergovernmental Panel on Climate Change*

MOLP: Programação linear multi-objetivo (*Multi-objective linear programming*)

MW: *Mega Watt*

MWh: *Megawatt hora*

GWh: *Gigawatt hora*

ONS: Operador Nacional do Sistema (Brasil)

PECG: Planejamento da Expansão de Capacidade de Geração

PSO: *(Particular swarm optimization)*

RPS: Padrões de Portfolios Renováveis

SIN: Sistema Interligado Nacional

UCF: Fator de Capacidade de utilização (*Utilization capacity factor*)

UK: Reindo Unido (*United Kingdom*)

UNFCCC: Convenção das Nações Unidas sobre mudança no clima *(United Nations on Climate Change Convention)*

SUMÁRIO

1 INTRODUÇÃO

O planejamento dos diferentes serviços públicos, como o de energia elétrica, os sistemas de abastecimento de água, as escolas e as estradas, entre outros, foram no geral, realizados aplicando a metodologia de expansão de capacidade, uma vez que a maioria desses sistemas já existe (HOUSE E WARFIELD, 1969; LUSS, 1982). O principal objetivo da expansão da capacidade é determinar os tamanhos de instalações a serem adicionadas, e quando isso deve acontecer, com custos mínimos (LUSS, 1982). Isto também pode exigir a consideração de outros objetivos, como a minimização das emissões de gases de efeito estufa e a incorporação de energias renováveis para mitigar impactos ambientais. Todas estas formulações devem ser realizadas considerando as características de ordem climática, política e econômica do ambiente em que o plano será implementado.

A respeito do clima, alterações em seu estado global têm sido identificadas; com o aquecimento do sistema climático, desde a década de 1950, e muitas das mudanças observadas não têm precedentes ao longo de décadas ou milênios. As emissões antropogênicas de gases de efeito estufa aumentaram desde a era pré-industrial. Seus efeitos, juntamente com os dos outros condutores antrópicos, foram detectados em todo o sistema climático e é extremamente provável que tenha sido a causa dominante do aquecimento observado desde meados do século XX. O setor elétrico é um dos que mais contribuiu nas emissões de CO_2, com 25% do total de emissões em 2010. Nas últimas décadas, as mudanças climáticas têm causado impactos nos sistemas naturais e humanos em todos os continentes e através dos oceanos (IPCC, 2014).

Assim, o uso de recursos renováveis é, atualmente, uma preocupação global, devido aos impactos ambientais e às alterações climáticas, fazendo com que os governos adotem políticas para a implantação de tecnologias com baixas emissões de carbono (IYER ET AL., 2015). Tais políticas são as chamadas políticas climáticas. A incorporação de políticas climáticas no planejamento adiciona complexidade e incerteza ao processo, assim, os planejadores devem levar em conta a incerteza adicionada à complexidade, se comparado com as condições do passado, uma vez que os fatores-chave, como a configuração econômica e política, mudam rapidamente e têm um grande impacto em todo o mundo (SCHWENKER E WULF, 2013).

Por sua vez, o planejamento dos sistemas elétricos, como definido por Seifi e Sepasian (2011), é um processo no qual o objetivo é decidir sobre novos elementos dos componentes existentes do sistema, ou sobre sua atualização, para satisfazer adequadamente às demandas de energia elétrica no futuro. Isso resulta na definição de um cronograma de investimento para a construção das plantas e dos *links* de interconexão, considerando um fornecimento econômico e confiável (GORENSTIN, CAMPODONICO ET AL., 1993). Os principais elementos componentes do sistema elétrico são: geração, transmissão, interconexão e distribuição (ELKARMI E ABUSHIKHAH, 2012). De entre eles, o planejamento da expansão da capacidade de geração é a primeira etapa decisiva em questões de planejamento de longo prazo (SEIFI E SEPASIAN, 2011), portanto deve lidar com as incertezas próprias do planejamento de longo prazo. Na sua vez, um dos recursos renováveis mais empregados para a geração elétrica é a água (TSP, 2017). Sendo por tanto de muito interesse para área de estudo do Planejamento e gestão dos recursos hídricos, motivo pelo qual é foco do presente trabalho é o componente de geração.

Metodologias de planejamento foram desenvolvidas para cada um destes componentes, sendo, cada um em si um importante objeto de estudo (IAEA, 1984). No caso do planejamento de expansão de geração de energia elétrica, a metodologia de programação dinâmica (DP) foi classificada como uma das mais utilizadas, entre outras, como técnicas de decomposição, otimização estocástica, algoritmo genético (GA), a teoria dos conjuntos difusos, redes neurais artificiais, fluxos de rede, recozimento simulado (*simulated annealing*), etc. (KAGIANNAS, ASKOUNIS e PSARRAS, 2004). Tekiner et al. (2010) fez uma revisão abrangente das metodologias aplicadas, indicando o emprego de métodos de otimização multi-objetivo com avaliação de riscos e incertezas, programação linear multi-objetivo (MOLP – *Multi Objective linear programming*), otimização estocástica, análise multicritério, análise de decisão e análise *trade-off*. As incertezas no planejamento dos sistemas elétricos têm sido focadas na demanda (DAVIS ET AL., 1987); e demanda e disponibilidade de recursos (GORENSTIN ET AL., 1993); demanda e parâmetros de preços (AHMED, KING E PARIJA, 2003).

Políticas para a incorporação de energias renováveis foram incluídas no planejamento da expansão da geração, na forma de restrições com percentuais mínimos de energias renováveis (LI *ET AL.*, 2014); ou como sistemas populares de incentivos: tarifas *feed-in*, imposição de quotas, comércio de emissões e imposto sobre o carbono (CARERI *ET AL.*, 2011); também como cumprimento das quotas de emissões (REBENNACK, 2014) ou uma função objetivo adicional de minimização de emissões de CO_2 (AGHAEI *ET AL.*, 2013; TEKINER, COIT E FELDER, 2010). Esforços recentes consideram modelar a inclusão de grandes quantidades de renováveis aos sistemas elétricos (VITHAYASRICHAREON, RIESZ E MACGILL, 2015), a través de uma metodologia de análise que aplica conceitos de modelagem de portfólio de geração, que consegue lidar com os diferentes riscos e incertezas das energias renováveis (i.e., incertezas de preços do gás e do carvão). Neste referido caso, para aplicação para a análise do papel do carvão, do gás e das energias renováveis nos futuros portfólios de geração no sistema elétrico da Austrália, para 2030. Assim, as políticas climáticas têm delineado as políticas energéticas. Todas estas análises, incorporando políticas climáticas ao planejamento, avaliam as incertezas das respostas dos diferentes instrumentos aplicados. Entretanto, no cenário de volatilidade atual, o fato é que as políticas climáticas vão mudar com frequência sobre a passagem do tempo, assim como as políticas energéticas.

A incorporação dos impactos das mudanças climáticas nos modelos de planejamento de geração de energia requer compreensão sobre os impactos nas fontes de geração. A maior parte da literatura foca nos efeitos das mudanças climáticas na energia hidrelétrica (SAMPLE, et al., 2015; FILION, 2000; LEHNER, CZISCH e VASSOLO, 2005; LIMA, COLISCHONN e MARENGO, 2014), com menor atenção para a energia eólica e fotovoltaica, dada a maior incerteza sobre essas fontes quando comparada à hidroelétrica (YAO, HUANG e LIN, 2012). Os impactos das mudanças climáticas foram considerados em termos de fator de capacidade, que indica a relação de energia que uma usina elétrica produz durante um determinado intervalo de tempo e energia que poderia produzir em sua capacidade máxima de operação contínua durante esse mesmo período.

1.1 IDENTIFICAÇÃO DA LACUNA

A Alemanha, um dos países que adotaram políticas para a implantação de tecnologias de baixo carbono, dobrou seus recursos de energias renováveis entre 2000 e 2009, das quais a geração eólica é a mais importante (REUTER ET AL., 2012). No entanto, a implementação deste tipo de políticas tem um custo. Em 2013, estimou-se um total de US$ 120 bilhões em subsídios globais para tecnologias de energia renovável (IEA, 2014). Recentemente, o Reino Unido anunciou que anteciparia para 2016 o fim aos subsídios para novos parques eólicos *on-shore* (BBC NEWS, 2015). Na Austrália, o primeiro-ministro proibiu o fundo federal de energia limpa de investir em energia eólica (SCHLANGER, 2015). As razões por trás destas mudanças de política foram apontadas como a necessidade de ajudar outros tipos de tecnologia e especulações de que os fundos dos subsídios ficaram sem recursos. Especial atenção merecem as mudanças nas políticas energéticas do Japão entre os anos 2009 e 2013, como consequência do desastre da usina nuclear de Fukushima, posterior ao sismo de março de 2011 e das mudanças na administração do governo (KURAMOCHI, 2015). Os citados exemplos mostram como as políticas não são isentas de mudar, seja pelo motivo que for.

A respeito das mudanças climáticas, um aspecto importante a se salientar é que ainda existem grandes incertezas sobre a severidade das alterações climáticas quanto ao impacto na geração e o custo das tecnologias necessárias para mitigar este problema, a eficácia dos instrumentos da política climática, tais como taxação ao carvão, mercados de emissões, *feed-in tariff* para renováveis. Porém, com o passar do tempo, mais informações sobre estes fatores serão obtidas, quer pela observação, quer pela aprendizagem através da realização de pesquisas. Estes novos conhecimentos precisarão ser incorporados nas políticas e os planos, consequentemente, necessitam ser atualizadas no decorre do tempo. (FUSS *ET AL*., 2009).

Assim, no planejamento da expansão da capacidade de geração de sistemas elétricos, por um lado, tem-se os custos da implementação das políticas climáticas que subsidiam as energias renováveis junto com a incerteza da mudança destas políticas no decorrer do tempo; por outro lado, nos países em desenvolvimento, tem-se a necessidade de reduzir as emissões de CO_2 a custos razoáveis (YEPEZ-GARCÍA, JOHNSON E ANDRÉS, 2010); ademais, tem-se anomalias climáticas impactando na geração. Porém, é necessário aprofundar o entendimento a respeito do impacto das mudanças deste tipo de políticas no decorrer do tempo, na busca por objetivos de redução de emissões de CO_2 e nos custos no planejamento da expansão da capacidade de geração, considerando os possíveis efeitos das mudanças climáticas.

A maioria dos trabalhos sobre a incerteza das políticas tem sido relatada em pesquisas financeiras, analisando as influências das mudanças políticas governamentais sobre os preços das ações, como mostrou Pástor e Veronesi (2012). Nesse trabalho, foram definidos dois tipos de incertezas: incerteza política, que diz respeito à incerteza sobre eventuais mudanças na atual política governamental; e efeito da incerteza que uma nova política do governo terá sobre a rentabilidade do setor privado. Os trabalhos no planejamento da expansão da capacidade de geração, como mencionado anteriormente, estão focados mais na aplicação dos instrumentos das políticas climáticas. Dessa forma, é preciso um melhor entendimento nesta área do planejamento da expansão da capacidade de geração.

Não estão identificados trabalhos que tenham considerado simultaneamente incertezas das políticas energéticas e das mudanças climáticas. Assim, sob a incerteza das políticas energéticas, a mudança de clima pode adicionar mais à variação na probabilidade da obtenção de determinados resultados esperados, tornando o planejamento da expansão da capacidade de geração elétrica mais desafiador (i.e., o que é esperado ser uma boa decisão sob um clima pode tornar-se completamente desfavorável sob outro).

1.2 DEFINIÇÃO DO PROBLEMA

As políticas vão mudar no decorrer do tempo, como definido anteriormente, e podem mudar pela nova informação ou conhecimento – como é feito na gestão adaptativa (*adaptative management)*: políticas de gestão são testadas para analisar as respostas – ou, simplesmente, pela decisão política do governo em turno. A partir desse ponto, o presente trabalho emprega o termo “política” para definir uma determinada estratégia de expansão. Assim, uma “política de expansão” do parque gerador de energia representa uma sequência de decisões de investimento em um determinado conjunto (*mix*) de fontes geradoras (o que será expandido e quando). A escolha da melhor política, ou eventuais mudanças de curso em uma política inicialmente definida fazem parte da atividade de Planejamento da Expansão da Capacidade de Geração (PECG). Cada política reflete as prioridades dadas pelos tomadores de decisão a objetivos como redução em gases de efeito estufa ou redução nos custos da expansão. Considerando-se que a política pode mudar para favorecer objetivos normalmente antagônicos (e.g. redução em gases efeito estufa e redução nos custos), coloca-se a seguinte questão:

É possível identificar e quantificar, na base de conhecimento, das condições iniciais de planejamento e das influências das mudanças climáticas, os impactos de mudanças nas políticas energéticas otimizadas nos objetivos iniciais do plano de expansão de capacidade de geração?

Derivam desta pergunta as seguintes:

1) É possível identificar e classificar as mudanças nas políticas a respeito de seus impactos finais no objetivo inicial do plano?
2) É possível identificar os efeitos das mudanças climáticas nas políticas?
3) E possível identificar políticas robustas que consigam manter a consecução dos objetivos inicias além das mudanças nas condições climáticas?

1.3 RELEVÂNCIA E JUSTIFICATIVA DA PESQUISA

Se as políticas mudam durante o processo de planejamento, serão necessários ajustes para prevenir o plano de se tornar obsoleto. Isso pode seduzir políticos e tomadores de decisões a optar por estratégias indicativas mais abrangentes que podem não ter clareza ou certeza sobre quais objetivos ou outros interesses a priorizar (PARKER E DOAK, 2012).

É importante conhecer com antecedência os possíveis impactos das mudanças das políticas sobre os objetivos originais no decorrer do plano sob as incertezas dos efeitos das mudanças climáticas, para dar subsídio relevante aos planejadores e tomadores de decisões das possíveis consequências das mudanças nestas políticas. Assim, será possível elaborar diretrizes para os ajustes necessários do plano, permitindo ao mesmo adaptar-se às novas condições, prioridades e contextos geopolíticos com menor impacto nos objetivos.

A relevância desta pesquisa na área de recursos hídricos é a identificação dos impactos das mudanças climáticas sobre as políticas energéticas, assim como as mudanças das políticas na seleção do *rol* destes recursos como uma das fontes renováveis de geração de energia elétrica. Esta informação pode ser considerada, posteriormente, na gestão dos recursos hídricos. Além do indicado, as técnicas e ferramentas podem ser aplicadas, com adequações, para o planejamento de capacidade de expansão de outros serviços públicos, como as plantas de tratamento de água e, inclusive, no planejamento da gestão dos recursos hídricos.

1.4 HIPÓTESES E OBJETIVOS DA PESQUISA

1.4.1 Hipóteses

O presente trabalho parte do pressuposto que não é suficiente apenas definir uma política "ótima" para expansão de um sistema gerador sem considerar os efeitos da mudança climática. Em vista de incertezas envolvidas e da necessidade de o planejamento ser flexível, políticas energéticas eventualmente passarão por mudanças e ajustes de curso. Nesse sentido, a hipótese considerada neste trabalho é que: "a configuração das mudanças nas políticas energéticas pode levar a resultados bem diferentes, sendo importante poder identificar também a melhor forma de se executar estas mudanças na expansão da capacidade, de modo a se alcançar o objetivo final".

1.4.2 Objetivos

Para responder à hipótese colocada, o objetivo da pesquisa é determinar os impactos e as influências das incertezas das políticas energéticas de expansão da capacidade no decorrer do planejamento sobre os resultados da expansão da capacidade de geração, como custos e emissões de CO_2, para diferentes condiciones climáticas.

Os objetivos secundários, que subsidiaram o objetivo principal:

1) Identificar e classificar as mudanças de políticas robustas que conseguem um melhor desempenho nos resultados finais, como custos e emissões de CO_2;
2) Identificar as influencias das condições climáticas nas políticas;
3) Elaborar a abordagem de análise das mudanças climáticas e das políticas no planejamento da expansão da capacidade de geração.

1.4.3 Limitações da pesquisa

A pesquisa se limita ao estudo dos impactos das mudanças nas políticas de expansão de fontes geradoras de energia ou preferência da seleção de um tipo de tecnologia de geração, sob a influência da mudança climática, nos resultados dos custos e emissões de CO_2. O foco é o planejamento estratégico de longo prazo, em nível de governo ou entidade reguladora. As condições de operação do sistema elétrico são simplificadas a uma restrição para o fator de capacidade de utilização. O fator de capacidade de utilização é considerado caraterístico da operação de um determinado sistema elétrico e sensível unicamente à disponibilidade de recursos hídricos no sistema. As incertezas das mudanças climáticas são expressas como cenários resultantes de aplicação de diferentes modelos climáticos para um único cenário de emissões de CO_2. Todas as outras variáveis (demanda, preços, etc.) que configuram o problema de expansão da capacidade do sistema elétrico permanecem constantes.

1.5 ESTRUTURA DO TRABALHO

O conteúdo desta tese é apresentado no formato de artigos. O presente capítulo apresentou uma introdução do tema abordado, a justificativa, a hipóteses e o objetivo da pesquisa.

No capítulo 2, apresenta-se um artigo publicado no periódico *Environmental Modelling & Software*, intitulado: "*Systems capacity expansion planning: Novel approach for environmental and energy policy changes analysis*". Neste artigo apresenta-se uma breve introdução ao conceito da expansão de capacidade, revisão literária sobre metodologias empregadas para o planejamento da expansão de capacidade e as incertezas nas políticas energéticas, uma metodologia desenvolvida para as análises das mudanças destas políticas e uma aplicação para um caso hipotético. A política energética conduze o planejamento da expansão da capacidade pela preferência de seleção de tecnologias segundo suas emissões de CO_2 ou seus custos embutidos. A metodologia gera vários diferentes cenários de mudanças das políticas energéticas e seus *trade-offs,* pelo acoplamento de optimização por programação dinâmica e programação linear multi-objetivo. Os resultados da aplicação para um exemplo hipotético apresentaram: uma clara frente de Pareto, cenários das mudanças políticas abruptas deveriam ser evitados no lugar daqueles graduais e que políticas energéticas mais "verdes" em um dado estágio do planejamento não são necessariamente as melhores se considerado o horizonte de planejamento completo.

No capítulo 3, apresenta-se um artigo pronto para submissão à publicação no periódico: *Renewable & sustainable energy reviews*, intitulado: "*Looking for a robust energy policy in generation expansion facing climate change uncertainties/impacts*". Neste artigo, é apresentada uma revisão literária focada na incorporação dos efeitos das mudanças climáticas no planejamento da expansão de capacidade. Apresenta-se uma segunda metodologia desenvolvida, incorporando na metodologia apresentada no capitulo 2, os efeitos das mudanças climáticas a través da introdução dos fatores de capacidade de utilização e considerando seis cenários com condições climáticas diferentes. Para a seleção de soluções robustas é apresentado um critério usando distâncias normalizadas. A metodologia é aplicada ao subsistema eléctrico da região Sul do Brasil. Os resultados indicam um claro impacto das condições climáticas na performance dos diferentes cenários de mudanças das políticas energéticas, condições mais secas resultam em altas incertezas nos custos e emissões de CO_2. Os cenários de política energética são mais prováveis de serem robustos se dão preferência no início por mudanças de políticas de baixos custos para políticas de baixas emissões de CO_2 no final.

No capítulo 4, apresentam-se as conclusões e recomendações, assim como a resposta às perguntas da pesquisa, subsidiadas pelos resultados apresentados nos capítulos 2 e 3.

2 Systems capacity expansion planning: Novel approach for environmental and energy policy change analysis.

Systems capacity expansion planning: novel approach for environmental and energy policy change analysis

Ada Liz Arancibia [1]; Guilherme Fernandes Marques [2]; Carlos André Bulhões Mendes[3]*

Abstract

Planning for power systems generation expansion follows environmental policies incorporating technologies based on renewables to reduce CO_2 emissions. These policies are susceptible to unpredictable changes, given dynamic economic and political contexts. This paper analyzes the impact of changes in energy policies, motivated by different environmental objectives. The analysis is done through a novel approach coupling Dynamic Programming and Multi-objective programming to generate several energy policy scenarios and their trade-offs, representing plausible policy changes in the different stages of the planning horizon. The results indicate a clear Pareto front and that energy policy scenarios with abrupt changes should be avoided in favor of scenarios with gradual changes. "Greener" energy policies in a given planning stage are not necessarily the best ones considering the full planning horizon, considering the unfolding impacts of current decisions into the future. The approach is useful in improving planners´ future vision from myopic into a perspicacious one.

Highlights

- Future energy policy decisions are highly uncertain and subject to change.
- Facing uncertainty requires knowledge of economic and environmental tradeoffs.
- Integrating MOLP to optimize DP sub problems allows tradeoffs identification.
- Energy policy changes along planning horizon is important in capacity expansion.
- Policies to reduce CO_2 emissions tend to perform better if implemented gradually.

Keywords

Energy Policy; capacity expansion; power system planning; Multi-objective optimization; Dynamic programming.

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1. Introduction

Advances in technology change the way we produce, use and allocate resources, especially energy and water. For example, desalination plants have long been incorporated into water supply systems, while photovoltaic and wind plants are now part of power systems. Integrating renewable power sources into power grids is a common agenda worldwide given concerns regarding CO_2 emissions and climate change, resulting in the adoption of low-carbon technologies (Iyer et al. 2015). However, economic growth policies still drive national plans, and the occurrence of financial crises, global markets, and economy volatility, among other factors, draw a complex environment for planning. Decision-making must take into account uncertainty and the added complexity that may motivate policy change (Schwenker and Wulf, 2013). While one cannot be sure about the future, it is possible to evaluate how to best adapt current policies as our perception, priorities and knowledge change. The methodology proposed in this paper fulfills this goal.

Capacity expansion methodology is applied in planning for different public services including electrical power, water resources, schools, and roads, given most of those systems already exist. The main objective of capacity expansion is to determine the size and timing of facilities to be added at minimal costs (Luss, 1982). It might also require consideration of other objectives like minimizing emissions of greenhouse gas effects and the incorporation of renewables. All in a highly uncertain environment.

For power generation expansion planning, Dynamic Programming (DP) approaches have been widely applied, among other methods including stochastic optimization, genetic algorithm (GA), fuzzy set theory, artificial neural networks, network flows and simulated annealing (Kagiannas et al., 2004). When other objectives need to be included, the problem can be addressed with multi-objective optimization, (e.g. multi-objective linear programming - MOLP), stochastic optimization, multi-criteria analysis, decision analysis and tradeoff analysis (Tekiner et al., 2010). Uncertainties have been included by focusing on demand (Davis et al. 1987), demand and resources availability (Gorenstin et al. 1993), demand and price parameters (Ahmed et al., 2003). Li et al. (2014) studied policies in generation expansion planning, including renewables as constraints with a minimum percentage. Popular incentive systems as feed-in tariffs, quota obligation, emission trade and carbon tax can also be incorporated as constraints (Careri et al. 2011). Rebennack (2014) included fulfillment of emissions quotas as an objective, while Aghaei et al. (2013); Tekiner et al. (2010) had minimization of CO_2 emissions as an additional objective function. Most recent efforts consider the inclusion of modeling high quantities of renewable generation (Vithayasrichareon et al., 2015). The methodology in the later applies generation portfolio analysis concepts to account for risk and uncertainties of gas and carbon prices. The role of coal, gas, and renewables is analyzed for peak demand in future (2030) generation portfolios in the Australian Power System.

The inclusion of policy uncertainty in recent literature about power systems expansion is still limited. Most of the work in environmental policy evaluates causal effects of policies implemented by governments and authorities in terms of achieving outcomes of interest (Percoco, 2014). In planning expansion capacity, Zhou et al. (2011) investigate an optimization approach to design incentive policy for investment in renewable energy in generation expansion planning. Zhou et al. (2013) apply a planning approach associated with a fractal-based robust methodology for environmental policy analysis.

When policy uncertainty is investigated, it often focuses on financial research and the influence of government policy changes over stock prices. As in Pástor & Veronesi (2012), who define two types of uncertainties: political uncertainty that relates to uncertainty about whether the current government policy will change; and impact uncertainty, corresponding to uncertainty about the potential impact of new government policy on the profitability of the private sector.

Some examples of environmental policy effectiveness and the impact related to renewable energy portfolios and others to climate policies such as taxation on fossil fuels are highlighted through the “green paradox” concept, put forth by Sinn (2012). Li (2014) warns about the undesirable effects of climate policies and the need for their improved design. Since climate policies are subject to uncertainty, they become vulnerable to changes.

Germany, one of the European countries that have adopted policies for deploying low-carbon technologies, has more than doubled its renewable energy sources between 2000 and 2009, where the wind power is the most important (Reuter et al. 2012). However, implementation of such policies has a cost. In 2013, it was estimated that an amount of US$120 billion was spent in global subsidies for renewable energy technologies (IEA, 2014). Recently the UK has announced an earlier end to subsidies for new on-shore wind farms (BBC NEWS, 2015). Australia’s prime minister banned the federal clean energy from investing in wind power (Schlanger, 2015). While reasons behind these policy changes are beyond the scope of this paper, they indicate how policies are subject to change.

If policies change during the planning process, adjustments are necessary to prevent the plan from becoming obsolete. This fact may tempt politicians to opt for broader indicative strategies that may not give clarity or certainty about other interests, as highlighted by Parker and Doak (2012). It will be useful for planners, managers and decision makers to understand in advance the possible impacts of the policy they intend to change on the main plan’s effectiveness.

This paper presents an approach for analyzing such impacts, using a combination of multi-objective optimization (MOLP) and dynamic programming (DP), applied to the power capacity expansion problem. Our approach considers specific policy changes at different stages of the time horizon plan and their outcome in terms of cost, CO_2 emissions and decisions to invest in different power sources. The approach generates a Pareto diagram with multiple possible policy change scenarios. To illustrate the methodology, a simplified planning generation capacity expansion is presented, where policy change scenarios have been analyzed and classified.

This paper contributes to the existing body of knowledge by introducing a novel approach to evaluate how a given change on "*energy policy"* may affect the final outcome in terms of cost and CO_2 emissions. While change may be unavoidable giving uncertain exogenous factors, how it is conducted may yield different trade-offs. The methodology proposed in this paper is designed to identify dominated, undesirable trade-offs, so the decision maker can focus on the best ones (at the Pareto frontier) when faced with necessary changes. The proposed methodology couples DP and MOLP to solve a multi-objective optimization problem in expansion capacity, classifying policy changes according to its impact on the optimal power expansion strategy. This illustrates that not all logical policy changes will deliver the expected results.

The remainder of this paper is organized as follows: Section 2 presents the proposed approach. Section 3 describes an application through a hypothetical planning generation capacity expansion. Section 4 shows the results of the application for different scenarios. Finally, in section 5 the conclusions are presented.

2. Proposed approach

The methodology proposed here analyzes energy policy changes and its effect through the planning time horizon over the generation capacity expansion in terms of costs, CO_2 emissions and mix of selected energy generation sources, considering:

a) Technologies that use different natural resources.

b) Intermediate decisions about the selection of technologies that will affect the final planning objectives.

c) Policies that could change from one stage to another during the planning process, which are the basis for technology decisions.

d) The leading objective of capacity expansion is fixed at the beginning of the process.

This approach is based on Bellman's Principle of Optimality, summarized by Lew & Mauch (2007) as "optimal policies have optimal sub- policies." The capacity expansion problem will be optimized with a policy of minimum costs ("*leading policy"*), with sub-problems divided into stages and solved using Dynamic programming (DP) for capacity expansion methodology.

In the capacity expansion problem, a possible total incremental capacity is represented by the decision variable *x*. For each possible *x* in a given DP stage, there are multiple combinations of individual power sources r that add up to *x*. A multi-objective linear programming algorithm – MOLP is run at each DP stage to optimize the values of *r* considering two objectives: minimize cost and minimize CO_2 emissions. The MOLP is constrained so that the sum of all *r* is equal to *x*. Given the two objectives, MOLP produces a Pareto front indicating the trade-offs (Meza et al., 2007) for each possible *x*, at each DP stage. Each point in the Pareto front is a combination of *r* values resulting in a given cost and a given CO_2 emission. The points also receive a label indicating the level of preference among the two objectives (e.g. a point with high cost and low CO_2 emission indicates a stronger preference towards environmental protection).

The question now is which point (i.e. combination of r values) should be selected so the DP can move to the next stage. To answer this, we first define "*energy policy*" as the level of preference between the two objectives behind a given point in the Pareto front. For example, a strongly environmental energy policy means a point at the far right of a given Pareto front (low CO_2 emission, high cost). We also define a "*change in the energy policy*" when the level of preference between the two objectives changes from one DP stage to the next. However, when and how the preferences (and the energy policy) change is highly uncertain. To deal with this uncertainty we now define an "*energy policy scenario*" as a sequence of energy policies in time where there may or may not be a change in the energy policy. Considering a Pareto front with *m* points and a DP with T stages one has a total of m^T energy policy scenarios to represent all possible changes in energy policy.

Thus, each possible energy policy scenario determines which point (i.e. combination of r values) should be selected so the DP can move to the next stage. We run the DP model m^T times to screen through all different possibilities. Generation of all possible scenarios is a methodology increasingly preferred among planners giving it represents a broader range of alternative situations rather than a relatively limited range of future conditions represented by probability distribution as stochastic approaches (Beh et al., 2015 ; Vithayasrichareon et al., 2015).

The results provided by the methodology proposed here could, for example, be used by decision-makers in a context where a given environmental target is defined in the future (i.e. a CO_2 reduction agreement which gives the joining parties some lead time to adapt). Starting from a current environmental policy, the results from our model evaluate the different possible energy policy scenarios (trajectories) that arrive at the designated target in the future, along with the trade-offs. Such evaluation will allow poorly performing (dominated) trajectories to be identified and avoided.

As pointed out in Loucks et al (1981), the solutions of capacity expansion models are not intended to be used as guidelines for the entire horizon plan, but rather a reference for the first stage when the decision is made. However, given environmental agreements (e.g. Kyoto Protocol) often require a lead time to be met, it is necessary to somehow represent the emissions´ target in the planning horizon and draw the decisions´ trajectory that will reach it, even though the future decisions are likely to be updated.

Given that the results from our model explore different combinations of energy policy change scenarios, it will also inform, for a given starting energy policy, the range of variation in the trade-offs for the next decision, which is a measure of uncertainty. By knowing this uncertainty, decision-makers can elaborate responses for the best and worst-case scenarios (e.g. creating environmental accounts to fund future change, CDM credits, emissions´ markets, subsidy or taxation programs).

The approach is implemented through three steps: problem configuration, mix sources optimization, and Dynamic programming, explained as follows.

Step 1: Problem Configuration.

First, the problem is configured to be solved with a backward-moving discrete dynamic programming algorithm. The state variable s_t represents the existing capacity at the beginning of stage t, and s_{t+1} represents the existing capacity at the end of stage t. The decision variable x_t represents the added capacity in stage t.

The objective function and respective constraints are formulated to minimize costs ("*<u>leading policy"</u>*) while satisfying the demands.

$$\boldsymbol{F_t(S_t) = minimum\,\{C_t(s_t, x_t) + F_{t+1}(s_{t+1})\}} \qquad (1)$$

s.t.

$$\boldsymbol{s_{t+1} = x_t \mp s_t \;\; ; \;\; \forall\, t} \qquad (2)$$

$$\boldsymbol{s_t \geq D_t \,; \;\; 0 \leq s_t \leq s_{max,t} \,; \;\; 0 \leq x_t \leq x_{max,t} \;\; ; \;\; \forall\, t} \qquad (3)$$

Where: $C_t(s_t, x_t)$ is the present value of the cost capacity expansion x_t at stage t given an initial capacity of s_t, considering the interest rate i; $F_{t+1}(s_{t+1})$ is the minimum optimized cost at stage $t+1$, with $F_{T+1}(s_{T+1}) = 0$. Equation (1) is the recursive equation and equation (2) is the state equation. D_t is the demand at the beginning of stage t, which can never exceed the capacity at that stage. Maximum values in equation (3) are defined by:

$$s_{max} = D_{T+1} \;\; ; \;\; x_{max,t} = D_{T+1} - s_t \; ; \quad \forall \, t \qquad \textbf{(4)}$$

From the formulation, the possible $\underline{x_t}$ values at each state t are subject to:

$$0 \leq \; x_t \leq D_{T+1} - D_t \qquad \textbf{(5)}$$

Figure 1 shows the definition of all the variables, as well the discretization of Demand at each stage and all the possible candidate values for x_t.

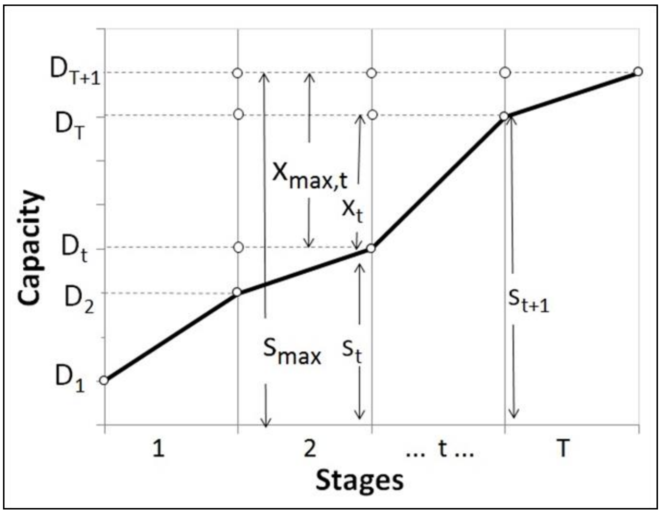

Figure 1. Capacity expansion formulation

Considering expression (5), a defined number of possible candidate values for x_t, in addition to zero, are generated for each stage as follows: for the first stage, $t=1$ there will be T possible values defined by: D_2-D_1, D_t-D_1…D_{T+1}-D_1; for the intermediate stages, t=2 to t=T-1 will be (T-1) + (T-2) + … + 1 possible values defined by the difference among possible next demands and the state variable at each stage; and for the final stage just 1 possible value for $x_t \neq 0$. For example, for 4 stages there is a total of 14 possible “candidate values” for x_t, besides zero. All these “candidate values” for x_t are the input for the next stage and are represented by x_t^c.

Step 2.Mix sources optimization.

Each possible candidate value x_t^c at stage t is composed by a mix of n different type of available power sources r, as defined by equation (6):

$$x_t^c = \; r_1 + r_2 + \cdots + r_n \;\; ; \quad \forall \, \boldsymbol{t} \qquad \textbf{(6)}$$

This is the “coupling equation”, which links the dynamic programming optimization and the MOLP. There are many different possible combinations of r_n resulting in the same x_t^c. The best mix values will be found through the MOLP, which has two optimization objectives: minimum costs and minimum CO_2 emissions. The multi-objective problem is formulated as:

$$\boldsymbol{FO_1}: \boldsymbol{minimum} \sum(\boldsymbol{IC_i}.\boldsymbol{r_i} + \boldsymbol{OC_i}.\boldsymbol{r_i}) \quad ; \quad \boldsymbol{i = 1 \dots n} \tag{7}$$

$$\boldsymbol{FO_2}: \boldsymbol{minimum} \sum \boldsymbol{CO_{2_i}}.\boldsymbol{r_i} \quad ; \quad \boldsymbol{i = 1 \dots n} \tag{8}$$

s.t.

Demand constraints: $$r_1 + r_2 + \cdots + r_n \geq x_t \,; \quad \forall\, \boldsymbol{t} \tag{9}$$

Operating constraints: $$OpC(r_i) \geq B \tag{10}$$

Where IC_i is the investment cost for each source r_i; OC_i is the operating cost related to the source r_i; CO_2 are the emissions related to the source r_i; $OpC(r_i)$ represents operating constraints as a function of the sources r_i and B is the respective condition of operation (e.g. limited capacity generation or reliability condition). Expression (7) and (8) are linear, considering that costs and CO_2 emissions depend on the values of r_i.

The formulated problem results in a multi-objective linear programming – MOLP, which is solved through an improved variation of the ε-constraint approach, denominated augmented ε-constraint (AUGMECON), which was introduced by Mavrotas (2009). The improvements introduced by the augmented ε-constraint approach can be summarized as follows. First, it uses a lexicographic optimization for every objective function, focusing on just Pareto optimal solutions. Second, it modifies the optimization expressions (objective functions and restrictions) forcing the algorithm to produce only efficient solutions. Finally, it improves the process through the early exit from a nested loop when the problem becomes infeasible. The last modification accelerates the algorithm significantly in the case of several (more than three) objective functions. For a more comprehensive explanation refer to Mavrotas (2009).

The solution of the problem defined in (7) through (10) provides a discrete Pareto front with *m* values of optimal Costs and CO_2 emissions for each possible combination of sources r_i for their correspondent possible values x_t^c. Figure 2 shows an example composed of three types of sources, with *m* points in the Pareto front. Each point represents a solution. In this example, the solution “*m-1*” in the Pareto front is related to the combination of energy sources “*m-1*”, mainly composed of sources r_1 and r_3 with a small portion of source r_2. This combination has a resulting low CO_2 emission and high costs (point located far on the right in the Pareto front), which represents a preference for environmental energy policies. Likewise, each particular solution represents an “energy policy” with its preferences.

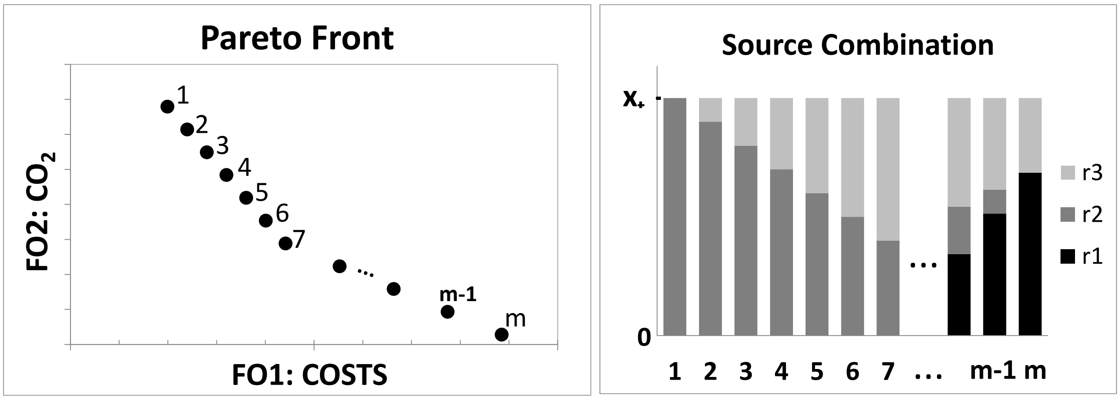

Figure 2. Example of MOLP for x_t^c

The process is the same for all the x_t^c at each stage, resulting in a Pareto front with a respective source combination for each x_t^c from the previous step. We call these optimal solutions “MOLP Pareto front”, and label each of the discrete points with a number that represents a level of preference among the two objectives, called “*energy policy.”*

Step 3. Dynamic Programming (DP)

To solve the generation capacity expansion with dynamic programming, following the “*leading policy”* of minimum costs, we define the values of the cost for each of the candidate value x_t^c in each stage. This is done by applying an “*energy policy*” for each stage. In addition, considering that “*energy policy”* could change from one stage to another, an “*energy policy scenario*” will be defined by a sequence of numbers indicating the points selected from the MOLP Pareto front at each stage. For instance, for 4 stages, an “*energy policy scenario*” could be: “1-1-2-2”; which means that for all possible candidate values x_t^c the point 1 will be selected from the respective MOLP Pareto Front for the first and second stage and the point 2 will be selected respectively for the third and fourth stage.

The problem defined by equations (1) through (4) is then solved with a backward moving dynamic programming algorithm, beginning at t=T and finishing at t=1. Equation (11) is considered to compute the CO_2 emissions along the time horizon planning:

$$\boldsymbol{Total\ CO_2 emissions} = \sum_{\boldsymbol{t=1\ldots T}} \boldsymbol{CO_2(x_t, s_t)} \tag{11}$$

Where $CO_2(x_t,s_t)$ are CO_2 emissions due to expansion x_t at stage t given an initial capacity s_t.

The final outputs of DP, resulting from the application of a defined "*energy policy scenario*", are the total cost of the capacity expansion, total emissions of CO_2 from the operation of the total capacity and the capacity expansion sequence with a mix of sources by stage.

To take into account the high uncertainty in the decision-making process involving energy policy, we have included multiple scenarios with different possible energy policy changes along the planning horizon. Thus, for T stages, it will result in $\boldsymbol{m^T}$ "*energy policy scenarios*", each with its respective values of x_t^c, r_{it}, $C_t(s_t,x_t^c)$ and $CO_2(x_t^c)$. DP runs through all those "*energy policy scenarios*".

The final output of the whole optimization process are $\mathbf{m^T}$ results of "*energy policy scenarios*", each one with their respective total Cost, total Emissions of CO_2 and capacity expansion sequence with a mix of sources by stage, as shown in Figure 3.

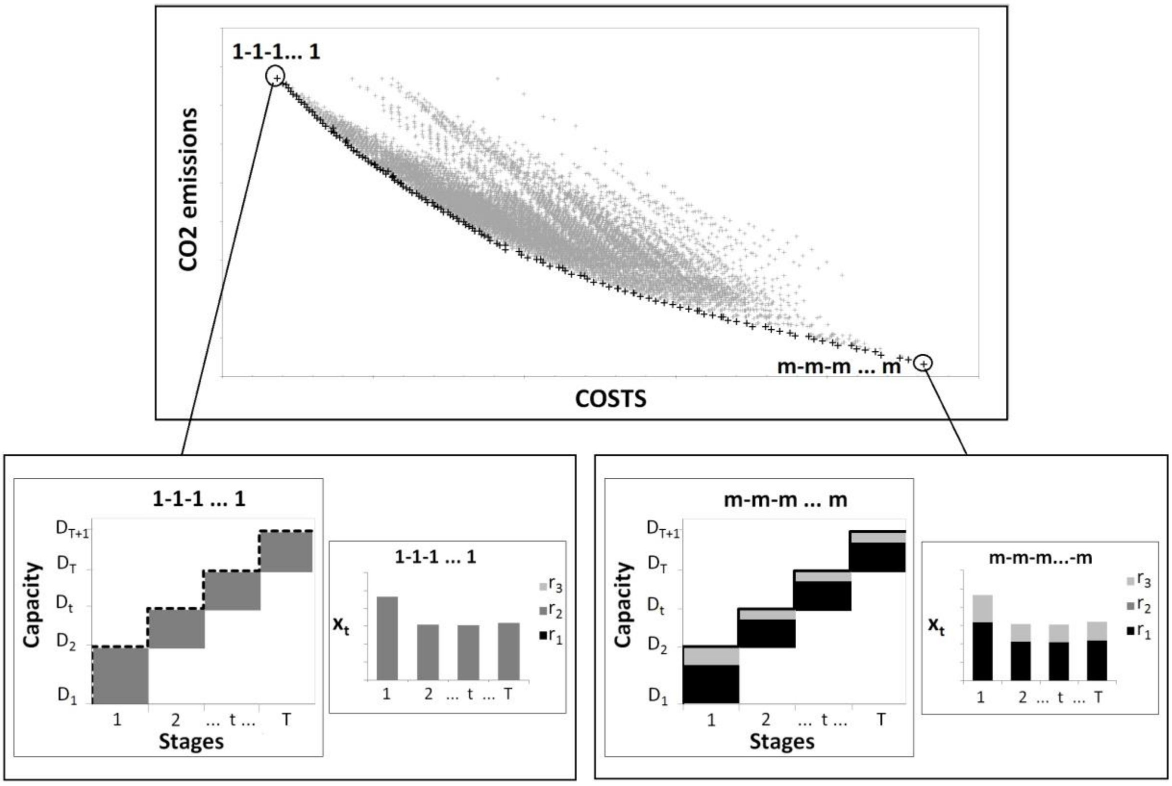

Figure 3. Final output

Figure 3 presents the $\boldsymbol{m^T}$ solutions. The extreme values correspond to opposite extreme "*energy policy scenarios*" of minimum costs (1-1-…-1), upper left corner, and minimum CO_2 emissions (m-m-…-m), lower right corner. The other values correspond to different policy mixes (such as 1-1-1…-m or 1-2-1-1…1), which represent changing policies from one stage to another (i.e. switching priorities between environmental and economic objectives). All the process is summarized in Figure 4.

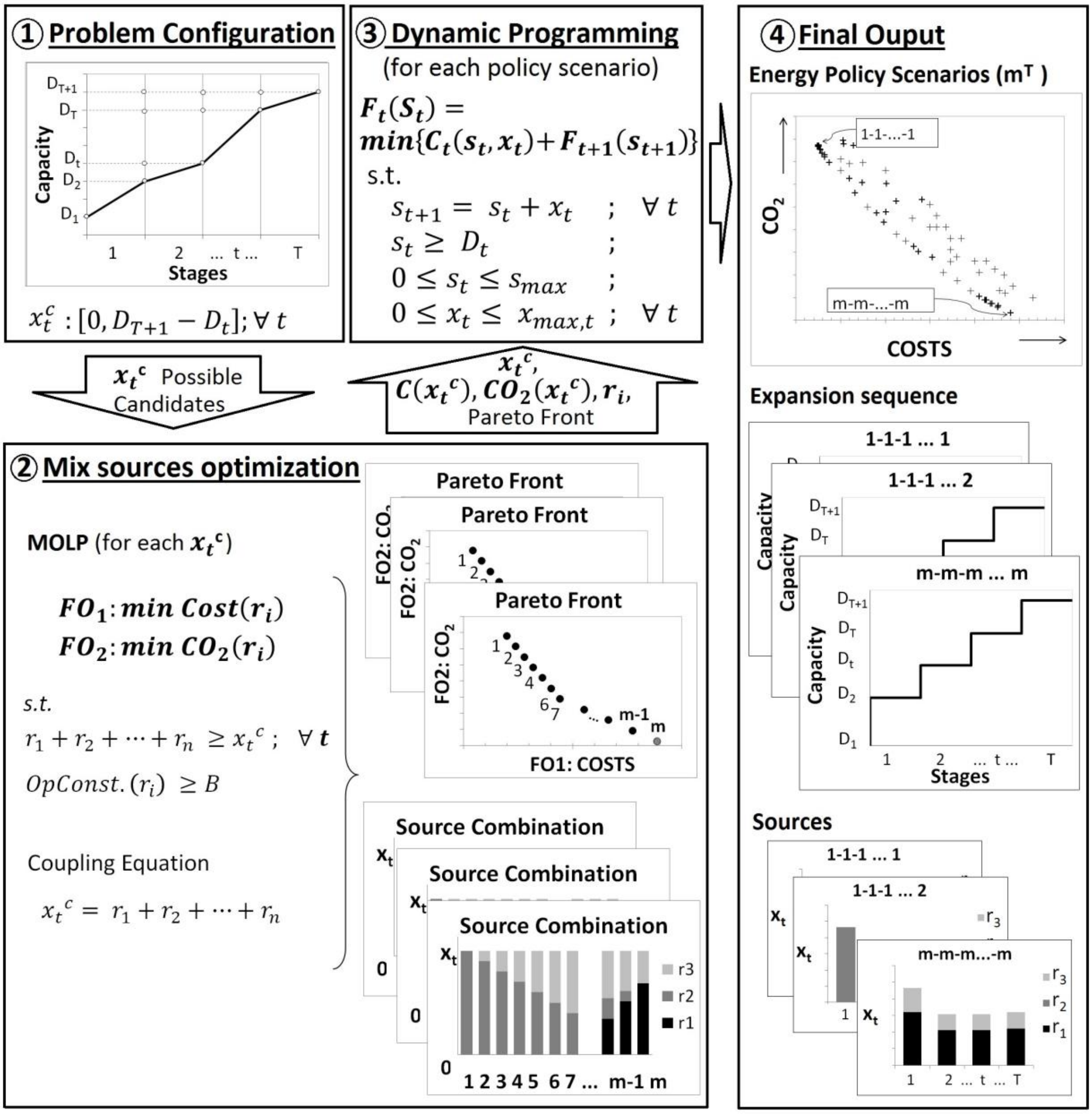

Figure 4. Process sequence

3. Application

The proposed approach is applied to a hypothetical generation capacity expansion problem to demonstrate its concept.

3.1 Problem configuration

A generation capacity expansion planning horizon of four stages is considered. At each stage, an expansion decision is made.

An Interest rate of 18% per stage is adopted. Future expected demands are shown in Table 1. The main characteristics of the available sources are shown in Table 2. The mean capacity factor of the whole system in the last 30 years was 0.49 from a range of 0.43 to 0.56. The inclusion of new units is expected to maintain at least the mean value, to guarantee efficient use of the installed capacity. The initial installed capacity is 122,614 MW.

Table 1 Capacity Demands by stage

Stage: t	**1**	**2**	**3**	**4**	**5**
Demand at beginning of stage: D_t (MW)	122,614	131,907	138,072	142,777	150,595

Table 2 Characteristics of the available sources

Source type	**Investment Costs (10^6 US$/MW)[1]**	**Variable Costs (US$/MWh)[1]**	**CO_2 emissions (Ton/GWh)[2]**	**Capacity Factor[1]**
Hydraulic	1.20	2.413	26	0.58
Thermal	0.867	10.233	628.67	0.85
Wind	1.00	10.00	26	0.25

Source: [1]. From Lucena, et al., (2010, p. 349)*, average values for Thermal considering natural gas and coal. [2] Mean values from WNA* (2011, p. 6)*, average values for Thermal considering natural gas and coal.*

3.2 Problem formulation

The first step is the generation of discrete values for the possible capacity expansion at each defined stage. There are three types of power sources: r_1 for hydraulic, r_2 for thermal and r_3 for wind, which are considered in the coupling equation. The values of *r* are expressed in MW, representing the generation capacity of each type of source.

Based on the costs, CO_2 emissions and operation conditions related to each source *r*, the MOLP is expressed by the dual objectives in (12) and (13).

$$\boldsymbol{FO_1: min\ Costs: 1.221.r_1 + 0.9566.r_2 + 1.0876.r_3} \qquad [10^6\ \text{US\$}] \qquad (12)$$

$$\boldsymbol{FO_2: min\ CO_2: 0.278.r_1 + 5.507.r_2 + 0.278.r_3} \qquad [10^3\ \text{Ton}] \qquad (13)$$

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall\, t$ [MW] (14)

Operating: $0.58.r_1 + 0.85.r_2 + 0.25.r_3 \geq 0.49.(r_1 + r_2 + r_3)$ [MW] (15)

Coefficients in equation (12) represent the total costs (investment + variable) in Millions of US$ for each MW of the sources *r*. Variable costs are estimated by year considering 8760 hours, same in equation (13), for CO_2 emissions related to each type of source. Equation (14) constrains the quantities sources to the demand both expressed in MWs. Equation (15) represents a relationship between the individual capacity factor and the required total system capacity factor. These are operational conditions of the power system.

The MOLP is solved using the AUGMECON methodology (Mavrotas, 2009). The parameters used are eps=1^{-3}, grid points: g_k = m-1 = 10. The solver CPLEX is chosen for the optimization, and a discrete Pareto front with the optimal solutions for CO_2 emissions and costs is generated. The number of discrete values are defined by the grid points, which for the current example results in eleven values. Each point of the MOLP Pareto front is labeled with a number *m*. Lower values of *m* represent preferences for lower cost policies and higher values close to 11 represent preferences for low CO_2 emissions.

The backward moving dynamic programming algorithm is implemented through Matlab. Considering four stages and the eleven values of the discrete Pareto front, all the possible permutations yield 11^4 = 14,641 energy policy scenarios.

3.3 Energy Policy scenarios

The analysis of the energy policy scenarios involves three parts: (a) all 14,641 energy policy scenarios are evaluated considering both the CO_2 emissions and cost objectives in order to identify the non-dominated ones (Pareto front); (b) all the energy policy scenarios are characterized in terms of how the energy policy changes in each scenario (i.e. the sequence of changes throughout the planning horizon) and (c) the non-dominated energy policy scenarios identified in (a) are then matched to the characteristics identified in (b). Five types of change are identified:

- *Resistant to change*: The energy policies selected are in the same position of the MOLP Pareto Front for all stages, (e.g. 1-1-1-1, 2-2-2-2, 11-11-11-11). This configuration represents a constant energy policy being adopted for the whole planning horizon. A preference for minimum CO_2 emissions for all the stages is represented by 11-11-11-11.

- *Constant change*: The energy policies selected are changing progressively in each stage (e.g.1-2-3-4, 2-3-4-5, 3-4-5-6). The configuration in this example represents a gradual change preference from minimum costs to minimum CO_2 emissions.

- Gradual changes: The energy policies selected change their preferences gradually. For example, considering a low-cost scenario (1-1-1-1), a gradual improvement on the CO_2 emissions objective may be represented by 1-1-1-2 or 1-1-2-2 or 1-2-2-2. The energy policies selected here are in the closest position of the MOLP Pareto Front.

- Abrupt changes: The energy policies selected change their preference abruptly (e.g. 1-1-1-11, 1-1-11-11, or 11-11-11-2, 2-2-2-11). This configuration represents a policy change from a strong minimum costs preference to minimum CO_2 emissions preference (or vice-versa). The energy policies selected here are far from the MOLP Pareto Front.

- Regretting changes: The energy policies present an initial pattern (resistant to change, constant change or gradual change) followed by an abrupt change and return to the previous pattern (e.g. 1-1-11-1, 1-2-11-3, 11-11-1-11). This configuration represents constant or gradual policy changes, followed by abrupt changes and then regret reverting to the initial pattern.

4. Results

Figure 5 shows the 14,614 different energy policy scenarios and their performance considering both CO_2 emission and cost objectives. The non-dominated values define a clear Pareto front (black dots), while most of the dominated values are concentrated in the middle concave part. The scattered points farther from the Pareto front (upper right of the chart) were identified as abrupt changes policies (e.g. 11-11-11-1) or regret abrupt changes (e.g. 11-11-1-11). Values close to the non-dominated ones come from resistant to change, constant or gradual policies (e.g., 8-9-10-11, 7-7-7-7 or 1-1-1-1). In the upper left region of the chart there are values with similar CO_2 emissions but different costs. These are policies that must be carefully observed as they represent failed attempts of policy changes to reduce CO_2 emissions that ended up with a significant cost increase. On the other extreme (lower right of the chart) we see no failed attempt to reduce costs (i.e. it is always possible to reduce costs, albeit with a given trade-off in terms of increased CO_2 emissions). All cost and CO_2 emission figures are totals for the whole planning horizon (20 years).

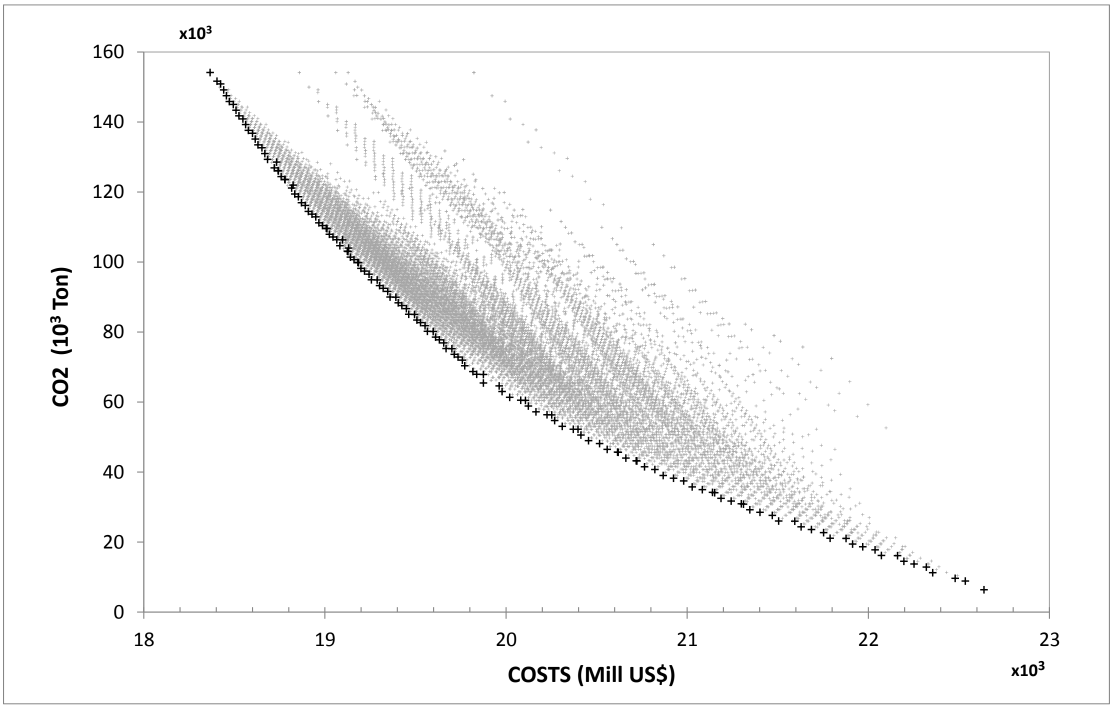

Figure 5. Total final results

From all 14,614 policies, 80 were selected besides the non-dominated ones (shown in Figure 6). These values represent samples of different policy scenarios described above.

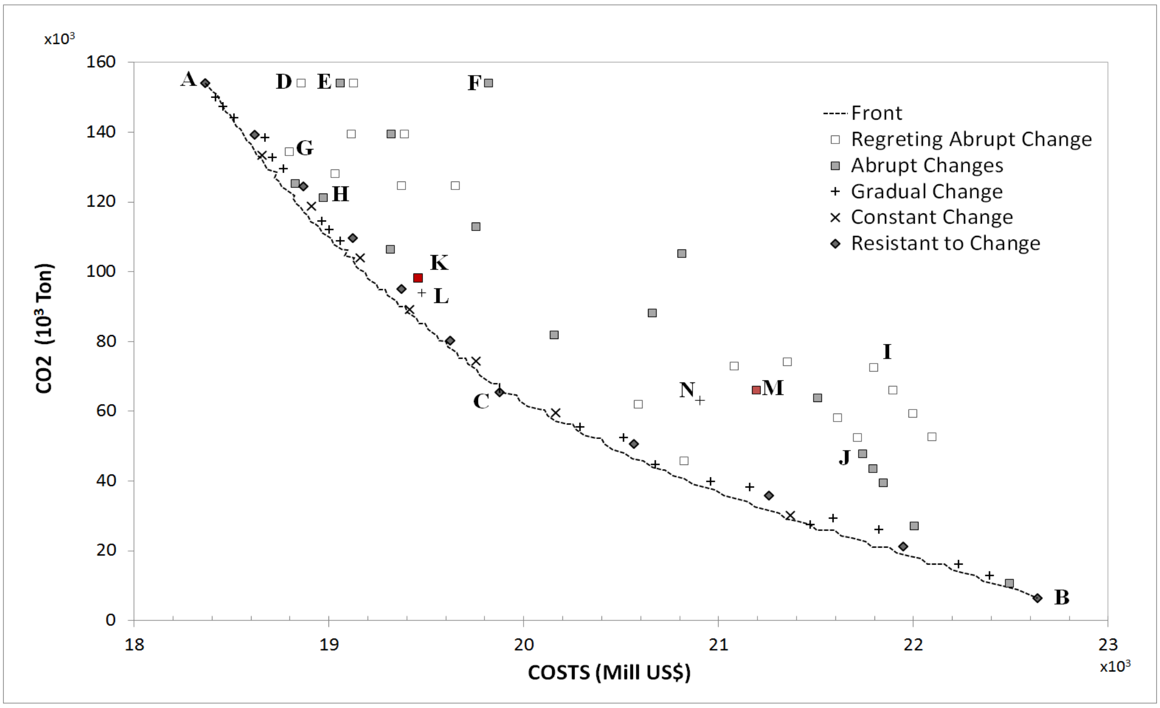

Figure 6. Selected results

Table 3 shows the values and the respective energy policy scenario for the solutions indicated from A to N. The values A, B, and C correspond to constant policies (resistant to change) which are non-dominated solutions. As shown in Figure 6, the other resistant to change policies are close to the non-dominated front.

Most of the gradual and constant change policies are close to the non-dominated front. Meanwhile, abrupt changes can be close or far from the front. Different energy policy scenarios might have the same CO_2 emissions values, but very different costs (e.g. A, D, E and F), as shown in Table 3. Some of these scenarios present poor performance and should be avoided because, despite the cost increase, there is virtually no reduction in CO_2 emissions (e.g. D, E and F, figure 6).

Table 3 Policy Scenarios A to M results

Scenario	**Policy**	**Costs Mill US$**	**CO_2 10^3 Ton**
A	1-1-1-1	18,365.837	154,091.367
B	11-11-11-11	22,638.454	6,351.687
C	7-7-7-7	19,874.884	65,447.559
D	1-1-**11**-1; 1-1-**10**-1	18,858.920	154,091.367
E	1-1-1-**11**; 1-1-1-**10**	19,060.174	154,091.367
F	1-**10**-1-**10**; 1-**10**-1-**11** 1-**11**-1-**10**; 1-**11**-1-**11**	19,822.556	154,091.367
G	1-1-**9**-1	18,797.015	134,217.447
H	1-1-1-**9**	18,973.010	121,068.140
I	11-11-**1**-11	21,798.126	72,473.127
J	11-11-11-**1**	21,741.063	47,630.727
K	1-2-9-9	19,462.186	97,939.095
L	1-4-8-9	19,475.140	93,913.095
M	11-11-2-2	21,194.127	65,860.983
N	11-8-7-2	20,903.701	63,205.143

All cost and CO_2 emission figures are totals for the whole planning horizon (20 years)

By comparing A, D, E and F, the impact of policy changes is evident. A decision maker only interested in reducing costs would choose policy scenario A (1-1-1-1), which results in poor CO_2 emissions performance (154.09 million tons) and an 18.36 US$ Billion cost (the lowest cost in the analysis). An attempt to provide a "greener" energy policy involving an abrupt change by switching investment in renewable energy sources in the last stage (e.g. policy scenario E: 1-1-1-11 or 1-1-1-10) would boost the costs to 19.06 US$ Billion but would result in no CO_2 reduction benefit.

This result can be explained by the selected increase capacity considering the minimum total cost for the time horizon plan. If a costlier "greener" energy policy takes place in the last stage, the earlier capacity expansion occurring in stage 3 is strongly based on non-renewables, which are less expensive. This behavior can be seen in figure 8 through the red line. While providing a lower total cost, this energy policy offsets the CO_2 emission reduction provided by the "greener" energy policy that takes place later. The final result is a more expensive overall solution with no CO_2 emission reduction. It indicates that a change in energy policy with apparently good performance in a given stage may prove to be a dominated solution in the long run. This type of energy policy scenario should be avoided.

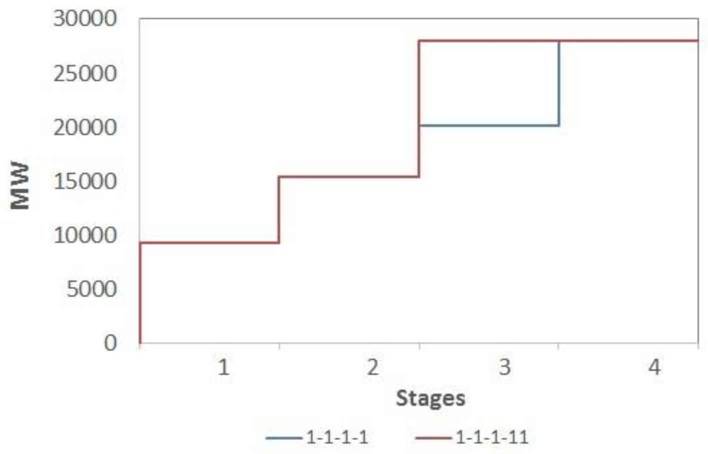

Figure 7. Capacity Increase

Energy policy scenario 1-1-1-10 has a result similar to 1-1-1-11. It is observed that different energy policy scenarios could generate the same Total Cost (Investment and operational) and CO_2 emissions in the time horizon plan, as shown in Table 3.

To achieve a reduction in CO_2, a different energy policy scenario must be applied. Following the same previous example, to reduce CO_2 emissions with a change in the energy policy at the last stage, one could adopt energy policy scenario 1-1-1-9 (scenario H), with 0.33 million tons of CO_2 less than energy policy scenario 1-1-1-1 and with an additional cost of US$ 0.61 Billion. If, however, the energy policy change is made in the third stage rather than in the last (scenario G: 1-1-9-1) the cost is reduced but with higher CO_2 emissions.

Efforts to reduce the final cost with abrupt policy change present different response. For example, an energy policy scenario with preference for minimum CO_2 emissions throughout the four stages of the planning horizon (11-11-11-11) would result in US$ 22.6 Billion total costs and 6.35 million ton CO_2. An attempt to switch to a cost saving energy policy in the last stage (11-11-11-1) would reduce the cost to US$ 21.7 Billion but boost the CO_2 emissions to 47.6 million ton, indicating a trade-off. If instead, the cost saving policy is adopted earlier (11-11-1-11) the final cost is similar (US$ 21.8 Billion), but the CO_2 emissions trade-off is significantly higher at 72.5 million ton. These results indicate that, in general, applying an environmental policy favoring lower cost technology (but with high CO_2 emissions) at the earlier stages will reduce the cost due to the effects of time value, but there will be exceptions that are explained as follows.

Table 4 shows costs for energy policy scenarios with an energy policy changing its position in the different stages. To illustrate, suppose a given energy policy (e.g. “9”) being selected in either one of the four decision stages, which results in four different energy policy scenarios (the first four lines in Table 4, from 1-1-1-9 to 9-1-1-1). The “costs difference” column refer to the cost of a given energy policy scenario minus the cost of the energy policy scenario in the previous line of the table.

Table 4 Energy Policy Scenarios and stage variability

Energy Policy Scenario	**Costs Mill US$**	**Costs difference**	**Costs difference Expectative**
1-1-1-9	18,973.01		9 in early stages produce higher costs than 9 in late stages. (+) Costs difference is expected.
1-1-9-1	18,797.01	-176	
1-9-1-1	19,032.51	235.5	
9-1-1-1	19,551.65	519.14	
11-11-11-1	21,741.06		1 in early stages produces lower costs than in final stages. (-) Costs difference is expected.
11-11-1-11	21,798.13	57.07	
11-1-11-11	21,508.93	-289.2	
1-11-11-11	20,662.88	-846.05	

Considering the value of money through time, one would expect that high-cost investments made earlier would produce higher total cost than high-cost investments made later. Energy

Policy 9 is costlier than 1, and its selection in early stages results in higher cost than in later stages, as shown in Table 4, except for the third stage. This exception could be explained by the lower minimal expansion required for the third stage (from table 1: 142,777 – 138,072 = 4,705 MW) as it can be seen in Figure 8. The effects of energy policy changes in the final selection of different sources, as well the scheduling of the increments can be seen in the same figure. A significant increase in just one of the sources in one stage as a result of policy scenario 11-11-1-11 (i.e. thermal in stage 3) and 11-1-11-11 (i.e. thermal in stage 2) could also result in higher risk, given it lacks the flexibility usually associated with a more diverse portfolio of energy sources.

For the illustrated case, energy policy changes at the last stages to reduce emissions haven't worked in a proportional way. Those changes could work for the case of cost reductions. But it will also depend on the projected demand of the different stages. Changes in policies also affect final investment scheduling.

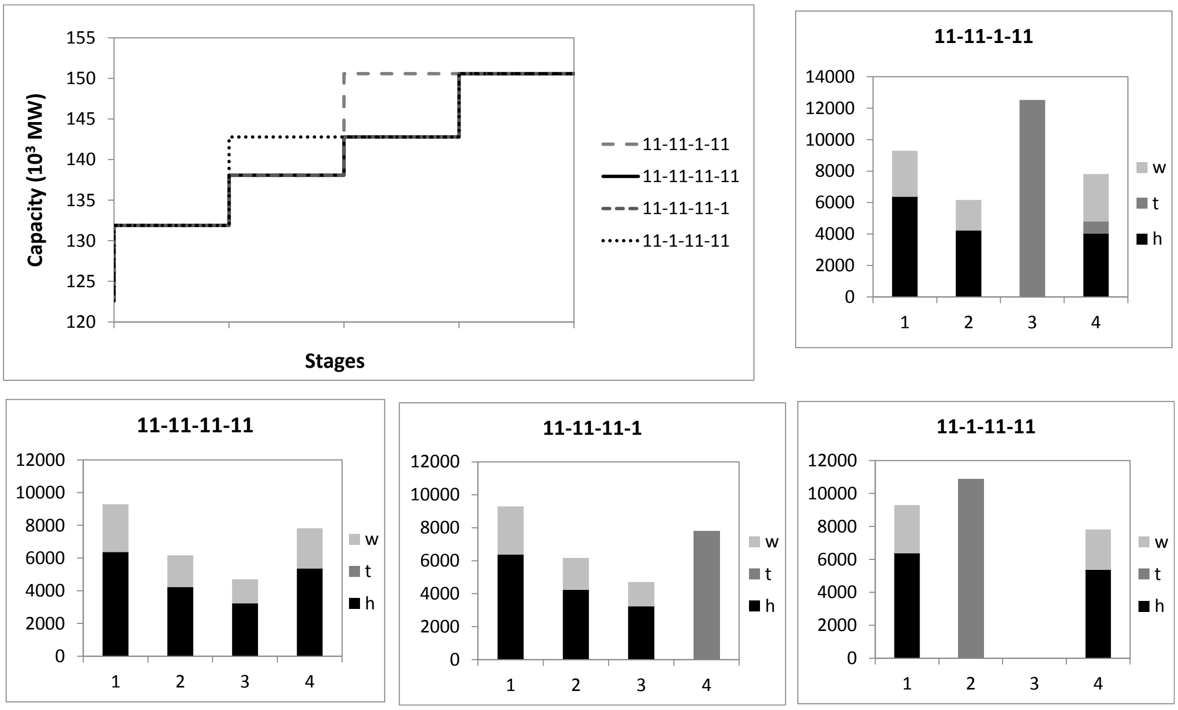

Figure 8. Expansion sequence and sources results

For energy policy scenarios defined as resistant to change, constant change or gradual changes, the results are localized very close or in the Pareto front. For example, policy scenario C (7-7-7-7) might be a good "greener" alternative to high CO2 emissions policy scenario A (1-1-1-1) with a US$ 1.53 billion cost increase and a considerable CO_2 emissions reduction (88.6 million tons less).

According to figure 6, the gradual change energy policy scenarios tend to perform better than the abrupt change scenarios for most the situations. For example, consider the least cost (US$ 18.36 billion) and high CO_2 emissions (154.09 million tons CO_2)energy policy scenario A (1-1-1-1). If one expects to improve environmental performance by establishing a CO_2 emissions goal by the end of the planning horizon, it could be attained in different ways. Suppose the goal is to arrive at energy policy scenario 9. If implementation of more renewable energy sources is delayed to end of the planning horizon, the energy policy may change abruptly, for example, producing a policy scenario such as K (1-2-9-9), with US$ 19.46 billion cost and 97.94 million tons CO_2. This presents a significant reduction in CO_2 emissions from policy scenario A, at a cost trade-off. However, if the change follows the more gradual route 1-4-8-9 (policy scenario L), the resulting cost is slightly higher, at US$ 19.48 billion, but emissions are much lower at 93.91 million tons CO_2. Both scenarios present very similar cost performance, but the gradual change does so at lower emissions. This indicates that the gradual energy policy scenario is likely a better approach.

Similar results are found comparing energy policy scenarios to reduce cost, in the context of recent policies that are removing subsidies from some renewable sources. For example, consider the least CO_2 emissions (6.35 million tons CO_2) and high cost (US$ 22.64 billion) energy policy scenario B (11-11-11-11). If one expects to reduce costs (e.g. by removing subsidies) by the end of the planning horizon, it could be attained in different ways. Suppose the goal is to arrive at energy policy scenario 2. If subsidies reduction is delayed to end of the planning horizon, the energy policy may change abruptly, for example, producing a policy scenario such as M (11-11-2-2), with US$ 21.19 billion cost and 65.86 million tons CO_2. However, if the change follows the more gradual route 11-8-7-2 (policy scenario N), the costs would be lower, at US$ 20.9 billion and there would be no emissions trade off (the emissions would actually be smaller as well, at 63.21 million tons CO_2).

Another interesting aspect emerges from this analysis. As results indicate, there is a high emissions trade-off to pay for a relatively small cost reduction, which shows that cost reduction policies based on shifting to less expensive energy sources have limited benefits, and significant changes (such as having the energy policy 2 as goal here) should be carefully evaluated.

As indicated before, the capacity expansion model presented here allows one to explore the uncertainty that unfolds in the next stage as a decision is made at present time. Consider the case of the same energy policy at the first stage, (e.g. energy policy 1, as in scenarios A, D, E, F, G, and H), which are all located in the same region (upper left corner, Figure 6). Given this region, it is possible to estimate the range of the impact of the energy policy decision at the first stage. For this example, the cost could vary from 18 Billion US$ (best case, scenario

A) to 19,8 Billion US$ (worst case, scenario F). The CO_2 emissions could vary from 121 million tons (best case, scenario A) to 154 million tons (worst case, scenario H). Such range of uncertainty can be useful to evaluate risk and identify preemptive responses.

These results are thus useful to evaluate in advance the impacts of the changes in the energy policies, which would allow decision makers to avoid dominated solutions when making necessary policy changes.

5. Conclusions

This paper presents a novel approach in systems capacity expansion planning that contributes to the analysis of energy policy changes. The approach is based on the optimality principle of Bellman. Dynamic programming and multi-objective linear programming have been used to generate energy policy scenarios and their trade-offs.

The approach was demonstrated through a hypothetical case of a generation capacity expansion, using three different available energy sources. 14,641 energy policy scenarios were evaluated considering different combinations of energy policy changes. We concluded that:

1. There is a clear Pareto front;

2. Energy policy scenarios characterized by gradual changes, resistant to changes and constant changes tend to perform better than policies with abrupt changes and regretting changes;

3. Policy change solutions that provide good results in a given stage do not necessarily perform better in the long run;

4. Different energy policies may result in the same performance, which indicates that there is room and flexibility for negotiating upon the “best” course of action. This is especially relevant given the political context where such decisions are often made.

5. There is a measurable range of uncertainty that unfolds into the next stage as soon as a decision is made in the current stage. This can be used for risk evaluation and design of early response measures.

Finally, the results indicate that policy change analysis through the planning process is useful to clarify decision maker's vision from a myopic to a more perspicacious view in respect of the future responses, as well as to provide several possible alternative policy scenarios.

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7. References

Aghaei, J., Akbari, M. A., Roosta, A., & Baharvandi, A. (2013). Multiobjective generation expansion planning considering power system adequacy. *Electric Power Systems Research*(102), 8-19.

Ahmed, S., King, A., & Parija, G. (2003). A Multi-Stage Stochastic Integer Programming Approach for Capacity Expansion Under Uncertainty. *Journal of Global Optimization*(26), 3-24.

BBC News. (2015). *BBC News. Business*. Retrieved July 22, 2015, from http://www.bbc.com/news/business-33177025

Beh, E., Maier, H., & Dandy, G. (2015). Scenario driven optimal sequencing under deep uncertainty. *Environmental Modelling and Software*(68), 181-195.

Careri, F., Genesi, C., Marannino, P., Montagna, M., Rossi, S., & Siviero, I. (2011, Novembre). Generation Expansion Planning in the Age of Green Economy. *IEEE Transactions on PowerSystems, 26*(4).

Davis, M., Dempster, M., Sethi, S., & Vermes, D. (1987). Optimal Capacity Expansion under Uncertainty. *Advances in Applied Probability, 19*(1), 156-176.

Gorenstin, B., Campodonico, N., Costa, J., & Pereira, M. (1993). Power System Expansion Planning under uncertainty. *IEEE Transactions on Power Systems, 8*(1), 129-136.

IEA. (2014). *World Energy Outlook. Executive Summary.* Paris: OECD/IEA.

Iyer, G., Hultman, N., Eom, J., McKeon, H., Patel, P., & Clarke, L. (2015). Diffusion of low-carbon technologies and the feasibility of long-term climate targets. *Technological Forecasting & Social Change*(90), 103-118.

Kagiannas, A., Askounis, D., & Psarras, J. (2004). Power generation planning: a survey from monopoly to competition. *Electrical Power and Energy Systems*(26), 413-421.

Lew, A., & Mauch, H. (2007). *Dynamic Programming A Computational Tool* (1 ed.). (J. Kcprzyk, Ed.) Berlin: Springer.

Li, S., Coit, D. W., Selcuklu, S., & Felder, F. A. (2014). Electric Power Generation Expansion Planning: Robust Optimization Considering Climate Change. *Proceedings of the 2014 Industrial and Systems Engineering Research Conference.* Y. Guan and H.Liao.

Li, Y. (2014, September 18). The Debate of the Green Paradox. *Review of Environment, Energy and Economics (Re3)*.

Loucks, D.P., Stedinger, J.R., Haith, D.A. (1981). *Water Resources Systems Planning and Analysis* (1 ed). (Prentice-Hall Ed.) New Jersey.

Lucena, A. F., Schaeffer, R., & Szklo, A. S. (2010). Least-cost adaptation options for global climate change impacts on the Brazilian electric power system. *Global environmental change*(20), 342 - 350.

Luss, H. (1982, September - October). Operations research and capacity expansion problems: a survey. *Operations Research, 30*(5), pp. 907 - 947.

Mavrotas, G. (2009). Effective implementation of the e-constraint method in Multi-Objective Mathematical Programming problems. *Applied Mathematics and Computation*(213), 455-465.

Meza, J. C., Yildirim, M., & Masud, A. (2007). A Model for the Multiperiod Multiobjective Power Generation Expansion Problem. *IEEE Transactions on Power Systems, 22*(2), 871-878.

Parker, G., & Doak, J. (2012). *Key Concepts in Planning* (1 ed.). (R. Kitchin, Ed.) London: SAGE.

Pástor, L., & Veronesi, P. (2012). Uncertainty about Goverment Policy and Stock Prices. *The Journal of Finance, LXVII*(4), 1219-1264.

Percoco, M. (2014). *Regional Perspectives on Policy Evaluation* (1 ed.). Springer.

Rebennack, S. (2014). Generation expansion planning under uncertainty with emissions quotas. *Electric Power Systems Research, 114*, 78-85.

Reuter, W. H., Szolgayová, J., Fuss, S., & Obersteiner, M. (2012). Renewable energy investment: Policy and market impacts. *Applied Energy*(97), 249-254.

Schlanger, Z. (2015). *Newsweek World*. Retrieved July 21, 2015, from http://www.newsweek.com/australia-prime-minister-bans-government-investment-wind-power-352912

Schwenker, B., & Wulf, T. (2013). An uncertain World. In B. Schwenker, & T. Wulf (Eds.), *Scenario-based strategic planning. Developing strategies in an uncertain world* (pp. 12-14). Springer Gabler.

Sinn, H.-W. (2012). *The Green Paradox: A Supply-side approach to global warming.* Mass: Mit Press Cambridge.

Tekiner, H., Coit, D. W., & Felder, F. A. (2010, July). Multi-period multi-objective electricity generation expansion planning problem with Monte-Carlo simulation. *Electric Power Systems Research*(80), 1394 - 1405.

Vithayasrichareon, P., Riesz, J., & MacGill, I. (2015). Using reneweables to hedge against future electricity industry uncertainties - An Australian case study. *Energy Policy*(76), 43-56.

WNA. (2011). *Comparison of lifecycle greenhouse gas emissions of various electricity generation sources.* London: WNA.

Zhou, Y., Li, Y., Huang, G., & Zhou, Y. (2013). A robust approach for planning electric power systems associated with environmental policy analysis. *Electric Power Systems Research*(95), 99-111.

Zhou, Y., Wang, L., & McCalley, J. (2011). Designing effective and efficient incentive policies for renewable energy in generation expansion planning. *Applied Energy*(88), 2201-2209.

3 Looking for a robust energy policy in generation expansion facing climate change uncertainties/impacts

Looking for a robust energy policy in generation expansion facing climate change uncertainties/impacts

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Abstract

Climate change brings several challenges to energy production, but it is not the only source of uncertainty. Demands, aging infrastructure and broader energy policies all contribute to a highly variable environment. This paper analyzes how possible future climate change scenarios uncertainty could impact the energy policy changes for generation capacity expansion. By using a hybrid dynamic programming/multi-objective approach, we analyze the energy production and CO_2 emissions to identify robust energy policy scenarios under different possible climate change future scenarios. The results indicate a clear impact of the climate conditions in the performance of energy policy scenarios; dryer conditions drive into higher uncertainties in costs and CO_2 emissions. Robust energy policy scenarios are more likely if follows policies changes preferences of low cost to a greener ones. The approach is useful in providing planners a tool to analyze uncertainties from different sources simultaneously.

Highlights

- Future energy policy decisions are highly uncertain and subject to change.
- Facing uncertainty requires knowledge of economic and environmental trade-offs.
- Integrating MOLP to optimize DP subproblems allows trade-offs identification.
- Identification of robust solutions for multi-objective optimization problems is possible using techniques from genetic algorithms analyses.
- Inclusion of climate change uncertainties with energy policy changes uncertainties along planning horizon is important in capacity expansion.

Keywords

Energy Policy; capacity expansion; power system planning; multi-objective optimization; dynamic programming; climate change; robustness solutions; renewable energy.

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1. Introduction

For energy planners, in the actual global scenario, volatility is the new norm [1]. In one side, climate change policies seek to mitigate CO_2 emissions [2] adopting low-carbon technologies, through integration of renewable power sources into power systems [3]. Renewable sources, however, as hydro and wind, have considerable uncertainty given their stochastic nature and are intensified by climate change effects [4]. On the other side, driving guidelines for national energy plans involving investment and subsidies are formulated by governments through public policies. Public policies are subject to change, given geopolitical contexts, domestic economic pressure and other aspects affecting political agenda [5]. In a context of global financial crises, markets, interconnectivity and economy volatility (public and industrial), among other factors as climate change, the energy planning process becomes more complex and uncertain [1,6].

In these circumstances, generation expansion planning of power systems requires taking into account uncertainty that could motivate changes in energy policies [6,7] (i.e., policy uncertainty) which could favor implementation of a determined energy source (e.g. renewables) and the added uncertainty brought in by renewable sources because of climate change [8,9] (i.e., climate uncertainty). All these aspects are combined under costs and CO_2 emissions minimization objectives.

Initially, generation expansion planning was based on capacity expansion methodology to determine the size and timing of facilities to be added at minimal costs, considering time value [10]. Advanced approaches consider the inclusion of stochastic optimization in Dynamic Programming (DP), and the use of computational intelligence as Genetic Algorithm (GA), fuzzy set theory and Artificial Neural Networks (ANN) [11].

Concerns about climate change and environmental protection have driven efforts to include energy, climate, and environmental policies in the generation expansion planning models. Most of the literature is focused in the inclusion of economic instruments including minimum percentage of renewables, feed-in tariffs, quota obligation, and emission trade and carbon taxes. Some approaches consider economic instruments as constraints [12] while others focus on their uncertainty [13–16].

Other literature investigating policies related to climate change mitigation have included as objectives the fulfillment of emissions quotas [17] and minimization of CO_2 emissions [18,19]. Portfolio analysis concepts to account for risk and uncertainties of gas and carbon prices is considered for modelling integration of high quantities of renewables [20]. However, few works have focused in the design of incentive policies for investments in renewables [21].

Recent events show how policies related to climate change and environmental care can change. As have been happened in United Kingdom - UK with the earlier end to subsidies for new on-shore wind farms [22]; in Australia, with the banishment of the federal clean energy investments in wind power [23]; and in Canada, Nova Scotia community, with the closing of the feed-in tariff program [24,25]. The two first ones without a clear cause, meanwhile the former one because of high costs as explained by COMFIT [25]. The implementation of those climate policies has a cost: by 2013, it was estimated that would be required US$120 billion to spend in global subsidies for renewable energy technologies [26].

Not only economic issues are the possible causes for those policies changes. A clear example of that is explained by Kuramochi in [27], through an analysis about changes in energy policies before and after Fukushima nuclear disaster by the tsunami on march 2011. Initial changes included restrictions of new nuclear plants in the energy plans and revision of CO_2 emissions targets, next to a new revision of CO_2 emissions by the new administration in the Japanese government of 2013. Natural disaster also can influence policy changes.

If policies change during the planning execution process, it is necessary to adjust the plan. Without any information about how future is going to be with the implementation of the new policies, politicians could be tempted to opt for broader indicative strategies that may not give clarity or certainty about other interests [7].

Arancibia et al. in [28] present a novel approach that considers the uncertainty on the energy policies to select a specific source of power generation. While energy policy can change at any stage within the planning time horizon, the goal is to minimize costs (investment and operation) during that time planning. This was done through coupling multi-objective linear programming (MOLP) and dynamic programming (DP) to account for the different possible changes on the energy policy that produce minimum costs and CO_2 emissions for each possible change, having a leading objective of minimum cost generation capacity expansion in a given time horizon. The output of the coupling process is composed by as many results as possible policies changes considered. The results show the trade-offs among CO_2 emissions and costs, identifying a clear Pareto front. The approach did not consider effects of climate change.

Climate change will affect temperature, rain patterns and also the economy [29–31], ultimately reflecting on the effectiveness of power expansion decisions. Effects on energy are related with the demand, production, and transmission [29,32]. Efforts to include those effects on generation planning have considered variations in the demand, hydropower generation capacity (because of changes in the hydrological patterns), decrement of the generation efficiency in thermal power plants (because of rising temperatures), as well as in wind and photovoltaic generation [33–35]. Most of these include mitigation measurements in the planning analysis, as reduction of sources with higher CO_2 emissions. The Integrated resource planning approach applied to Brazilian Power Systems is applied in one case [33], and a multistage interval-stochastic integer programming model is applied in the other case [35]. The work carried out in [36] presents a generation expansion planning model considering climate change impacts based on deterministic linear programming, including parameters as capacity factor, transmission capacity, and demand, affected by changes in climate parameters as precipitation and temperature and increasing frequency of extreme events. Climate change uncertainty is analyzed by discrete scenarios. Where each scenario is established by the definition of values for each one of the climate parameters considered. Two optimization models for decision making are presented. The limitations are properly from the complexity of power systems capacity expansion problems and uncertainty of climate conditions, amplified by the number of the climate parameters considered.

Incorporation of climate change impacts in power generation planning models requires understanding about the impacts on the generation sources. Most of the literature have focused in climate change effects in hydropower [8,37–43], with less attention to wind power and photovoltaic, given the higher uncertainty on those sources when compared to hydropower [44]. The impacts of climate change were considered in terms of the capacity factor, which indicates the ratio of energy that an electric power plant produces during a certain time interval and the energy that could produce in its maximum capacity of continuous operation during that same period.

Under policy uncertainty, climate change can further add to variation in the likelihood of certain outcomes, turning the generation capacity expansion planning more challenging as what is expected to be a good decision under one climate can prove quite unfavorable under another one. Given these uncertainties in the planning process, it becomes necessary to evaluate how robust a given expansion decision is. This paper builds upon the work done by [28], presenting an improved methodology to identify robust energy policies for generation expansion planning under climate change. The climate change impacts are limited to thermal and hydro power. We adopt the term “capacity utilization factor”, that depends on the climate conditions (e.g. very dry, dry, normal, wet or very wet) and represent the operational conditions of a hydrothermal power system. Policy uncertainty is represented by the different possible energy policy change scenarios. Where, energy policy denotes the preference for selecting determined generation source and the change scenarios the changes in the selecting preferences by stage through the planning time. The uncertainty of climate change is represented by different scenarios and results from different climate models (terrestrial and global) for the same location. The approach generates for each climate scenario a Pareto diagram with multiple possible policy change scenarios. Robust solutions are then identified by a selection considering minimum average distance to the Pareto front in different climate scenarios. To illustrate the methodology, a simplified planning generation capacity expansion is presented.

This paper contributes to the existing body of knowledge by combining policy and climate uncertainties in the generation expansion planning, with the objective to identify and characterize robust energy policies. While energy policies might be pressed to change responding to uncertain exogenous factors, how to implement such changes through time may yield different results and trade-offs. When the climate is also expected to change, the trade-offs are also uncertain, and one needs to verify if a “good” time change in the energy policy is also robust. Here “good” refer to low cost and low CO_2 emission. The methodology proposed in this paper is thus designed to identify robust trade-offs, so the decision maker can focus on the best ones (closer to the Pareto frontier) when faced with necessary changes. The proposed methodology includes climate change impacts through the “*utilization capacity factor*” into multi-objective linear programming (MOLP) coupled to dynamic programming (DP) to solve a multi-objective optimization problem in expansion capacity, identifying robust policy changes, classifying them per its impact on the optimal power expansion strategy.

The remainder of this paper is organized as follows: Section 2 presents the proposed approach. Section 3 describes an application through a hypothetical planning generation capacity expansion. Section 4 shows the results of the application for different scenarios. Finally, in section 5, the conclusions are presented. Annex A shows details in the determination of the Utilization capacity factors used in the case study. Annex B shows the information used to define the hydrological conditions used in the case study. Annex C shows the MOLP formulation by stage of climate scenarios.

2. Methodology

The objective of the present paper is to identify robust energy policies considering climate change and energy policies uncertainty, and analyzing in those robust solutions the energy policy changes and its effect through the planning time horizon over the generation capacity expansion in terms of costs, CO_2 emissions and mix of selected energy generation sources. The methodology has four main stages: (i) problem formulation as capacity expansion problem to be solved by backwards DP; (ii) climate uncertainty representation through a relationship between the “*utilization capacity factor*” – UCF, local climate conditions and the operation conditions of the power system; (iii) generation of all possible pathways of capacity expansion generation (each one related to a policy change sequence) including the climate effects for a determined number of scenarios and (iv) identification of robust energy policies for all the established scenarios in the previous stage. The method is presented through a case study in the Brazilian southern power sub-system. The Brazilian power system is hydro-thermal, with hydroelectric, wind, solar and thermal (coal, gas, nuclear) power plants all connected in major system through transmission lines. A summary of the overall method appears on figure 1.

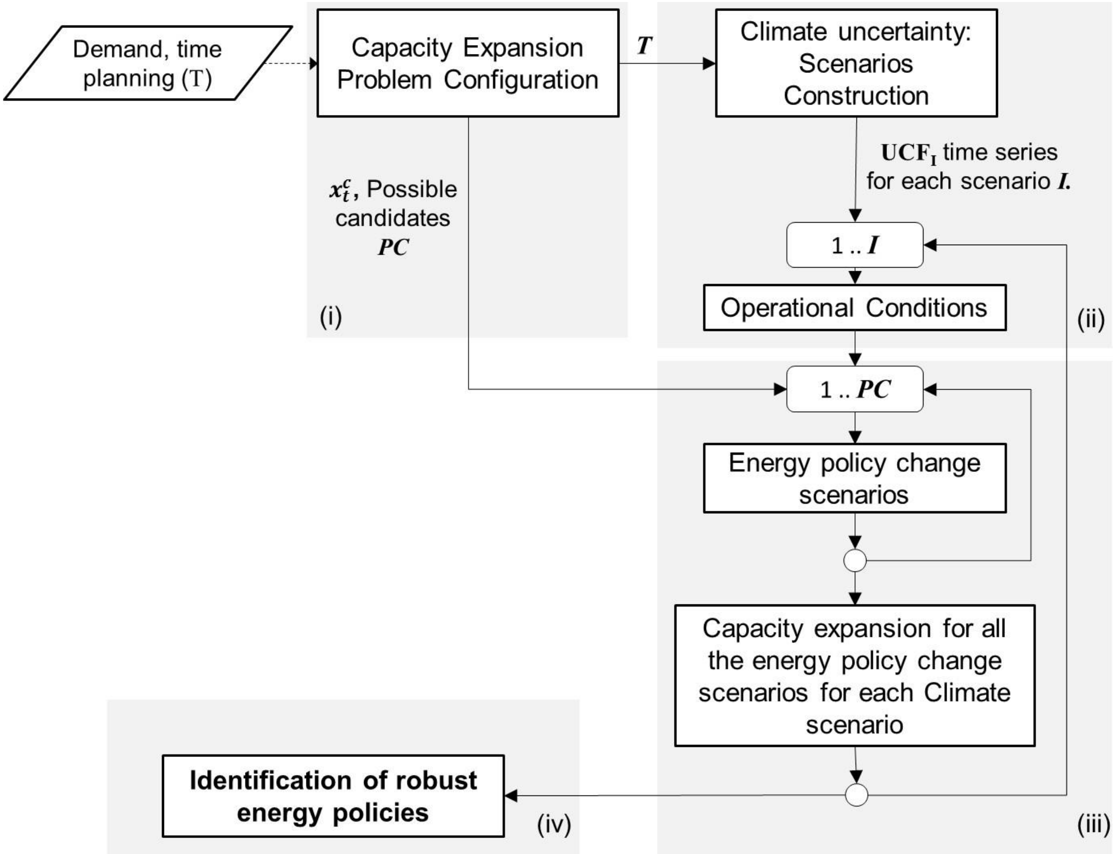


Figure 1. Overall method

Policy change uncertainty is tackled by scenario analysis approach. Here we define an *energy policy* as any particular choice of expansion in a given set of power sources at a given decision stage. As this set of expanded power sources may change from one stage to the next (i.e. varying the amount expanded in a given power source), we also define an *energy policy scenario* as a particular time sequence of *energy policies.* An energy policy scenario may include a set with any combination of energy policies.

Climate uncertainty is also tackled by scenario analysis approach. Climate scenarios were established through results of different climate change models applied at the same localization. We prefer scenario analysis over stochastic approaches since the first one represents a wide range of possible alternative conditions and the second one just a limited variety of scenarios [20,45].

The applications of the methodology proposed here could be used, mainly for two purposes. Firstly, to help in the design or formulation of energy policies to be applied in the capacity expansion planning. In these case, the results of the identification of the robust policies and their characterization will help to formulate the more likely suitable energy policies to apply in the different stages of the time horizon plan. These will provide a broader range of flexible energy policies (could change from one stage to another). Secondly, to provide a tool for decision makers facing unavoidable change of plans. For example, initially an energy policy was applied to achieve certain objectives (costs and CO_2 emissions), but after an analysis of international compromises come up the necessity for changing the initial energy policy to reduce the target of CO_2 emissions. There are financial limitations not allowing big increments in the costs. Results of the different possible energy policy for different climate condition showing trade-offs of costs and CO_2 emissions enable the analysis. The analysis will provide information on how much it will cost achieve the new CO_2 emission target respect to the previous energy policy. This situation could happen at any time of the planning process.

As mentioned by [46], results of capacity expansion models are a good reference for initial decisions to be done at the first stage, more than guidelines for the whole horizon plan. However, energy policy definition as well environmental agreements require time to be implemented, then it is necessary a driving reference, even though changes will come up later with the corresponding modelling update.

Since our model explore costs and CO_2 emissions trade-offs under different climate conditions, it will also provide information about the uncertainty of costs and CO_2 emissions related to determined climate conditions (i.e. whether costs or CO_2 emissions are more susceptible to change regarding climate conditions changing).

2.1 Problem formulation

The model time planning horizon T is divided into t stages. D_t represents demands at the beginning of each stage t, D_{T+1} represents demand at the end of the stage T, while initial conditions of generation capacity and interest rate are represented by $\boldsymbol{int}$.

The problem is configured to be solved with a backward-moving discrete dynamic programming algorithm to minimize costs (*"leading policy"*), as in (1) through (3).

$$\boldsymbol{F_t(S_t) = minimum\,\{C_t(s_t, x_t) + F_{t+1}(s_{t+1})\}} \quad (1)$$

s.t.

$$\boldsymbol{x_t = s_{t+1} - s_t} \;\; ; \quad \forall\, \boldsymbol{t} \quad (2)$$

$$\boldsymbol{s_t \geq D_t}\,; \quad \boldsymbol{0 \leq s_t \leq s_{max,t}}\,; \quad \boldsymbol{0 \leq x_t \leq x_{max,t}} \;\; ; \; \forall\, \boldsymbol{t} \tag{3}$$

Where s_t is the existing capacity at the beginning of the stage t (state variable); x_t is the added capacity at the beginning of the stage t (decision variable); $C_t(s_t, x_t)$ is the present value of the cost given capacity expansion x_t at stage t and an initial capacity of s_t and interest rate ***int***; $F_{t+1}(s_{t+1})$ is the minimum optimized cost at stage $t+1$, considering $F_{T+1}(s_{T+1}) = 0$. Equation (1) is the recursive equation and equation (2) is the state equation. Demands D_t can never exceed the capacity stage t. Maximum values of state and decisions variables are:

$$\boldsymbol{s_{max} = D_{T+1}} \;\; ; \; \boldsymbol{x_{max,t} = D_{T+1} - s_t}\,; \quad \forall\, \boldsymbol{t} \tag{4}$$

$$\boldsymbol{0 \leq \; x_t \leq D_{T+1} - D_t} \tag{5}$$

A set of possible candidate values for x_t in each of the stages is generated to define the state space grid, considering that more than one x_t is possible for each stage. For instance, if there were 4 stages there will be a total of 14 possible “candidate values” for x_t, besides zero. All these “candidate values” for x_t are the input for the next step and are represented by x_t^c.

2.2 Climate uncertainty

Climate conditions have a significant influence in the operation of renewables plants as hydropower given their high dependence in water availability, with less influence on wind and thermal generation [30,32]. For long-term planning purposes, the “utilization capacity factor” – *UCF* could be a good indicator of climate and operational influences [47]. The *UCF* indicates how much of the installed generation capacity of a power plant is being used in each time and operating conditions, which could include its temporal shutdown. *UCF* for annual operation is defined by (6):

$$UCF = \frac{Total\ annual\ energy\ generated\ [MWh]}{Installed\ Capacity\ [MW] \times 8760[h]} \times 100 \tag{6}$$

Inclusion of climate influence in the power system operation is done by the analysis of historical data of UCF from each type of generation (e.g., hydro, thermal and wind) and climate conditions. Doing that the operational criteria are captured, and it is considered will be the same at future. In the case of a hydrothermal based power system such as the one used as example in the present paper, we have identified a correlation between the UCF and discharges, as follows:

$$\boldsymbol{UCF_{t,i} = \; f(Q_t)}; \qquad \forall \boldsymbol{t} \;\; \in [\boldsymbol{1..T}] \tag{7}$$ and

$$\boldsymbol{UCF_{t,TOTAL} = \; f(UCF_{t,i})}\,; \quad \forall \boldsymbol{t} \;\; \in [\boldsymbol{1..T}] \tag{8}$$

Where $\boldsymbol{UCF_{t,i}}$ is the utilization capacity factor of the technology type $\boldsymbol{i}$, in the year $\boldsymbol{t}$ and $\boldsymbol{UCF_{t,TOTAL}}$ is the utilization capacity factor of the whole power system in the year t. In the first case UCF depend on the $\boldsymbol{Q_t}$: characteristic discharge in the year $\boldsymbol{t}$. The $\boldsymbol{UCF_{t,TOTAL}}$ depends on the values of $\boldsymbol{UCF_{t,i}}$.

The climate uncertainty representation is made in two steps. First, climate conditions scenarios are defined, followed by inclusion of the influence in the operational conditions.

2.2.1 Climate Conditions Scenarios Definition

Climate conditions scenarios are constructed with discharges time series $\boldsymbol{Q_t}$, with the same extension that the time horizon planning for capacity expansion and one value for each year. Usually, discharge time series results are expressed in monthly values (twelve values per year), then an average of the monthly discharges of a year is considered as the one value for that year. From time series $\boldsymbol{Q_t}$, and expressions (6) and (7) the respective UCF are calculated. For the purpose of this work, other factors that could influence in the UCF values (i.e. demand, price fuels, etc.) are neglected.

Finally, each scenario is represented by a time series of UCF values: $\boldsymbol{UCF_{t,i}}$ and $\boldsymbol{UCF_{t,TOTAL}}$. For the current analysis, a total of six climate scenarios are considered.

2.2.2 Influence in the operational conditions

The energy policy change scenarios are generated as result of the multi-objective linear programming problem (MOLP) defined by the equations 9 to 12, for $\boldsymbol{m^T}$ different scenarios, considering $\boldsymbol{T}$ stages and m different energy policies (for the same climate conditions) [33].

$$\boldsymbol{FO_1}: \boldsymbol{minimum} \sum(\boldsymbol{IC_i} \times \boldsymbol{r_i} + \boldsymbol{OC_i} \times \boldsymbol{r_i}) \quad ; \quad \boldsymbol{i = 1 \dots n} \tag{9}$$

$$\boldsymbol{FO_2}: \boldsymbol{minimum} \sum \boldsymbol{CO_{2_i}} \times \boldsymbol{r_i} \quad ; \quad \boldsymbol{i = 1 \dots n} \tag{10}$$

s.t.

Demand constraints: $$r_1 + r_2 + \cdots + r_n \geq x_t^c \; ; \quad \forall\, t \tag{11}$$

Operating constraints: $$OpC(r_i) \geq B \tag{12}$$

Where $\boldsymbol{IC_i}$ is the investment cost for each source $\boldsymbol{r_i}$; $\boldsymbol{OC_i}$ is the operating cost related to the source $\boldsymbol{r_i}$; $\boldsymbol{CO_2}$ are the emissions related to the source $\boldsymbol{r_i}$. Expressions (9) and (10) are linear, considering that costs and CO_2 emissions just depend on the values of $\boldsymbol{r_i}$. $\boldsymbol{OpC(r_i)}$ represents operating constraints as a function of the sources r_i and B is the respective condition of operation (e.g., limited capacity generation or reliability condition).

Since climate condition influences in the system operation, the terms related to the operation system in equations (9) and (10) are described as follows:

$$OC_i = \left(\sum_t UCF_{t,i} \times oc_i/(1+int)^{t-1}\right) \times 8760 \quad ; \quad t = 1 \ldots DT \qquad (13)$$

$$CO_{2_i} = CO_2emiss_i \times \left(\sum_t UCF_{t,i}\right) \times 8760 \quad ; \quad t = 1 \ldots DT \qquad (14)$$

Where oc_i are variable costs of the generated energy of the technology type i, int is the annual interest rate, t is the number of years, CO_2emiss_i is the CO_2 emissions for the generated energy of the technology type i, DT is the number of years of the respective stage.

Expression (11) is the “coupling equation” among MOLP and Dynamic Programming; it expresses the different sources r_i compounding the candidate capacity expansion x_t^c.There are expected different optimized sources of combination of the r_i values for a x_t^c, as shown in figure 2.

Operating constraint represented by the expression (12) is a set of different constraints defined by the operational characteristics of the modeled power system. The number of these constraints depends on the information available and depends of the number of unknow variables. One of the operational constraints is represented by (15):

$$\sum_i (\overline{UCF}_i . r_i) \geq UCF_{TotalSystem} \times \left(\sum_i r_i\right) \qquad (15)$$

Where UCF_i is the average utilization capacity factor in the respective stage of the DT years of each i generation type, and $UCF_{TotalSytem}$ is the utilization capacity factor of the entire power system in the same stage. For more than 3 generation technology type (i >3), it is necessary include more restrictions than the represented by expression (15). It is going to require more information about operational conditions from all the sources.

The problem defined by (9) through (15) is solved for a specific set of climate conditions scenario through the augmented ε-constraint (AUGMECON) algorithm [48].

Solving the problem results in a Pareto set with *m* paired values for CO_2 emissions and costs, along with the respective combination of sources r_i and their respective added capacity decisions x_t^c. One Pareto set is produced for each climate scenario. An example appears on figure 2 including three energy sources (on the right chart) and *m* points defining a Pareto front (chart on the left). Solution point “1” shows only expansion on energy source r_2, with the least cost and highest CO_2 emission. The introduction of r_3 in the bundle produces a trade-off, reducing emissions at a cost expense (points 2 through 7). By introducing energy source r_1 the CO_2 emissions can be further reduced, replacing r_3. Each combination of energy sources reflects a policy bias, or preference, with stronger bias towards environmental protection to the right, and towards cost savings to the left. Thus, a given energy source expansion investment bundle (r1, r2, r3) also represent an *energy policy.*

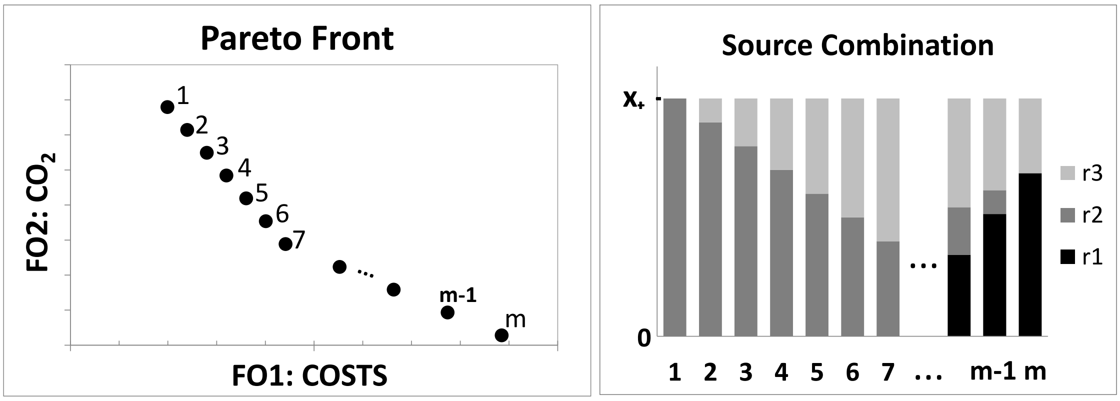


Figure 2. Example of MOLP for x_t^c, [28].

The process is the same for each climate condition scenario, for all the x_t^c at each stage, producing a Pareto front with the energy source expansion investment bundle for each x_t^c. This is the “MOLP Pareto front.” Each point receives a label representing the preference among the two objectives (minimize cost and minimize CO_2 emissions) defining the *energy policy.*

2.3 Capacity Expansion

The generation capacity expansion problem defined by equations (1) trough (4) is solved with dynamic programming (with a backward moving dynamic programming algorithm, beginning at t=T and finishing at t=1), following the “*leading policy”* of minimum costs, for the values of the cost for each of the candidate value x_t^c in each stage. As we have multiple stages, there is a finite number of energy policies combinations through time. Each particular time sequence of *energy policies* thus represents an *energy policy scenario*. Thus, for T stages, it will result in m^T “*energy policy scenarios*”, each with its respective values of x_t^c, r_{it}, $C_t(s_t, x_t^c)$ *and* $CO_2(x_t^c)$. While we can’t predict if a scenario will happen, we can compare different likely ones for total costs and CO_2 emissions, in order to identify dominated solutions that should be avoided, as presented in [33]. However, as additional uncertainty is brought in by climate change, we can no longer be certain if a non-dominated solution will remain so if a different climate unfolds. To address this limitation, we build upon the work in [33] and improve the model to identify robust solution considering climate change uncertainty.

The expression (16) is considered to compute the corresponding CO_2 emissions along the time horizon planning:

$$\boldsymbol{Total\ CO_2 emissions} = \sum_{t=1\ldots T} \boldsymbol{CO_2}(\boldsymbol{x_t}, \boldsymbol{s_t}) \tag{16}$$

Where $CO_2(x_t,s_t)$ are CO_2 emissions due to expansion x_t at stage t given an initial capacity s_t.

The final outputs of DP, resulting from the application of a defined "*energy policy scenario*", are the total cost of the capacity expansion, total emissions of CO_2 from the operation of the added capacity and the capacity expansion sequence with a mix of sources by stage.

The final output of the whole optimization process are $\mathbf{m}^{\mathbf{T}}$ results of "*energy policy scenarios*", each one with their respective total Cost, total Emissions of CO_2 and capacity expansion sequence with a mix of sources by stage, as shown in figure 2. No persistence policy is considered since actual political global condition is highly uncertain.

Figure 3 presents the $\boldsymbol{m^T}$ solutions from a climate scenario. The extreme values correspond to opposite extreme "*energy policy scenarios*" of minimum costs (upper left), and minimum CO_2 emissions (lower right). The other values correspond to different policy trajectories representing alternative changes in the energy policy from one stage to another (i.e. switching priorities between environmental and economic objectives).

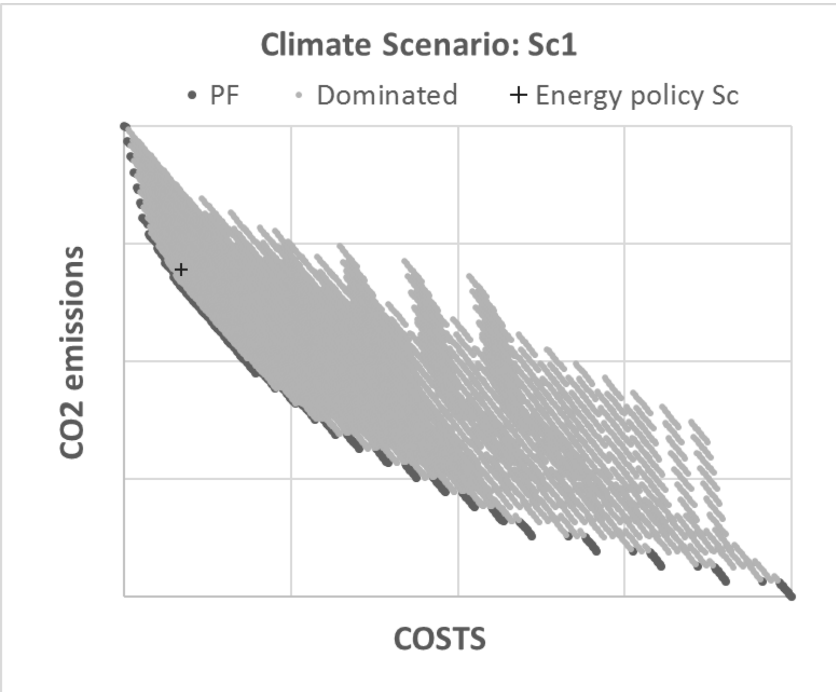


Figure 3. Final output

This is done for each one of the climate scenarios; resulting in $\boldsymbol{m^T}$ solutions for each climate scenario. The next step is identifying the robust solutions, i.e. best "energy policy scenarios" under different climate conditions.

2.4 Identification of robust energy policies

The same "*energy policy scenario*" followed under different climate conditions results in a different costs and CO_2 emissions. When evaluating the performance of the different energy policy scenario it is necessary to identify which one could maintain desired results for any likely future climate conditions, in terms of costs and CO_2. Desired results are the ones at, or close, the Pareto front. This means identifying the robust energy policy scenarios.

Evolutionary algorithms have been used to evaluate effectiveness of multi-objective optimization through different indicators [49–52]. The indicators are categorized in four core groups by [51]: capacity, convergence, diversity and convergence-diversity. The more suitable for our purposes are the ones measuring convergence. Convergence metrics measure the proximity of the set of solutions to the Pareto front. In our case, the result to be analyzed has the configuration shown in figure 4, with dominated and non-dominated solutions and a clear identification of the Pareto front. There are two possibilities for a solution (energy policy scenario): (a) non-dominated, i.e., it is part of the Pareto Front and (b) dominated (not a part of the Pareto front) in any given climate scenario. Robust solutions will be the ones in or nearest to the Pareto Front in any of the climate change scenarios considered here.

The normalized distance is used to measure the proximity of a solution (energy policy scenario) to the Pareto Front in each climate scenario. The normalized distance between two solutions *a* and *b* with two objectives functions f_1 and f_2 is defined by (17).

$$\boldsymbol{d(a,b)} = \sqrt{\left(\boldsymbol{f_1^*(b)} - \boldsymbol{f_1^*(a)}\right)^2 + \left(\boldsymbol{f_2^*(b)} - \boldsymbol{f_2^*(a)}\right)^2} \quad (17)$$

where: $\boldsymbol{f_i^*}(.)$ is the objective function *i* normalized according the set of all solutions for each scenario. The normalized function in x is defined by (18).

$$f_i^*(x) = 100 \times \frac{f_i(x) - f_i^{min}}{f_i^{max} - f_i^{min}} \quad (18)$$

Where: f^{min} is the minimum attainable value for objective i considering all possible solutions in a given climate scenario, while f^{max} is maximum attainable value for the same objective i. For each climate scenario, the maximum distance d_I is identified in a two-step procedure: first, we calculate, for a given dominated solution, all the possible distances to all points in the Pareto front, and then select the shortest one. This is repeated to all dominated solutions, resulting in a set of minimum distances, one for each dominated solution. Finally, the maximum distance among this set is selected, which the maximum distance d_I as shown in figure 4.

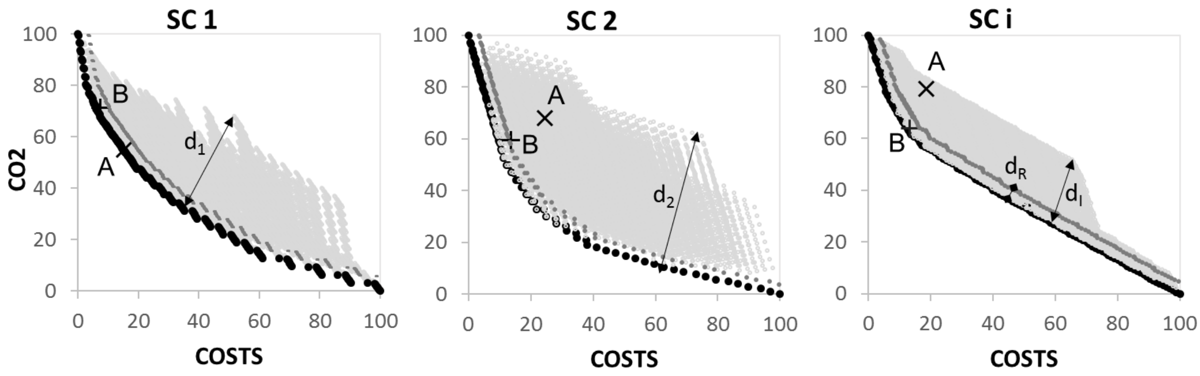


Figure 4. Distances to Pareto Front and robust solutions

This procedure is repeated for all climate scenarios considered, resulting in a set of d_I distances, once for each climate scenario. The distance d_R from the Pareto Front is then defined by the expression 19, where $\max_{I=1..n} d_I$ and $\min_{I=1..n} d_I$ are the maximum and minimum d_I values in the set of d_I distances, respectively. The parameter p is a number to define a desired accuracy. For our case study, we considered p =0.15 given that, pre-feasibilities studies find an accuracy of 30% for costs estimations as acceptable, then considering 15% of the average cost variation, it will be enough for this application.

$$d_R = p \times \left(\max_{I=1..n} d_I + \min_{I=1..n} d_I\right)/2 \qquad (19)$$

If an energy policy scenario has a distance $\boldsymbol{d}$ to their respective Pareto Front equal or lower than d_R in each one of the climate condition scenarios evaluated, it is defined as a “robust energy policy”. In the example presented in figure 4, energy policy scenario A is not a robust solution, while solution B is a robust one. Solution B presents a better performance (i.e. it is closer to the Pareto front) in any of the climate condition scenarios.

After identification of the robust energy policy scenarios, the values are analyzed to evaluate robustness. Such evaluation searches for patterns in the sequence of energy policies. When evaluating robustness, we look for solutions that have considerable variation on the distances among the different climate scenarios, by measuring and comparing their variability. Finally, we analyze the configuration of capacity expansion increments, considering the different climate scenarios and a robust energy policy.

3. Case study

The proposed approach is applied to the generation capacity expansion problem of the hydrothermal Brazilian southern power system.

3.1 Brazilian southern power subsystem

The Brazilian South Subsystem consists of the generating companies installed in the states of Rio Grande do Sul, Santa Catarina, and Paraná. The installed generating capacity in 2015, according to [53] is 29,805 MW. The power source mix is more than 80% hydropower (HPP: hydroelectric plants and PCH: small hydropower plants), followed by thermal (UTE: thermoelectric plants) with 14%, and a small but significant part of wind (EOL: wind power) 6%, as shown in figure 5. More than 40% of thermal power is based on coal as fuel, and more than 30% uses natural gas [58]. From the historical records, the generation capacity expansion in the period 2009 – 2015, was around 4,714 MW total, from which 55.2% in hydropower, 10.7% in thermoelectric power and 34.1% in wind power.

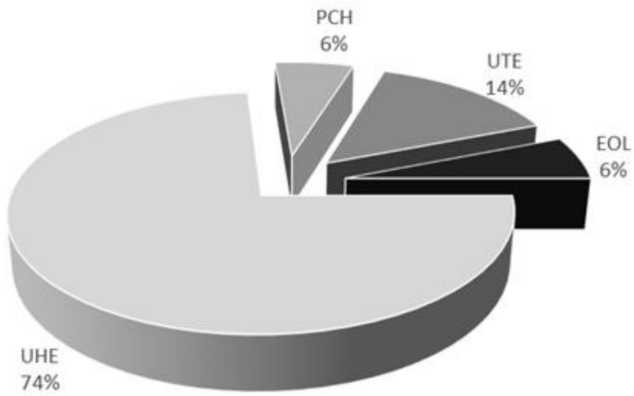


Figure 5. Generation Sources in Southern Brazilian Power System

Basically, the Power System is mainly a hydrothermal power system, with significant reliance on water availability. Since the region has a "homogeneous" climate characteristic (i.e. Cfa and Cfb from Köppen classification [54]), it is possible make a climate characterization through the water discharges of their main river basins (as is discussed in the next section). The main river basins of the region are the Uruguay River basin, Atlantic Southeast basin and the Parana River basin. From the historical records of generation, installed capacity and power generation was possible to compute the capacity factor of each technology (calculated using expression 6). Then after an analysis of the relationship among hydrological conditions and utilization capacity factor (corresponding yearly historical values), establish the values of the utilization capacity factors related to each one of the hydrological shown in Table 1. Also, establish a correlation of the utilization capacity factor for the whole power system with the capacity factor of each one of the indicated sources.

Table 1. UCF and hydrological conditions

Yearly Hydrological Conditions – YHC	Very Dry 1	Dry 2	Normal 3	Wet 4	Very wet 5
UCF_{Hydro}	0.17	0.23	0.29	0.34	0.40
UCF_{Thermo}	0.39	0.35	0.30	0.25	0.21
UCF_{Wind}	0.21	0.21	0.21	0.21	0.21
$UCF_{Total\ System} = 0.0064 + 0.823UCF_{Hydro} + 0.151UCF_{Thermo} + 0.003UCF_{Wind}$					

A detailed description of the process is shown in the Appendix A.

3.2 Climate change in Brazil

The climate variability and changes are studied using a set of climate models, at different scales: global, regional or terrestrial models [55]. Global climate models are more useful for the long-term and variability analysis, but they are limited by their scale, since adaptation measures for climate change require information at regional scales, as it was pointed in [56,57], regional models are required too.

For climate simulations in South America, specifically in Brazil, a regional climate model, named ETA (40), have been used for representing the “present climate” (i.e. period 1961 – 1990) and for representing the “future climate” (i.e. 2010 – 2100), in the scenario of greenhouse gas emissions A1B. The model ETA (40) is a numerical atmospheric complex model with a resolution of 40 km, that is nested by four boundary conditions (named as unperturbed, low, medium and high) of the global model HadCM3, that shows a good concordance with the temperature and precipitation patterns of South America for the years 1961 – 1990, when compared with historical observations of the Climate Research Unit – CRU from University of East Anglia [57].

ETA (40) and global climate models as GFCM, HADC, MPEH, MRCG, and NCC are used for analyzing hydrological impacts of future climate in Brazil in their main river basins (the ones configuring the Brazilian Power System) [58]. The main findings about anomalies of the “future climate” (period 2011-2040) respect the “actual climate” (1961-1990), regarding mean monthly naturalized discharges are:

ETA40 – Control (ETA40-CTL). The results of this model show increments of more than 15% for the southern basins (mainly Rio Grande do Sul) and reduction until 15% in the Paranaíba river (tributary of the Paraná river).

GFCM. The results of this model show reduction in most of the river basin, the reduction is more than 15%. Even for the southern part of Brazil, the main river basins show reduction for more than 5% or even bigger than 15%, with a few river basins (small ones) presenting increments around 5% and more than 15%.

HADC. The results show increment between 5% to 15% just for the bigger river basin in the Southern Brazil, but reductions for the rest of the river basin in this region from 5% to more than 15%.

MPEH. For this model, results show increments until 15% in most of the main river basins of the southern part of Brazil.

MRCG. The results show increment between 5% to 15% in most of the river basins, including the bigger one, of the Southern region. Variability of -5% to 5% for some basins located in the Santa Catarina state.

NCCC. For this model, results show increments until 15% in most of the main river basins of the southern part of Brazil, but a variability from -5% to 5% for the bigger river basins in this region.

There is not a coincidence about the results of future climate conditions projections (for the same scenario of emissions A1B). There are river basins showing reduction for one model and increment for the other.

Then with the results of those models, it is possible to build future climate scenarios, that will include conditions of increment and reduction of water availability. From the previous description of the results, it is possible define that the worst-case scenario could be represented by the results from the model GFCM (reports reductions), while the best-case scenario could be done with the results coming from the models ETA40-CTL or MPEH (since shows increments). The results of the other models could configure intermediate scenarios.

For a better understanding of the differences regarding water availability in the same period of analysis (i.e. 2012 – 2036, same period to be used for the capacity expansion problem), from the resulting discharges of the explained methods, the monthly naturalized discharges were rearranged to obtain one value for year (monthly average discharge). The total natural discharges were computed for the identified river basin in the Brazilian southern power subsystem (see Appendix B).

From the results shown in the figure 6, it is possible identify that, as it was supposed, with the results of the model GFCM is possible to represent a worst case for water availability, and with the model, MPEH to represent the best case of water availability. And the results from the other models configure intermediate scenarios from low to high water availability ETA40-CTL, HADC, MRCG, and NCCC. These scenarios will represent the climate uncertainty.

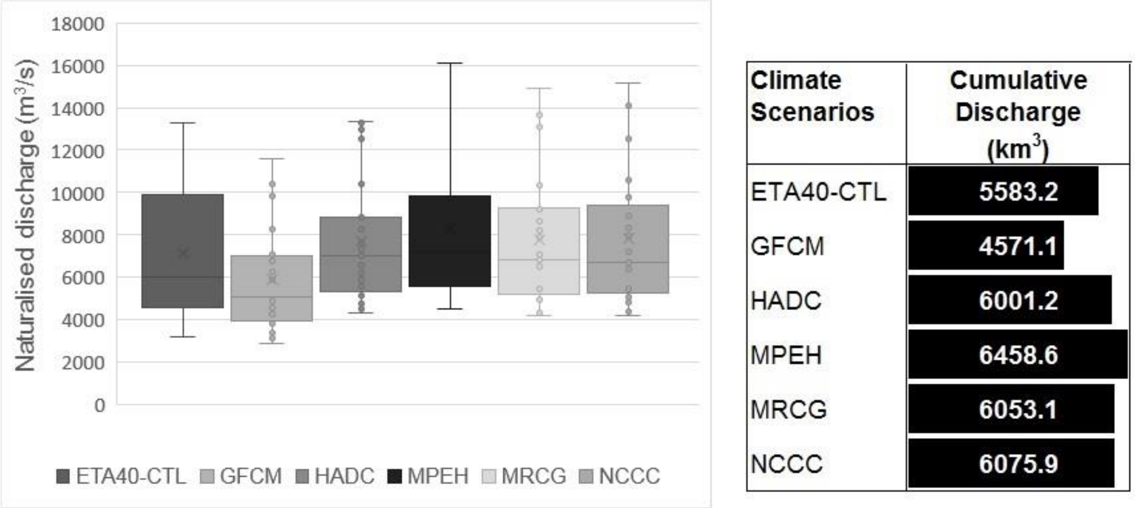


Figure 6. Water availability for the different climate change models

Based on the processed information from the described models each year was classified using the “frequency curve” into five equally likely classes of hydrological conditions: very wet, wet, normal, dry and very dry. The reference discharges used was the corresponding to the ETA40-CTL, from 1961 – 1990, as representing actual climate conditions. The boundaries for the classification were defined as shown in Table 2.

Table 2. Definition of yearly hydrological conditions

Yearly Hydrological Conditions	**Low boundary (m^3/s)**	**Upper boundary (m^3/s)**	**Class (m^3/s)**
Very dry: 1	3,879.3619	4,593.631	4,110.026
Dry: 2	4,593.6310	6,071.313	5,049.314
Normal: 3	6,071.313	7,366.839	6,271.416
Wet: 4	7,366.839	8,767.756	7,743.603
Very wet: 5	8,767.756	14,324.468	11,476.270

For further information about the determination of these classification see Appendix B.

3.3 Problem configuration

Considering the following conditions, the generation capacity expansion planning at the Brazilian southern power subsystem was studied. A time horizon of 24 years was divided in four stages each one of 6 years, starting at the year 2012. An annual interest rate of 8% is adopted. The cost and CO_2 emissions for each type of technology are shown in Table 7.

Table 3. Characteristics of the available sources

Technology type	Investment Costs (10^6 US$/MW)[1]	Variable Costs (US$/MWh)[1]	CO_2 emissions (ton/GWh)[2]
Hydraulic	1.20	2.413	26
Thermal	0.867	10.233	628.67
Wind	1.00	10.00	26

Source: [1] From [33]*, page 349, average values for thermal considering natural gas and coal. [2] Mean values considering lifecycle approach from* [59] *page 6, average values for thermal considering natural gas and coal.*

The initial installed capacity is 27,783 MW. The Table 4 shows the future demands of installed capacity (first column) and the yearly hydrological conditions for the period 2012 – 2036 as result of the generated discharges of regional and global models. These values configure equally likely “climate scenarios.”

3.4 Problem formulation

After identification of the demands at the beginning of each of the four stages, and at the end of the last stage, all the possible capacity expansion $\boldsymbol{x_t^c}$ at each established stage are defined as was explained in 2.1.

Contemplating actual conditions of the Brazilian southern Power subsystem, there are three types of technology to consider as be part of the possible capacity expansion $\boldsymbol{x_t^c}$: r_1 for hydraulic, r_2 for thermal and r_3 for wind, which could configure are part of the coupling equation (11). The values of r are expressed in MW, representing the generation capacity of each type of technology. Each possible capacity expansion $\boldsymbol{x_t^c}$, has costs and CO_2 emissions attached, not only because $\boldsymbol{x_t^c}$ value but also for different climate conditions influencing in the variable costs and the operational conditions.

The next step is the generation of the set of m^T energy policy change scenarios, one set for each climate scenario, then will be six sets. Considering m=11 and the four stages, each set is composed by 11^4 = 14,641 energy policy change scenarios.

Given climate conditions are different from year to year (see Table 4), so are the operational conditions, which are represented by the utilization capacity factor (i.e. $UCF_{t,i}$ and $UCF_{t,TOTAL}$), and conform equations (13) and (14). It is expected that the operational conditions and the related to these will change from one stage to another stage. Then the formulation of the MOLP through the application of the expressions (9) to (15) will generate different coefficients of the MOLP formulation from stage to stage.

Table 4. Projected Demands and Yearly Hydrology Conditions

Year	Capacity (MW)	ETA40-CTL	GFCM	HADC	MPEH	MRCG	NCCC
2012	27,783	3	4	5	5	5	5
2013	28,470	4	3	5	5	5	5
2014	29,157	4	2	3	3	3	3
2015	29,844	2	2	3	3	3	3
2016	30,531	1	3	5	5	5	5
2017	31,218	1	5	5	5	5	5
2018	31,905	1	5	5	5	5	5
2019	32,592	2	3	4	5	4	4
2020	33,279	4	1	2	2	2	2
2021	33,966	3	3	4	5	4	4
2022	34,653	2	1	2	2	2	2
2023	35,340	5	1	1	1	1	1
2024	36,027	5	1	1	2	1	2
2025	36,714	4	3	4	4	4	5
2026	37,401	5	2	3	4	3	3
2027	38,088	5	1	2	2	2	2
2028	38,775	5	1	3	2	2	2
2029	39,462	5	1	2	2	1	1
2030	40,149	4	1	2	2	1	1
2031	40,836	3	1	3	3	3	3
2032	41,523	1	1	2	2	1	1
2033	42,210	1	2	4	4	4	4
2034	42,897	2	5	5	5	5	5
2035	43,584	3	5	5	5	5	5
2036	44,271	2	2	3	3	3	3

Applying the equations (9) to (15), the expressions defining the MOLP for each stage, considering climate conditions resulting from ETA40-CTL are:

Stage 1:

$$\boldsymbol{FO_1: min\ Costs: 1.228 \times r_1 + 1.008 \times r_2 + 1.092 \times r_3} \quad [10^6\ \text{US\$}] \qquad (20)$$

$$\boldsymbol{FO_2: min\ CO_2: 0.351 \times r_1 + 10.629 \times r_2 + 0.287 \times r_3} \quad [10^3\ \text{Ton}] \qquad (21)$$

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \ \geq \ x_t$; $\forall\, t$ [MW] (22)

Operating: $0.257{\times}r_1 + 0.322{\times}r_2 + 0.210{\times}r_3 \ \geq 0.267{\times}(r_1 + r_2 + r_3)$ [MW] (23)

<u>Stage 2:</u>

$\boldsymbol{FO_1}$: $\boldsymbol{min\ Costs}$: $\mathbf{1.228{\times}r_1 + 1.007{\times}r_2 + 1.092{\times}r_3}$ [10^6 US$] (24)

$\boldsymbol{FO_2}$: $\boldsymbol{min\ CO_2}$: $\mathbf{0.378{\times}r_1 + \ 10.188{\times}r_2 \ + 0.287{\times}r_3}$ [10^3 Ton] (25)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \ \geq \ x_t$; $\forall\, t$ [MW] (26)

Operating: $0.277{\times}r_1 + 0.308{\times}r_2 + 0.210{\times}r_3 \ \geq 0.281{\times}(r_1 + r_2 + r_3)$ [MW] (27)

<u>Stage 3</u>:

$\boldsymbol{FO_1}$: $\boldsymbol{min\ Costs}$: $\mathbf{1.241{\times}r_1 + 0.964{\times}r_2 + 1.092{\times}r_3}$ [10^6 US$] (28)

$\boldsymbol{FO_2}$: $\boldsymbol{min\ CO_2}$: $\mathbf{0.533{\times}r_1 + \ 7.159{\times}r_2 \ + 0.287{\times}r_3}$ [10^3 Ton] (29)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \ \geq \ x_t$; $\forall\, t$ [MW] (30)

Operating: $0.390{\times}r_1 + 0.2167{\times}r_2 + 0.210{\times}r_3 \ \geq 0.361{\times}(r_1 + r_2 + r_3)$ [MW] (31)

<u>Stage 4</u>:

$\boldsymbol{FO_1}$: $\boldsymbol{min\ Costs}$: $\mathbf{1.226{\times}r_1 + 1.013{\times}r_2 + 1.092{\times}r_3}$ [10^6 US$] (32)

$\boldsymbol{FO_2}$: $\boldsymbol{min\ CO_2}$: $\mathbf{0.339{\times}r_1 + \ 10.904{\times}r_2 \ + 0.287{\times}r_3}$ [10^3 Ton] (33)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \ \geq \ x_t$; $\forall\, t$ [MW] (34)

Operating: $0.248{\times}r_1 + 0.330{\times}r_2 + 0.210{\times}r_3 \ \geq 0.261{\times}(r_1 + r_2 + r_3)$ [MW] (35)

The expressions for the other climate scenarios are shown in the Appendix C.

The MOLP for each stage of the corresponding climate scenario is solved using the AUGMECON methodology [48], with the parameters eps=1^-3, grid points: gk = m-1 = 10. The SOLVER CPLEX is chosen for optimization, resulting in a discrete Pareto front with the optimal solutions for CO_2 emissions and costs for each possible x_t. The discrete Pareto is composed by eleven values (grid points + 1). Points at the Pareto front are labeled with numbers to represent preferences. The lower the number, the higher the preference for low-cost energy. The higher the number, the higher the preference for low CO_2 emissions.

3.5 Energy Policy scenarios

The identification of robust energy policy scenarios now considers the six climate conditions. The characterization of how the energy policies change throughout the planning horizon is now established by the conditions indicated in Table 5. The conditions are defined qualitatively through the difference between the label of the energy policy in one stage and the previous one, totalizing three differences (e.g., Dif.1, Dif.2, and Dif.3). Qualitatively, the higher the difference, the more abrupt is the change in preference from one objective to another (i.e. low cost to low emissions or the other way around).

Table 5. Characterization of energy policy scenarios

Energy Policy scenario characterization	Condition
Resistant to change. Policies are in the same position of the MOLP Pareto Front for all stages.	|Dif.1|=|Dif.2| & |Dif.2|=|Dif.3| & |Dif.3|=0 Examples: 1-1-1-1, 2-2-2-2, 11-11-11-11
Constant change. Policies are changing progressively in each stage.	|Dif.1|=|Dif.2| & |Dif.2|=|Dif.3| & |Dif.3|=1 Examples: 1-2-3-4, 2-3-4-5, 3-4-5-6
Gradual changes. Policies change their preferences gradually. The policies are in the closest position of the MOLP Pareto Front.	|Dif.1| or |Dif.2| or |Dif.3| <= 6 Examples: 1-1-1-1, 1-1-2-2, 1-2-2-2
Abrupt changes. Policies change their preferences abruptly. The policies are in their far positions on the MOLP Pareto Front.	|Dif.1| or |Dif.2| or |Dif.3| > 6 Examples: 1-1-1-11, 11-11-11-2, 2-2-2-11
Regretting abrupt changes. Constant or gradual energy policies try to change abruptly, but it regrets the decision and reverts to the previous pattern.	Dif.1 or Dif.2 or Dif.3 > - 6 Examples: 1-1-11-1, 1-2-11-3, 11-11-1-11

4. Results

For four stages and the eleven discrete values at the Pareto front, the number of possible permutations is 11^4 = 14,641 energy policy scenarios, shown in Figure 7 along with their respective CO_2 emission and cost objectives at the end of the time horizon for each one of the six different climate change scenarios. The non-dominated values define a clear Pareto front (black dots), while dominated values are differently distributed, depending on the hydrologic conditions. Among all climate, maximum costs are around US$ 11,2 billion, with minimum CO_2

emissions around 20 million tons. The GFCM climate scenario, followed by the ETA40-CTL presented the 14,641 solutions distributed over the largest area in the objectives region (higher spread in the dots on Fig. 7), while the MPEH followed by HADC presented the solutions concentrated over a smaller area (dots more concentrated on Fig. 7), and with lower values of CO_2 emissions.

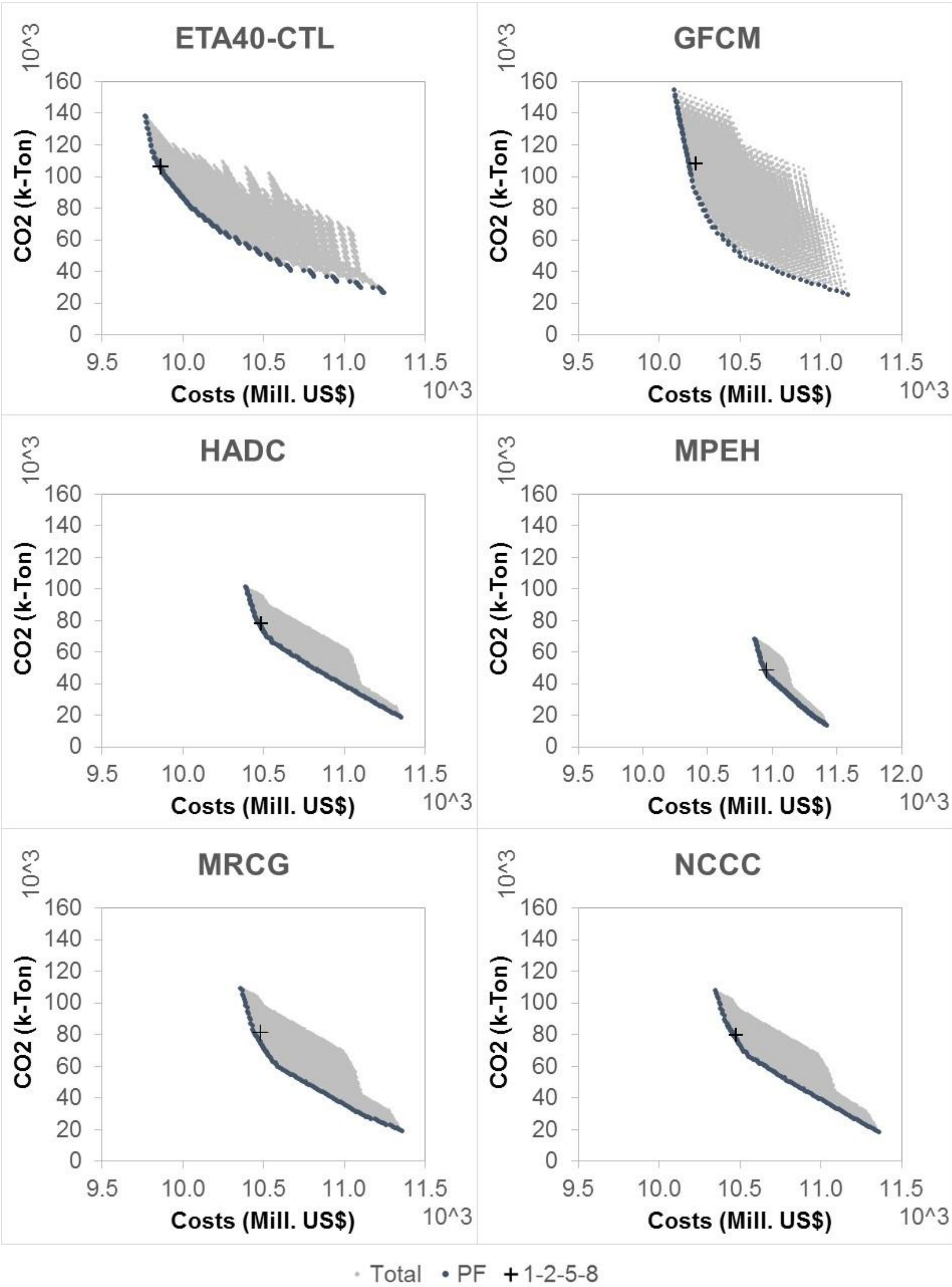


Figure 7. Energy policy scenarios under different climate change scenarios

The high-water availability for the MPEH scenario explains the low CO_2 emissions because water availability reduces thermal power operation, consequently lowering CO_2 emissions and increasing costs.

On the other hand, the lowest discharges in the GFCM model results in a preferred use of the thermal source, generating higher CO_2 emissions. Compared to ETA 40 – CTL (Fig. 5) the small difference in water availability impact in the CO2 emissions with a small reduction. In general, the effects of the climate conditions (through the analysis of the climate scenarios) explains that high CO_2 emissions happen because lower water availability (smaller low flows) leads to increase preference for thermal power generation to fulfill energy demands, while higher water availability explains the lower CO_2 emissions.

Table 6 shows the extreme values of costs and CO_2 emissions for the different climate conditions and the accumulative discharge for the analysis time horizon expressed in volume. It is possible verify that higher volume (higher water availability) in the time horizon of analysis corresponds to more concentrated energy policy scenarios, with smaller differences across likely costs and CO_2 emissions (i.e. smaller difference in the values at the extremes. The opposite is also true. Lower volume (lower water availability) corresponds to more distributed energy policy scenarios (which is the case for GFCM and ETA40-CTL. More distributed solutions across the state region also means higher uncertainty about the results.

Table 6. Extreme values of Costs and CO2 emissions by climate condition

Climate conditions	**Costs (Billion US$)**			**CO_2 (Million tons)**			**Cumulative discharge (km^3)**
	Max	**Min**	**Delta**	**Max**	**Min**	**Delta**	
ETA40-CTL	11.25	9.77	1.48	137.57	25.84	111.73	5,583
GFCM	11.17	10.10	1.07	154.45	24.57	129.88	4,571
HADC	11.36	10.39	0.97	100.55	18.29	82.26	6,001
MPEH	11.43	10.87	0.56	67.97	13.23	54.79	6,459
MRCG	11.36	10.36	1.00	108.93	18.59	90.34	6,053
NCCC	11.36	10.35	1.01	107.12	18.24	88.88	6,076
Maximum	11.43	10.87		154.45	25.84		
Minimum	11.17	9.77		67.97	13.23		
Delta (%)*	**2**	**10**		**56**	**49**		

* Difference between the maximum and minimum values divided by the maximum

The uncertainty resulting from the climate change in terms of costs is lower than uncertainty about CO_2 emissions. Costs could vary around 2% for the maximum values and about 10% for the minimum values. CO_2 emissions could vary around 56% for the maximum values and about 49% for the minimum values. Thus, power expansion decisions targeting CO_2 emissions are much sensitive to climate conditions.

Figure 7 also shows how the energy policy scenario “1-2-5-8” changes its performance under the different climate conditions. This energy policy scenario was selected as an example as it represents an initial preference for low-cost technologies at the first stage (“1”) and a final preference for low CO_2 emissions technologies (“8”). This resembles current context in several countries where cleaner energy sources are under discussion and deployment to reduce CO_2 emission in the long run as the possible reformulation of green target is being discussing in the UK [60]. As energy policy scenario 1-2-5-8 is located close to the Pareto front for different climate conditions, it might be considered a robust solution, with a maximum normalized distance d (expression 17) of 3.35. Table 7 shows the performance of energy policy scenario 1-2-5-8 under different climate conditions. Again, the uncertainty about CO_2 emissions is higher than the costs uncertainty. Even though in one of the climate scenarios the distance to the Pareto front is zero, in the other scenarios it is located farther away from the Pareto front, indicating that climate change will make finding perfect solutions (always at the Pareto front) nearly impossible. Rather, one should seek solutions that present a good compromise under uncertain future changes.

Table 7. Energy policy scenario 1-2-5-8 results

Models	**Costs (Billion US$)**	**CO_2 (Million tons)**	**Normalized distance d**
ETA40-CTL	9.86	106.53	0
GFCM	10.23	108.17	3.44
HADC	10.48	78.09	0.78
MPEH	10.95	48.47	1.28
MRCG	10.48	81.31	3.35
NCCC	10.47	80.08	1.00
Maximum	10.95	108.17	3.35
Minimum	9.86	48.47	0
Delta (%)*	10	55	Average: 1.64

* Difference between the maximum and minimum values divided by the maximum

To identify the robust solutions, we normalized the CO_2 and cost results. Considering the normalized distance to the Pareto front for the six evaluated climate scenarios with p=0.15, (19) yields $\boldsymbol{d_R} \mathbf{= 5.669}$**,** which is adopted as the maximum distance for an energy policy to be classified as a robust solution. For the d_R value calculated a total of 880 robust energy policy scenarios were identified, representing more than 5% of the total energy policy scenarios. The results are shown in the figure 8 as the dark gray points close to the Pareto Front.

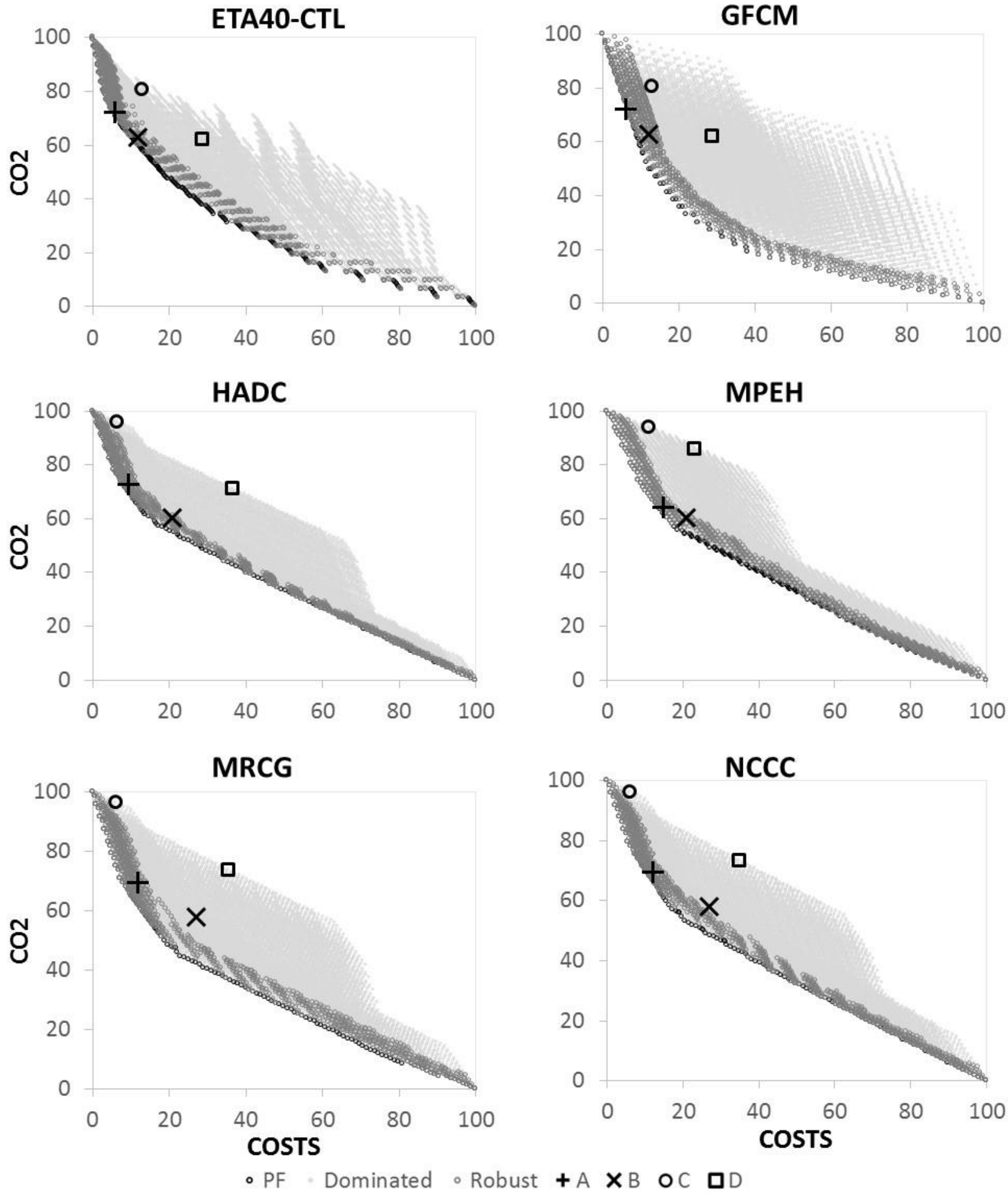


Figure 8. Normalized results

To explain the results, we select four energy policy scenarios, representing different trajectories from low cost policies ("1") to low CO_2 ("8") and also the opposite ("7" to "1"): A (1-2-5-8), B (1-5-5-8), C (7-1-1-1) and D (7-7-1-1). As seen, the energy policies change differently among the example scenarios. The purpose is to show how climate change affects the performance of a given energy policy scenario. Energy policy scenario as A is always inside the area of robust solutions regardless of the climate (its d distance is always < $\boldsymbol{d_R}$ **= 5.669)**. Other Energy policy scenarios, such as B, might be in the robust area (even be part of a Pareto

Front) in a given climate scenario but outside in another. This indicates that B is not robust and presents a higher risk of not delivering the expected performance given climate change.

Energy policy scenarios C and D are always outside of the robust area and are also non-robust solutions. These should be avoided. Relative localization among some of the policies presents some repeating pattern: energy policy A is always above and to the left side of B (higher CO_2 emissions and lower costs) given it delays the adoption of renewable energy sources one stage to the future if compared to B. The same happens with policy C respect to D.

Another observation in figure 8 is the concentration of the robust solutions. In the six climate scenarios, most of the solutions are located in the upper part of the robust area. This must be expected since the leading policy is optimization of minimum costs.

Besides the normalized distance, it is interesting to investigate which other characteristics the robust solutions have in common, especially related to the type of energy policy. Considering the defined 880 robust solutions with a maximum d_R= 5.669, we have sorted and classified the results considering the energy policy in the first stage (Start policy) and the policy in the last stage (End policy). Table 8 shows a summary of the computation.

Column 1 shows the total number of energy policy scenarios starting with energy policy in column 3. Column 2 shows how many of the energy policy scenarios in column 1 are robust. For example, 311 of the energy policy scenarios starting with energy policy 1 are robust (first row) and, out of this robust set, 30 policies end in 4 (1-#-#-4).

These results are useful for one important decision faced by energy planners: “Where to aim” the changes, or, which should be the final energy policy (i.e., the target). While this decision involves tradeoffs and likely included other parties, some insights are possible. For example, if the current energy policy is heavily fossil fuel based, high CO_2 emitting and lower cost (e.g. “1”) there are 11 final policies to aim at, including maintain the current policy 1. Table 8 indicates that most robust policies are located in the ending policy #8 (44), while only 14 robust policies are located in the “greener” ending energy policy #10. This indicates there are more alternative robust decision trajectories (robust energy policy scenarios) towards 8 than towards 10. Given there are 121 possible combinations of energy policies that start in 1 and end in 8 (last row), as well as end in 10, to end in 8 we have 44/121 = 36.3% available robust decision trajectories, while to end in 10 we have 14/121 = 11.6% available robust decision trajectories. This means that if ending policy 8 is chosen, there could be a higher chance that it will be reached with an energy policy scenario that maintains good performance throughout climate uncertainty (closer to the Pareto front).

In the other hand, if the current energy policy is slightly “greener” (e.g. “3”) than aiming at 8 as an ending energy policy now have significantly fewer robust decision trajectories (10/121 = 8.3%) while aiming at 10 still maintains a similar number (13/121 = 10.7%). In this case, having 10 as final energy policy provides the planner with slightly more robust alternatives than 8.

Also important, in the vast majority of the cases, returning from a “greener” energy policy to a least cost one (i.e. moving down in the number labels) is almost never a good decision, as the number of zeros below the main diagonal in Table 8 indicates. There are very few robust alternatives in this region

Table 8. Computation of different arrangement of the robust policies

Total	Robust	Start	End 1	2	3	4	5	6	7	8	9	10	11
1331	311	1	25	25	27	30	30	35	39	44	30	14	12
1331	258	2	24	24	25	27	25	29	33	26	13	12	20
1331	105	3	3	8	8	8	8	11	11	10	10	13	15
1331	40	4	0	0	0	0	0	0	2	7	9	10	12
1331	29	5	0	0	0	0	0	0	0	4	6	8	11
1331	25	6	0	0	0	0	0	0	0	1	5	8	11
1331	27	7	0	0	0	0	0	0	0	1	5	10	11
1331	27	8	0	0	0	0	0	0	0	1	5	10	11
1331	20	9	0	0	0	0	0	0	0	1	2	6	11
1331	19	10	0	0	0	0	0	0	0	1	2	6	10
1331	19	11	0	0	0	0	0	0	0	1	2	6	10
TOTAL	880	Robust	52	57	60	65	63	75	85	97	89	103	134
	TOTAL	Start-end	121	121	121	121	121	121	121	121	121	121	121

Besides presenting the most robust energy policies, this methodology provides decision makers a tool for analysis of the impacts of policy changes under different climate scenarios.

Consider, for example, a situation where a future expansion plan is initially devised, and the decision maker faces the necessity to change it, given a change in the final goal (e.g. further reduce CO_2 emissions). In this situation, the original power generation expansion plan, referred here a “base energy policy scenario” could be defined as 4-4-4-4 (this is an example). This plan now needs to be revised under a more stringent emissions protocol, which will bring the final energy policy to reduce the amount of CO_2 emissions and move from “4” to “9”. There are several possible alternative energy policy scenarios to reach the new final goal: 4-4-4-9, 4-6-8-9 and 4-9-9-9 are some of them. The first delays the adoption of renewable energy sources to reduce CO_2 emissions as far as possible into the future, the second implements a gradual change and the third anticipates the change to the beginning of the planning period.

As expected, each path to reach the final goal has very different results both in terms of cost and total CO_2 emissions along its development.

Table 9 summarizes the results, including, for each one of the six climate scenarios, the costs, CO2 emissions and the normalized distance to the respective Pareto Front. The alternative energy policy scenarios to the original plan 4-4-4-4 achieve the goal of reducing CO_2 emissions with a cost trade-off. The same results are shown in figure 9.

Table 5. Results of policies 4-4-4-4, 4-4-4-9, 4-6-8-9 and 4-9-9-9

	Base energy policy sc.			Alternative energy policy scenarios								
	4-4-4-4			4-4-4-9			4-6-8-9			4-9-9-9		
	Costs (Billion US$)	CO_2 (Million tons)	d	Costs (Billion US$)	CO_2 (Million tons)	d	Costs (Billion US$)	CO_2 (Million tons)	d	Costs (Billion US$)	CO_2 (Million tons)	d
Sc1	9.95	104.05	4.6	10.02	85.72	0.80	10.15	76.89	2.7	10.35	66.06	6.2
Sc2	10.29	115.49	10.92	10.39	97.52	15.53	10.46	72.73	9.85	10.63	57.36	34.28
Sc3	10.58	75.87	8.73	10.60	72.55	7.77	10.82	51.31	2.20	11.05	37.42	19.65
Sc4	10.98	51.54	8.12	11.00	48.23	7.68	11.15	32.62	1.89	11.23	26.85	19.39
Sc5	10.56	81.83	10.79	10.60	75.30	10.79	10.76	53.39	3.73	10.97	39.33	24.45
Sc6	10.55	80.45	8.20	10.59	73.92	8.15	10.81	52.60	2.70	11.04	38.69	19.27
d_{max}			10.92			15.53			9.85			34.28

In figure 9, the results for each of the energy policy scenarios are shown in a specific color, i.e. base energy policy scenario in green, and the others in brown, yellow and orange respectively. The results for each of the climate scenarios are labeled with Sc1 through Sc6. The results of the alternatives energy policies, for the same climate scenario, are all below at the right side of the results of the "base energy policy", indicating a reduction of CO_2 emissions with cost trade-off

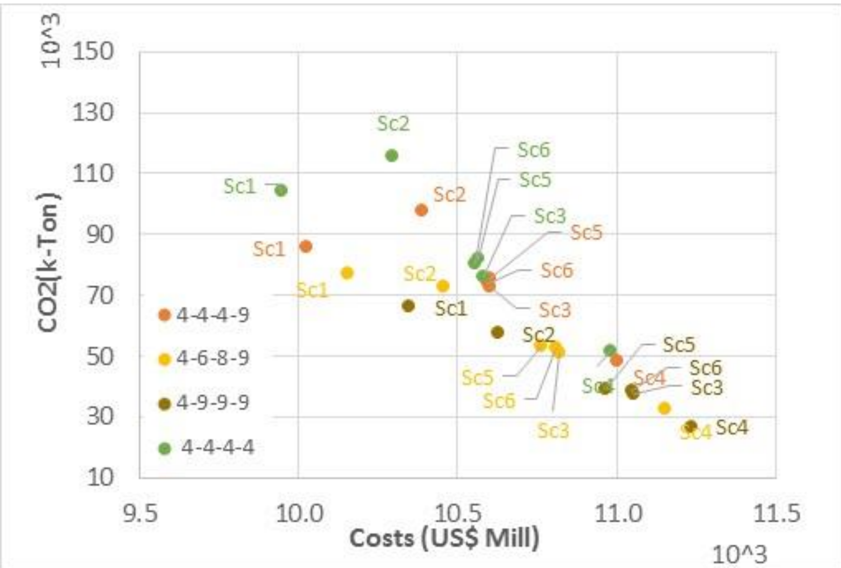


Figure 9. Variation in the results for energy policies

Given the differences among the energy base policy and their alternatives are different in each of the six climate scenarios, a numerical analysis of the differences might be helpful to analyze changes in costs and emissions. Those differences are shown in Table 10. The increase in cost in millions of US$ and the reduction of CO_2 emissions in thousands of tons. Also, a ratio of how much it costs the reduce one ton of CO_2.

Table 10. Difference of costs increase, and CO_2 emissions reductions of alternative policies respect base policy 4-4-4-4

	4-4-4-9			4-6-8-9			4-9-9-9		
	D. Costs Mill US$	D. CO_2 k-Ton	US$/Ton	D. Costs Mill US$	D. CO_2 k-Ton	US$/Ton	D. Costs Mill US$	D. CO_2 k-Ton	US$/Ton
Sc1	77.0	-18333.3	**4.199**	207.8	-27153.0	7.654	402.6	-37993.0	10.598
Sc2	92.5	-17966.8	5.150	163.0	-42759.7	**3.812**	333.3	-58124.6	5.734
Sc3	17.8	-3318.7	**5.356**	234.9	-24562.5	9.565	468.3	-38454.0	12.179
Sc4	17.8	-3318.7	**5.356**	168.4	-18921.5	8.902	249.4	-24694.6	10.101
Sc5	39.5	-6531.2	**6.049**	199.0	-28440.1	6.995	402.4	-42497.9	9.468
Sc6	39.5	-6531.2	**6.049**	255.6	-27853.7	9.177	490.1	-41764.9	11.734
		Average	5.4		Average	7.7		Average	10.0

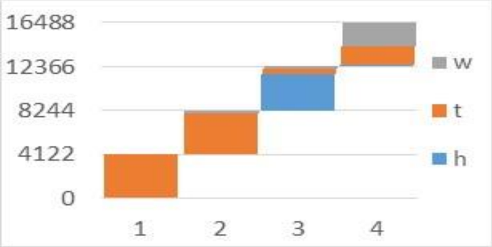
Then, to select one of the three alternatives energy policy scenarios, it is necessary a decision criteria. The possible criteria could be: (a) select the alternative based on a minimum amount of CO_2 emissions that needs to be reduced; (b) select the alternative that meets a maximum Cost or (c) select the alternative with the smallest cost per ton of CO_2 emissions removed (cost efficiency).

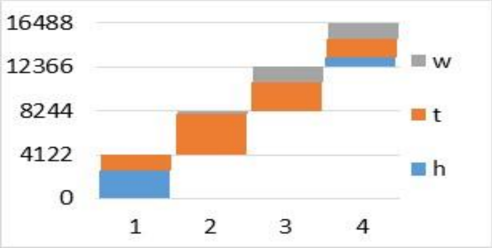
For example, if the decision criterion is achieving a minimum reduction of 20,000 k-Ton, the alternative energy policy scenario 4-9-9-9 is preferred given it is more likely to achieve a reduction of at least 24,694 k-Ton under all evaluated climate conditions. If the decision criterion is achieving a maximum cost of 260 Mill of US$, there are two possible alternatives (i.e. 4-4-4-9 and 4-6-8-9) that are more likely to achieving the criterion. From those alternatives, 4-4-4-9 has the lowest costs, but also the smallest CO_2 emissions reductions for any of the climate scenarios and hence a trade-off. If the decision criterion is to select the one that is more cost efficient, the ratio of how much does it cost (US$) to reduce one Ton of CO_2 drives the selection process. The minimum rates of US$//ton are the ones corresponding to the energy policy 4-4-4-9 (Table 10). Even though the energy policy scenario 4-6-8-9 has the lowest cost per ton for the climate scenario Sc2 (GFCM), the average value of 4-4-4-9 as well the variation of the values, makes alternative 4-4-4-9 the promise one.

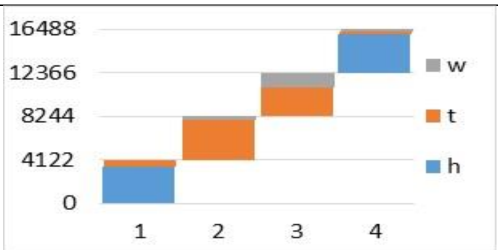
Other aspect to be analyzed in the results is the increments stage by stage, which represent the deployment of different technologies through time under different climate scenarios. Table 11 summarizes the incremental capacity expansions for energy policy A. The results for each one of the different six scenarios stage by stage are presented in the “increments sequence” column: the x-axis displays the decision stage, along with the respective average hydrological conditions AHC, while the y-axis presents the installed power considering the generation technologies considered in the model (w for wind, t for thermal, h for hydropower). The second column “increments by stage in %” presents the % distribution of added power capacity. Given each stage has six years and each year has a defining hydrological condition from 1 to 5 (very dry - 1, dry - 2, normal - 3, wet - 4 and very wet - 5), the average hydrological condition reflects the ordinal rank of the hydrological conditions of the six years in the respective stage. For example, a value of 2.5 for the stage 1 means an intermediate condition between 1 and 2, and so on. The total expansion in the energy policy scenario A for all the stages is 4,122 MW. In general, after an analysis of all the results (14,614) for the, each one of the six climate scenarios, the total expansion follow the same pathway of increments (i.e. 4,122 MW at each stage).

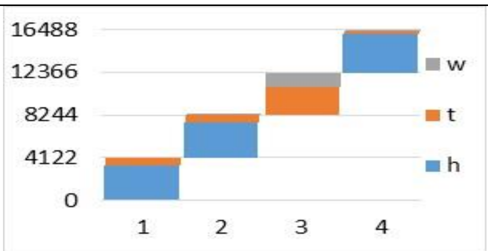
As energy policy scenario A (1-2-5-8) gradually moves from lower cost/higher CO_2 emissions energy policies to lower CO_2 emissions/higher costs policies, a corresponding change is observed in the generation technology mix. However, the exact changes depend on the future climate scenario. As a general trend, thermal generation is set to be reduced as we move through the stages. In the two drier climate scenarios, an increasing trend in wind power helps replacing the decreasing thermal. For the remaining four wetter scenarios, investment in wind power is halted and faces a reduction as we approach the end of the planning period (stage 4), being replaced by less expensive hydropower investment given higher water availability. The energy policy scenario A is robust in terms of CO_2 emissions and Costs due to its proximity to the Pareto front (optimal solutions). These results can be helpful in assisting the decision making about the generation mix. As shown in Table 11, five out of six climate scenarios pointed to significant investments in hydropower for the first stage and the last one. While the result for the first stage can be used immediately, later stages depend on how long does it take for a given technology to be commissioned, once a decision is made. For example, hydropower projects usually take longer given complex licensing and construction. Thus, for a hydropower to be available in each stage, the decision must be made two or three stages before. In our model, that means planning in hydro expansion for stage one (given five out of six climate scenarios pointed out to mostly hydropower investment in stage 1) and running the model again after the stage one is realized to verify the solution for stage 3 (former stage 4, which had dominant hydro investment in the previous model run). If dominant hydropower investment still holds for stage 3 (former stage 4) then a decision should be made to start the hydropower expansion.

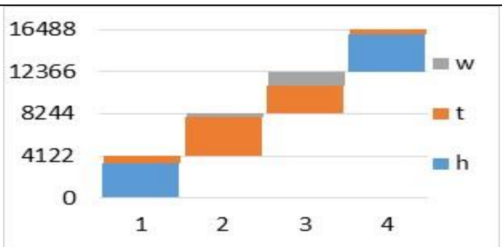
Table 11. Increment Results for Energy Policy Scenario A (1-2-5-8)

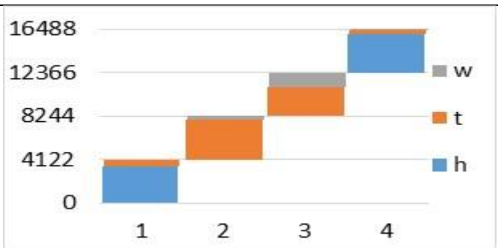
<table>
<tr><td></td><td>Increments sequence</td><td>Increments by stage in %</td></tr>
<tr><td>Sc1</td><td>

AHC 2.5 2.8 4.83 2.33</td><td>ETA40-CTL
<table>
<tr><td></td><td>st1</td><td>st2</td><td>st3</td><td>st4</td></tr>
<tr><td>w</td><td>0%</td><td>8%</td><td>7%</td><td>54%</td></tr>
<tr><td>t</td><td>100%</td><td>92%</td><td>10%</td><td>41%</td></tr>
<tr><td>h</td><td>0%</td><td>0%</td><td>83%</td><td>4%</td></tr>
</table></td></tr>
<tr><td>Sc2</td><td>

AHC 3.17 2.33 1.5 2.5</td><td>GFCM
<table>
<tr><td></td><td>st1</td><td>st2</td><td>st3</td><td>st4</td></tr>
<tr><td>W</td><td>0%</td><td>8%</td><td>36%</td><td>36%</td></tr>
<tr><td>T</td><td>36%</td><td>92%</td><td>64%</td><td>41%</td></tr>
<tr><td>H</td><td>64%</td><td>0%</td><td>0%</td><td>22%</td></tr>
</table></td></tr>
<tr><td>Sc3</td><td>

AHC 4.33 3 2.5 3.5</td><td>HADC
<table>
<tr><td></td><td>st1</td><td>st2</td><td>st3</td><td>st4</td></tr>
<tr><td>W</td><td>0%</td><td>9%</td><td>34%</td><td>4%</td></tr>
<tr><td>T</td><td>17%</td><td>91%</td><td>66%</td><td>5%</td></tr>
<tr><td>H</td><td>83%</td><td>0%</td><td>0%</td><td>90%</td></tr>
</table></td></tr>
<tr><td>Sc4</td><td>

AHC 4.33 3.33 2.67 3.5</td><td>MPEH
<table>
<tr><td></td><td>st1</td><td>st2</td><td>st3</td><td>st4</td></tr>
<tr><td>W</td><td>0%</td><td>0%</td><td>34%</td><td>4%</td></tr>
<tr><td>T</td><td>17%</td><td>18%</td><td>66%</td><td>5%</td></tr>
<tr><td>H</td><td>83%</td><td>82%</td><td>0%</td><td>90%</td></tr>
</table></td></tr>
<tr><td>Sc5</td><td>

AHC 4.33 3 2.17 3.17</td><td>MRCG
<table>
<tr><td></td><td>st1</td><td>st2</td><td>st3</td><td>st4</td></tr>
<tr><td>W</td><td>0%</td><td>9%</td><td>34%</td><td>1%</td></tr>
<tr><td>T</td><td>17%</td><td>91%</td><td>66%</td><td>10%</td></tr>
<tr><td>H</td><td>83%</td><td>0%</td><td>0%</td><td>89%</td></tr>
</table></td></tr>
<tr><td>Sc6</td><td>

AHC 4.33 3 2.5 3.17</td><td>NCCC
<table>
<tr><td></td><td>st1</td><td>st2</td><td>st3</td><td>st4</td></tr>
<tr><td>w</td><td>0%</td><td>9%</td><td>34%</td><td>1%</td></tr>
<tr><td>t</td><td>17%</td><td>91%</td><td>66%</td><td>10%</td></tr>
<tr><td>h</td><td>83%</td><td>0%</td><td>0%</td><td>89%</td></tr>
</table></td></tr>
</table>

Due to the scope of this paper, six climate change scenarios were investigated. If more scenarios are available, the method can be applied to provide similar results and indicate the technology investment most likely to provide the desired outcome (minimum costs and CO_2) emissions.

These results are thus useful to evaluate in advance the impacts of the energy policy changes, which one of them are more robust in terms of optimization cost and reductions of CO_2 emissions for different climate scenarios.

5. Conclusions

This paper presents a new approach to consider energy policy uncertainties and climate conditions simultaneously in power systems capacity expansion planning. The approach is based on the optimality principle of Bellman and scenarios analysis. Dynamic programming and multi-objective linear programming have been used to generate energy policy scenarios and their trade-offs. Utilization capacity factor have been defined to include climate change effects in operational conditions. Techniques for measuring multi-objective performance have been used to identify robust energy policies.

The approach was demonstrated through a case of generation capacity expansion of the Southern Brazilian power subsystem, using three different available energy sources for six different scenarios of climate conditions. For each climate scenario, 14,641 energy policy scenarios were evaluated considering different combinations of energy policy changes. We concluded that:

1. There is a clear Pareto front in each set of solutions for each climate scenario;

2. The performance of energy policy is sensitive to the climate scenario where it is applied, being able to go from being a non-dominated solution (Pareto Front) in a climate scenario to being a dominated solution in another climate scenario (out of the Pareto Front);

3. Climate conditions have influence in the uncertainty about Costs and CO_2 emissions. Climate scenarios with higher water availability presents lower uncertainties in the costs – CO_2 emissions tradeoffs, while drier conditions in the scenario yields in higher uncertainty in the costs – CO_2 trade-offs. Being the bigger impact in terms of CO_2 emissions;

4. Energy policy scenarios characterized by ascending changes (from a low cost to greener energy policy) are more likely to be a robust solution in terms of costs and CO_2 emissions.

Finally, the results indicate that policy change analysis considering climate conditions uncertainty through the planning process is useful to give decision maker's a broader vision about the magnitude of the attached uncertainties and the related risk of the decision making of today in the future.

6. Acknowledgments

The authors are grateful for the financial support provided by the Brazilian National Counsel of Technological and Scientific Development – CNPq (grant number: 141197/2013-7) through the postgraduate scholarship program. The authors also thank CAPES for support in collaborative research under CsF PVE (grant 88881.065004/2014-01). Finally, the first author also thanks, National University of Engineering from Perú (UNI) and the company CESEL Ingenieros. for the provided support.

Appendix A. UCF historical analyses

The analysis of the utilization capacity factor for the Brazilian Southern Power System was based in historical records from the ONS. Table A-1 shows the determination of the UCF for the three main technologies used in the Power System.

Table A-1. UCF from historical records

Year	Hydropower			Thermal power			Wind power			TOTAL
	Generated (GW-h)	Installed (MW)	UCF	Generated (GW-h)	Installed (MW)	UCF	Generated (GW-h)	Installed (MW)	UCF	UCF
2000	46601	16767	0.32	8258	2772	0.34	0	0	0.00	0.32
2001	55341	16942	0.37	10454	3031	0.39	0	0	0.00	0.38
2002	51244	18095	0.32	7776	3521	0.25	0	3	0.00	0.31
2003	42617	18320	0.27	7173	3564	0.23	0	3	0.00	0.26
2004	46818	18455	0.29	9143	3577	0.29	0	8	0.00	0.29
2005	47260	19319	0.28	8765	3585	0.28	0	8	0.00	0.28
2006	29598	19491	0.17	10264	3593	0.33	0	167	0.00	0.20
2007	59003	20459	0.33	8998	3595	0.29	408	167	0.28	0.32
2008	60094	20842	0.33	8260	3610	0.26	422	167	0.29	0.32
2009	58009	21182	0.31	6548	3742	0.20	389	167	0.27	0.30
2010	75897	22173	0.39	7871	3759	0.24	419	176	0.27	0.37
2011	86510	22387	0.44	5696	4146	0.16	641	553	0.13	0.39
2012	53746	22954	0.27	10487	4161	0.29	909	669	0.16	0.27
2013	78492	23484	0.38	12167	4176	0.33	1003	756	0.15	0.37

To analyze the UCF and the hydrological conditions for the same period 2000 – 2013, the methodology explained in Appendix B was done. For these case, was used historical records of the natural discharges from the ONS (1931-2013). The same river basins from table B-1 were considered, the discharges and their respective hydrological conditions are shown in Table A-2.

An analysis of correspondence between hydrological conditions and UCF, considering the average, maximum and minimum, together with historical values, shown in Table A-3 was done. The analysis of "correlation" is shown in the figure A-1. Considering these correlation, the UCF for the three technologies were established as shown in Table 1.

Table A-2. Discharges and Yearly Hydrological Conditions – YHC.

Year	Q (m^3/s)	YHC
2000	7683	4
2001	7319	4
2002	7729	4
2003	6794	3
2004	7100	3
2005	8089	5
2006	6328	3
2007	8034	4
2008	7310	4
2009	8800	5
2010	8633	5
2011	9530	5
2012	6271	2
2013	8287	5

Table A-3. UCF and YHC considered

	YHC	UCF_{Hydro}	YHC	UCF_{Thermo}
Historical average conditions	4 3 5	0.31 0.27 0.37	4 3 5	0.28 0.31 0.24
Minimum Average Maximum	1 3 5	0.17 0.32 0.44	5 3 1	0.16 0.28 0.39

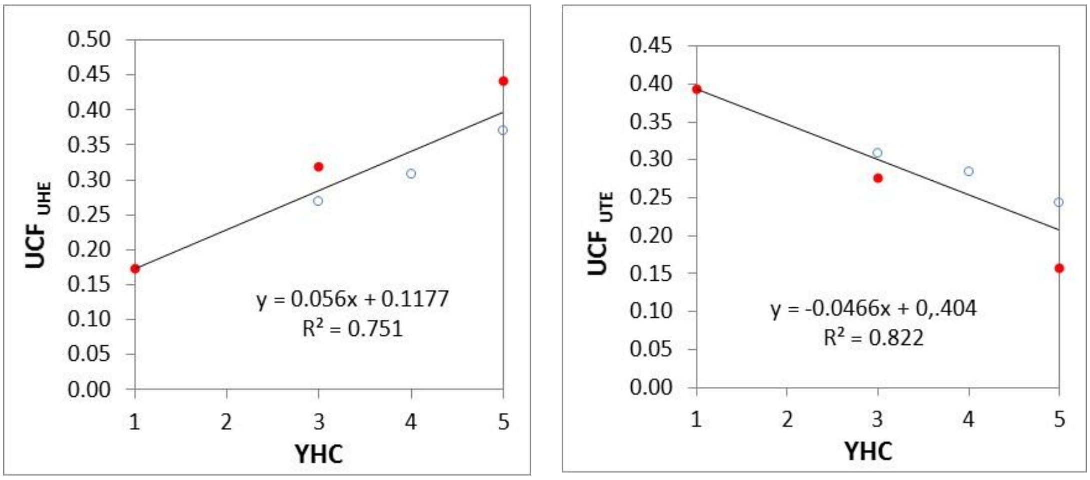


Figure A-1. Correlation between UCF and Yearly hydrological conditions

Appendix B. Hydrological conditions definition

Hydrological conditions in the Brazilian Southern Power subsystem related to power generation are defined by the natural discharge of their main river basins. In these case the gauge stations considered for the analysis (due to its location downstream of main hydropower) are shown in Table B-1.

Table B-1. Main Hydropower river basin of Brazilian Southern Power System

ONS code	Hydropower	River	River Basin	State
113	Itaúba	Jacuí	Jacuí	RS
98	Castro Alves	das Antas	Antas	RS
66	Itaipu	Paraná	Paraná	PR
217	Machadinho	Uruguai	Uruguai	SC

To establish the hydrological conditions of dry (1), very dry (2), normal (3), wet (4) and very wet (5), the data corresponding to ETA40-CTL ATUAL (current situation scenario) from [41] was used. Then variations on the discharge will be perceived since the hydrological conditions were established for the current situation. From that data, the monthly average discharge for each year at each river basin indicated in Table A-1 was computed. The total discharge was calculated adding the values from each one of the four river basins, except the corresponding to Paraná. For the Paraná river basin, since the power generation recorded as Brazilian production is the half, only 50% of the corresponding discharge in Paraná river was taken. Table B-2 shows the results.

With this data, a cumulative frequency curve was elaborated, and the limits for the five equally like hydrological conditions were established considering 20% for each one. The resultant values are shown in Table 2.

Table B-2. Monthly average discharges for Brazilian Southern hydropower system

Year	Q (m^3/s)	Year	Q (m^3/s)	Year	Q (m^3/s)
1961	7,366.839	1971	7,784.158	1981	6,071.313
1962	9,877.998	1972	4,722.814	1982	4,136.828
1963	8,767.756	1973	3,879.362	1983	7,435.482
1964	6,366.738	1974	4,275.056	1984	12,983.287
1965	6,194.529	1975	7,675.177	1985	12,525.804
1966	8,922.667	1976	6,663.445	1986	6,243.386
1967	1,4324.468	1977	5,069.987	1987	4,593.631
1968	1,2931.911	1978	5,262.641	1988	5,439.488
1969	8,324.024	1979	4,088.038	1989	7,875.939
1970	5,207.327	1980	4,170.846	1990	6,089.089

Appendix C. MOLP formulation for climate scenarios: GFCM, HADC, MPEH, MRCG and NCCC

C.1 Climate Scenario GFCM

<u>Stage 1:</u>

$$\boldsymbol{FO_1}: \boldsymbol{min\ Costs}: \mathbf{1.231}\times\boldsymbol{r_1} + \mathbf{0.999}\times\boldsymbol{r_2} + \mathbf{1.092}\times\boldsymbol{r_3} \quad [10^6\ \text{US\$}] \quad \text{(C-1)}$$

$$\boldsymbol{FO_2}: \boldsymbol{min\ CO_2}: \mathbf{0.405}\times\boldsymbol{r_1} + \mathbf{9.693}\times\boldsymbol{r_2} + \mathbf{0.287}\times\boldsymbol{r_3} \quad [10^3\ \text{Ton}] \quad \text{(C-2)}$$

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t\ ; \quad \forall\, t$ [MW] (C-3)

Operating: $0.297\times r_1 + 0.293\times r_2 + 0.210\times r_3 \geq 0.295\times(r_1 + r_2 + r_3)$ [MW] (C-4)

<u>Stage 2:</u>

$$\boldsymbol{FO_1}: \boldsymbol{min\ Costs}: \mathbf{1.227}\times\boldsymbol{r_1} + \mathbf{1.011}\times\boldsymbol{r_2} + \mathbf{1.092}\times\boldsymbol{r_3} \quad [10^6\ \text{US\$}] \quad \text{(C-5)}$$

$$FO_2 : min\ CO_2 : 0.339 \times r_1 + 10.188 \times r_2 + 0.287 \times r_3$$ [10^3 Ton] (C-6)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-7)

Operating: $0.248 \times r_1 + 0.330 \times r_2 + 0.210 \times r_3 \geq 0.261 \times (r_1 + r_2 + r_3)$ [MW] (C-8)

Stage 3:

$$FO_1 : min\ Costs : 1.221 \times r_1 + 1.031 \times r_2 + 1.092 \times r_3$$ [10^6 US$] (C-9)

$$FO_2 : min\ CO_2 : 0.273 \times r_1 + 12.171 \times r_2 + 0.287 \times r_3$$ [10^3 Ton] (C-10)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-11)

Operating: $0.200 \times r_1 + 0.368 \times r_2 + 0.210 \times r_3 \geq 0.227 \times (r_1 + r_2 + r_3)$ [MW] (C-12)

Stage 4:

$$FO_1 : min\ Costs : 1.226 \times r_1 + 1.016 \times r_2 + 1.092 \times r_3$$ [10^6 US$] (C-13)

$$FO_2 : min\ CO_2 : 0.351 \times r_1 + 10.684 \times r_2 + 0.287 \times r_3$$ [10^3 Ton] (C-14)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-15)

Operating: $0.257 \times r_1 + 0.323 \times r_2 + 0.210 \times r_3 \geq 0.267 \times (r_1 + r_2 + r_3)$ [MW] (C-16)

C.2 Climate Scenario HADC

Stage 1:

$$FO_1 : min\ Costs : 1.238 \times r_1 + 0.974 \times r_2 + 1.092 \times r_3$$ [10^6 US$] (C-17)

$$FO_2 : min\ CO_2 : 0.497 \times r_1 + 7.930 \times r_2 + 0.287 \times r_3$$ [10^3 Ton] (C-18)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-19)

Operating: $0.363 \times r_1 + 0.240 \times r_2 + 0.210 \times r_3 \geq 0.342 \times (r_1 + r_2 + r_3)$ [MW] (C-20)

Stage 2:

$$FO_1 : min\ Costs : 1.231 \times r_1 + 0.998 \times r_2 + 1.092 \times r_3$$ [10^6 US$] (C-21)

$$\boldsymbol{FO_2: min\ CO_2: 0.389 \times r_1 + 9.913 \times r_2 + 0.287 \times r_3} \quad [10^3 \text{ Ton}] \quad \text{(C-22)}$$

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t\ ; \quad \forall\, t$ [MW] (C-23)

Operating: $0.285 \times r_1 + 0.300 \times r_2 + 0.210 \times r_3 \geq 0.287 \times (r_1 + r_2 + r_3)$ [MW] (C-24)

Stage 3:

$$\boldsymbol{FO_1: min\ Costs: 1.227 \times r_1 + 1.012 \times r_2 + 1.092 \times r_3} \quad [10^6 \text{ US\$}] \quad \text{(C-25)}$$

$$\boldsymbol{FO_2: min\ CO_2: 0.353 \times r_1 + 10.684 \times r_2 + 0.287 \times r_3} \quad [10^3 \text{ Ton}] \quad \text{(C-26)}$$

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t\ ; \quad \forall\, t$ [MW] (C-27)

Operating: $0.258 \times r_1 + 0.323 \times r_2 + 0.210 \times r_3 \geq 0.268 \times (r_1 + r_2 + r_3)$ [MW] (C-28)

Stage 4:

$$\boldsymbol{FO_1: min\ Costs: 1.232 \times r_1 + 0.995 \times r_2 + 1.092 \times r_3} \quad [10^6 \text{ US\$}] \quad \text{(C-29)}$$

$$\boldsymbol{FO_2: min\ CO_2: 0.430 \times r_1 + 9.197 \times r_2 + 0.287 \times r_3} \quad [10^3 \text{ Ton}] \quad \text{(C-30)}$$

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t\ ; \quad \forall\, t$ [MW] (C-31)

Operating: $0.315 \times r_1 + 0.278 \times r_2 + 0.210 \times r_3 \geq 0.308 \times (r_1 + r_2 + r_3)$ [MW] (C-32)

C.3 Climate Scenario MPEH

Stage 1:

$$\boldsymbol{FO_1: min\ Costs: 1.238 \times r_1 + 0.974 \times r_2 + 1.092 \times r_3} \quad [10^6 \text{ US\$}] \quad \text{(C-33)}$$

$$\boldsymbol{FO_2: min\ CO_2: 0.497 \times r_1 + 7.930 \times r_2 + 0.287 \times r_3} \quad [10^3 \text{ Ton}] \quad \text{(C-34)}$$

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t\ ; \quad \forall\, t$ [MW] (C-35)

Operating: $0.363 \times r_1 + 0.240 \times r_2 + 0.210 \times r_3 \geq 0.342 \times (r_1 + r_2 + r_3)$ [MW] (C-36)

Stage 2:

$$\boldsymbol{FO_1: min\ Costs: 1.233 \times r_1 + 0.992 \times r_2 + 1.092 \times r_3} \quad [10^6 \text{ US\$}] \quad \text{(C-37)}$$

$$\boldsymbol{FO_2: min\ CO_2: 0.417 \times r_1 + 9.472 \times r_2 + 0.287 \times r_3} \quad [10^3 \text{ Ton}] \quad \text{(C-38)}$$

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-39)

Operating: $0.305{\times}r_1 + 0.287{\times}r_2 + 0.210{\times}r_3 \geq 0.301{\times}(r_1 + r_2 + r_3)$ [MW] (C-40)

<u>Stage 3</u>:

$\boldsymbol{FO_1}$: $\boldsymbol{min\ Costs}$: $\mathbf{1.228{\times}r_1 + 1.008{\times}r_2 + 1.092{\times}r_3}$ [10^6 US$] (C-41)

$\boldsymbol{FO_2}$: $\boldsymbol{min\ CO_2}$: $\mathbf{0.364{\times}r_1 + 10.464{\times}r_2 + 0.287{\times}r_3}$ [10^3 Ton] (C-42)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-43)

Operating: $0.267{\times}r_1 + 0.317{\times}r_2 + 0.210{\times}r_3 \geq 0.274{\times}(r_1 + r_2 + r_3)$ [MW] (C-44)

<u>Stage 4</u>:

$\boldsymbol{FO_1}$: $\boldsymbol{min\ Costs}$: $\mathbf{1.232{\times}r_1 + 0.995{\times}r_2 + 1.092{\times}r_3}$ [10^6 US$] (C-45)

$\boldsymbol{FO_2}$: $\boldsymbol{min\ CO_2}$: $\mathbf{0.430{\times}r_1 + 9.197{\times}r_2 + 0.287{\times}r_3}$ [10^3 Ton] (C-46)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-47)

Operating: $0.315{\times}r_1 + 0.278{\times}r_2 + 0.210{\times}r_3 \geq 0.308{\times}(r_1 + r_2 + r_3)$ [MW] (C-48)

C.4 Climate Scenario MRCG

<u>Stage 1:</u>

$\boldsymbol{FO_1}$: $\boldsymbol{min\ Costs}$: $\mathbf{1.238{\times}r_1 + 0.974{\times}r_2 + 1.092{\times}r_3}$ [10^6 US$] (C-49)

$\boldsymbol{FO_2}$: $\boldsymbol{min\ CO_2}$: $\mathbf{0.497{\times}r_1 + 7.930{\times}r_2 + 0.287{\times}r_3}$ [10^3 Ton] (C-50)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-51)

Operating: $0.363{\times}r_1 + 0.240{\times}r_2 + 0.210{\times}r_3 \geq 0.342{\times}(r_1 + r_2 + r_3)$ [MW] (C-52)

<u>Stage 2:</u>

$\boldsymbol{FO_1}$: $\boldsymbol{min\ Costs}$: $\mathbf{1.231{\times}r_1 + 0.998{\times}r_2 + 1.092{\times}r_3}$ [10^6 US$] (C-53)

$\boldsymbol{FO_2}$: $\boldsymbol{min\ CO_2}$: $\mathbf{0.389{\times}r_1 + 9.913{\times}r_2 + 0.287{\times}r_3}$ [10^3 Ton] (C-54)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-55)

Operating: $0.285 \times r_1 + 0.300 \times r_2 + 0.210 \times r_3 \geq 0.287 \times (r_1 + r_2 + r_3)$ [MW] (C-56)

Stage 3:

$\boldsymbol{FO_1: min\ Costs: 1.225 \times r_1 + 1.017 \times r_2 + 1.092 \times r_3}$ [10^6 US$] (C-57)

$\boldsymbol{FO_2: min\ CO_2: 0.326 \times r_1 + 11.180 \times r_2 + 0.287 \times r_3}$ [10^3 Ton] (C-58)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-59)

Operating: $0.238 \times r_1 + 0.338 \times r_2 + 0.210 \times r_3 \geq 0.254 \times (r_1 + r_2 + r_3)$ [MW] (C-60)

Stage 4:

$\boldsymbol{FO_1: min\ Costs: 1.230 \times r_1 + 1.001 \times r_2 + 1.092 \times r_3}$ [10^6 US$] (C-61)

$\boldsymbol{FO_2: min\ CO_2: 0.403 \times r_1 + 9.638 \times r_2 + 0.287 \times r_3}$ [10^3 Ton] (C-62)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-63)

Operating: $0.295 \times r_1 + 0.292 \times r_2 + 0.210 \times r_3 \geq 0.294 \times (r_1 + r_2 + r_3)$ [MW] (C-64)

C.5 Climate Scenario NCCC

Stage 1:

$\boldsymbol{FO_1: min\ Costs: 1.238 \times r_1 + 0.974 \times r_2 + 1.092 \times r_3}$ [10^6 US$] (C-65)

$\boldsymbol{FO_2: min\ CO_2: 0.497 \times r_1 + 7.930 \times r_2 + 0.287 \times r_3}$ [10^3 Ton] (C-66)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall t$ [MW] (C-67)

Operating: $0.363 \times r_1 + 0.240 \times r_2 + 0.210 \times r_3 \geq 0.342 \times (r_1 + r_2 + r_3)$ [MW] (C-68)

Stage 2:

$\boldsymbol{FO_1: min\ Costs: 1.231 \times r_1 + 0.998 \times r_2 + 1.092 \times r_3}$ [10^6 US$] (C-69)

$\boldsymbol{FO_2: min\ CO_2: 0.389 \times r_1 + 9.913 \times r_2 + 0.287 \times r_3}$ [10^3 Ton] (C-70)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall\, t$ [MW] (C-71)

Operating: $0.285 \times r_1 + 0.300 \times r_2 + 0.210 \times r_3 \geq 0.287 \times (r_1 + r_2 + r_3)$ [MW] (C-72)

Stage 3:

$\boldsymbol{FO_1: min\ Costs: 1.228 \times r_1 + 1.011 \times r_2 + 1.092 \times r_3}$ [10^6 US$] (C-73)

$\boldsymbol{FO_2: min\ CO_2: 0.353 \times r_1 + 10.739 \times r_2 + 0.287 \times r_3}$ [10^3 Ton] (C-74)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall\, t$ [MW] (C-75)

Operating: $0.258 \times r_1 + 0.325 \times r_2 + 0.210 \times r_3 \geq 0.269 \times (r_1 + r_2 + r_3)$ [MW] (C-76)

Stage 4:

$\boldsymbol{FO_1: min\ Costs: 1.230 \times r_1 + 1.001 \times r_2 + 1.092 \times r_3}$ [10^6 US$] (C-77)

$\boldsymbol{FO_2: min\ CO_2: 0.403 \times r_1 + 9.638 \times r_2 + 0.287 \times r_3}$ [10^3 Ton] (C-78)

s.t.

Demand/coupling: $r_1 + r_2 + r_3 \geq x_t$; $\forall\, t$ [MW] (C-79)

Operating: $0.295 \times r_1 + 0.292 \times r_2 + 0.210 \times r_3 \geq 0.294 \times (r_1 + r_2 + r_3)$ [MW] (C-80)

References

[1] World Energy Council. World Energy Issues Monitor. 2016.

[2] Tsur Y, Zemel A. Policy tradeoffs under risk of abrupt climate change. J Econ Behav Organ 2016. doi:10.1016/j.jebo.2016.05.020.

[3] Iyer G, Hultman N, Eom J, McJeon H, Patel P, Clarke L. Diffusion of low-carbon technologies and the feasibility of long-term climate targets. Technol Forecast Soc Change 2015;90:103–18. doi:10.1016/j.techfore.2013.08.025.

[4] Haurie A, Tavoni M, van der Zwaan BCC. Modeling Uncertainty and the Economics of Climate Change: Recommendations for Robust Energy Policy. Environ Model Assess 2011;17:1–5. doi:10.1007/s10666-011-9271-5.

[5] Pástor Ľ, Veronesi P. Uncertainty about Government Policy and Stock Prices. J Finance 2012;67:1219–64. doi:10.1111/j.1540-6261.2012.01746.x.

[6] Schwenker B, Wulf T, Krys C. Scenario-based strategic planning: Developing strategies in an uncertain world. 2013. doi:10.1007/978-3-658-02875-6.

[7] Parker G, Doak J. Key Concepts in Planning. 1st ed. 2012.

[8] Sample JE, Duncan N, Ferguson M, Cooksley S. Scotland′s hydropower: Current capacity, future potential and the possible impacts of climate change. Renew Sustain Energy Rev 2015;52:111–22. doi:10.1016/j.rser.2015.07.071.

[9] Abdmouleh Z, Alammari R a. M, Gastli A. Review of policies encouraging renewable energy integration & best practices. Renew Sustain Energy Rev 2015;45:249–62. doi:10.1016/j.rser.2015.01.035.

[10] Luss H. Operations research and capacity expansion problems: a survey. Oper Res 1982;30:907–47. doi:10.1287/opre.30.5.907.

[11] Kagiannas AG, Askounis DT, Psarras J. Power generation planning: a survey from monopoly to competition. Electr Power Energy Syst 2004;26:413–21. doi:10.1016/j.ijepes.2003.11.003.

[12] Careri F, Genesi C, Marannino P, Montagna M, Rossi S, Siviero I, et al. Generation expansion planning in the age of green economy. IEEE Trans Power Syst 2011;26:2214–23. doi:10.1109/TPWRS.2011.2107753.

[13] Fuss S, Johansson DJA, Szolgayova J, Obersteiner M. Impact of climate policy uncertainty on the adoption of electricity generating technologies. Energy Policy 2009;37:733–43. doi:10.1016/j.enpol.2008.10.022.

[14] Bistline JE, Weyant JP. Electric sector investments under technological and policy-related uncertainties: A stochastic programming approach. Clim Change 2013;121:143–60. doi:10.1007/s10584-013-0859-4.

[15] Bistline JE. Electric sector capacity planning under uncertainty: Climate policy and natural gas in the US. Energy Econ 2015;51:236–51. doi:10.1016/j.eneco.2015.07.008.

[16] Nazari MS, Maybee B, Whale J, McHugh A. Climate Policy Uncertainty and Power Generation Investments: A Real Options-CVaR Portfolio Optimization Approach. Energy Procedia 2015;75:2649–57. doi:10.1016/j.egypro.2015.07.367.

[17] Rebennack S. Generation expansion planning under uncertainty with emissions quotas. Electr Power Syst Res 2014;114:78–85. doi:10.1016/j.epsr.2014.04.010.

[18] Aghaei J, Akbari MA, Roosta A, Baharvandi A. Multiobjective generation expansion planning considering power system adequacy. Electr Power Syst Res 2013;102:8–19. doi:10.1016/j.epsr.2013.04.001.

[19] Tekiner H, Coit DW, Felder FA. Multi-period multi-objective electricity generation expansion planning problem with Monte-Carlo simulation. Electr Power Syst Res 2010;80:1394–405. doi:10.1016/j.epsr.2010.05.007.

[20] Vithayasrichareon P, Riesz J, MacGill IF. Using renewables to hedge against future electricity industry uncertainties-An Australian case study. Energy Policy 2015;76:43–56. doi:10.1016/j.enpol.2014.10.016.

[21] Zhou Y, Wang L, McCalley JD. Designing effective and efficient incentive policies for renewable energy in generation expansion planning. Appl Energy 2011;88:2201–9. doi:10.1016/j.apenergy.2010.12.022.

[22] BBCNews. Earlier end to subsidies for new UK onshore wind farms. BBC News - Bus 2015. http://www.bbc.com/news/business-33177025 (accessed January 1, 2016).

[23] Schlanger Z. Australia's premier bans government investment in wind power. Newsweek World 2015. http://www.newsweek.com/australia-prime-minister-bans-government-investment-wind-power-352912 (accessed January 1, 2016).

[24] Kirby A. Canadians pull the plug on renewable energy scheme. Clim News Netw 2015. http://climatenewsnetwork.net/canadians-pull-the-plug-on-renewable-energy-scheme/ (accessed January 1, 2016).

[25] COMFIT. COMFIT - Community Feed-in Tariff. Programs Proj n.d. http://energy.novascotia.ca/renewables/programs-and-projects/comfit.

[26] IEA. World Energy Outlook. Executive Summary. Paris: 2014.

[27] Kuramochi T. Review of energy and climate policy developments in Japan before and after Fukushima. Renew Sustain Energy Rev 2015;43:1320–32. doi:10.1016/j.rser.2014.12.001.

[28] Arancibia AL, Marques GF, Bulhões Mendes CA. Systems capacity expansion planning: Novel approach for environmental and energy policy change analysis. Environ Model Softw 2016;85:70–9. doi:10.1016/j.envsoft.2016.08.010.

[29] IPCC. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva, Switzerland: 2014.

[30] VijayaVenkataRaman S, Iniyan S, Goic R. A review of climate change, mitigation, and adaptation. Renew Sustain Energy Rev 2012;16:878–97. doi:10.1016/j.rser.2011.09.009.

[31] Nema P, Nema S, Roy P. An overview of global climate changing in current scenario and mitigation action. Renew Sustain Energy Rev 2012;16:2329–36. doi:10.1016/j.rser.2012.01.044.

[32] ECF, WEC, CJBS, CISL. Climate change: Implications for the energy sector. Key findings from the IPCC. 2014:15.

[33] de Lucena AFP, Schaeffer R, Szklo AS. Least-cost adaptation options for global climate change impacts on the Brazilian electric power system. Glob Environ Chang 2010;20:342–50. doi:10.1016/j.gloenvcha.2010.01.004.

[34] Vine E. Adaptation of California’s electricity sector to climate change. Clim Change 2012;111:75–99. doi:10.1007/s10584-011-0242-2.

[35] Li YP, Huang GH. Electric-power systems planning and greenhouse-gas emission management under uncertainty. Energy Convers Manag 2012;57:173–82. doi:10.1016/j.enconman.2011.12.018.

[36] Li S, Coit DW, Felder F. Stochastic optimization for electric power generation expansion planning with discrete climate change scenarios. Electr Power Syst Res 2016;140:401–12. doi:10.1016/j.epsr.2016.05.037.

[37] Filion Y. Climate Change: Implications for Canadian Water Resources and Hydropower Production. Can Water Resour J 2000;25:255–69. doi:10.4296/cwrj2503255.

[38] Lehner B, Czisch G, Vassolo S. The impact of global change on the hydropower potential of Europe: A model-based analysis. Energy Policy 2005;33:839–55. doi:10.1016/j.enpol.2003.10.018.

[39] Soito JLDS, Freitas MAV. Amazon and the expansion of hydropower in Brazil: Vulnerability, impacts and possibilities for adaptation to global climate change. Renew Sustain Energy Rev 2011;15:3165–77. doi:10.1016/j.rser.2011.04.006.

[40] Hamududu B, Killingtveit A. Assessing climate change impacts on global hydropower. Energies 2012;5:305–22. doi:10.3390/en5020305.

[41] Marangon Lima JW, Colischonn W, Marengo JA. Efeitos das mudanças climáticas na geração de energia elétrica. 1ra ed. São Paulo: Hunter books; 2014.

[42] Almeida Prado F, Athayde S, Mossa J, Bohlman S, Leite F, Oliver-Smith A. How much is enough? An integrated examination of energy security, economic growth and climate change related to hydropower expansion in Brazil. Renew Sustain Energy Rev 2016;53:1132–6. doi:10.1016/j.rser.2015.09.050.

[43] Majone B, Villa F, Deidda R, Bellin A. Impact of climate change and water use policies on hydropower potential in the south-eastern Alpine region. Sci Total Environ 2016;543:965–80. doi:10.1016/j.scitotenv.2015.05.009.

[44] Yao Y, Huang GH, Lin Q. Climate change impacts on Ontario wind power resource. Environ Syst Res 2012;1:1. doi:10.1186/2193-2697-1-2.

[45] Beh EHY, Maier HR, Dandy GC. Scenario driven optimal sequencing under deep uncertainty. Environ Model Softw 2015;68:181–95. doi:10.1016/j.envsoft.2015.02.006.

[46] Loucks D, Beek E, Stedinger J, Dijkman J, Villars M. Water Resources Sytems Planning and Management: An introduction to methods. models and applications. Paris: 2005.

[47] Arancibia Samaniego AL, Pereira Assunção Galdino CH, Fernandes Marques G. FATOR DE CAPACIDADE DE UTILIZAÇÃO COMO INDICADOR DA OPERAÇÃO DO SISTEMA ELETRICO PARA O PLANEJAMENTO DE EXPANSÃO DE GERAÇÃO. ESTUDO DE CASO SUBSISTEMA SUL DO BRASIL. X CBPE - Congr. Bras. Planej.

Energético. Ofer. e Demanda Energ. – o Pap. da Tecnol. da informação na Integr. dos Recur., Gramado, Rio Grande Do Sul: 2016, p. 1–13.

[48] Mavrotas G. Effective implementation of the ε-constraint method in Multi-Objective Mathematical Programming problems. Appl Math Comput 2009;213:455–65.

[49] Knowles J, Corne D. On Metrics for Comparing Non-Dominated Sets 1 Introduction 2 EMO Objectives and Outper- formance Relations 3 Analysis of NDSCMs. Knowl Creat Diffus Util 2001:1–6.

[50] Arroyo JEC, Dos Santos Ottoni R, De Paiva Oliveira A. Multi-objective variable neighborhood search algorithms for a single machine scheduling problem with distinct due windows. Electron Notes Theor Comput Sci 2011;281:5–19. doi:10.1016/j.entcs.2011.11.022.

[51] Jiang S, Ong YS, Zhang J, Feng L. Consistencies and contradictions of performance metrics in multiobjective optimization. IEEE Trans Cybern 2014;44:2391–404. doi:10.1109/TCYB.2014.2307319.

[52] Hutchison D. Modified distance calculation in generational distance and inverted generational distance. Int. Conf. Evol. Multi-Criterion Optim., vol. II, 2015, p. 110–25. doi:10.1007/978-3-319-15892-1.

[53] ANEEL - Agência Nacional de Energia Elétrica. Banco de Informações de Geração. “Resumo estadual” n.d. http://www2.aneel.gov.br/aplicacoes/ResumoEstadual/ResumoEstadual.cfm (accessed March 8, 2016).

[54] Alvares CA, Stape JL, Sentelhas PC, Gonmçalves JLDM, Sparovek G. Köppen`s climate classification map for Brazil. Meteorol Zeitschrift 2014;22:711–28. doi:10.1127/0941-2948/2013/0507.

[55] Stocker TF, D. Q, G-K. P, L.V. A, S.K. A, N.L. B, et al. Technical Summary. Clim. Chang. 2013 Phys. Sci. Basis. Contrib. Work. Gr. I to fifth Assess. Rep. Intergov. Panel Clim. Chang., 2013, p. 33–115.

[56] Alves LM, Marengo J. Assessment of regional seasonal predictability using the PRECIS reginal climate modeling system. Theor Appl Climatol 2010:337–50.

[57] Chou SC, Marengo JA, Lyra AA, Sueiro G, Pesquero JF, Alves LM, et al. Downscaling of South America present climate driven by 4-member HadCM3 runs. Clim Dyn 2012;38:635–53. doi:10.1007/s00382-011-1002-8.

[58] Bravo JM, Collischonn W, da Silva BC, Rodriguez D, Fan FM, Quiroz K, et al. Impacto nas afluências das principais bacias. Efeitos das mudançcas climáticas na geração Energ. elétrica, 2014, p. 245–82.

[59] WNA (World Nuclear Association). Comparison of Lifecycle Greenhouse Gas Emissions of Various Electricity Generation Sources. London: 2011.

[60] Gosden E. What would Brexit mean for Britain's green targets? Telegr News 2017. http://www.telegraph.co.uk/news/0/what-would-brexit-mean-for-britains-green-targets/ (accessed February 15, 2017).

4 CONCLUSÕES

O planejamento da expansão da capacidade de geração dos sistemas elétricos, que visa garantir às futuras demandas de energia elétrica com custos mínimos e baixas emissões de CO_2, aplica políticas energéticas que, por sua natureza, vão mudar ao longo do tempo (por diferentes razões), num contexto de condições climáticas anômalas, geradas pela mudança climática.

Confrontado com este problema, a seguinte questão motivou o desenvolvimento desta tese: *É possível identificar e quantificar, na base do conhecimento, das condições iniciais de planejamento e das influências das mudanças climáticas, os impactos de mudanças nas políticas energéticas otimizadas nos objetivos iniciais do plano de expansão de capacidade de geração?*

Para aprofundar o entendimento a respeito do problema apresentado, foi desenvolvida uma nova abordagem na optimização da expansão da capacidade para considerar as incertezas da política energética e as condições climáticas simultaneamente. A abordagem baseia-se no princípio da otimização de Bellman e análise de cenários. A programação dinâmica e a programação linear multi-objetivo têm sido utilizadas para gerar cenários de política energética e seus *trade-offs*. O fator de capacidade de utilização foi definido para incluir os efeitos da mudança climática nas condições operacionais. Técnicas para medir o desempenho de algoritmos genéticos multi-objetivo têm sido utilizadas para identificar políticas energéticas robustas. As incertezas foram incluídas através de formulação de cenários, onde as fontes de incerteza políticas energéticas e mudança climática, configuram diferentes possíveis cenários.

A abordagem foi demonstrada através de um caso de expansão da capacidade de geração do Sistema de Energia do Sul do Brasil, utilizando três diferentes fontes de energia disponíveis para seis diferentes cenários de condições climáticas. Para cada cenário climático foram avaliados 14.641 cenários de política energética, considerando diferentes combinações de mudanças na política energética. Uma versão inicial da abordagem sem considerar os efeitos das mudanças climáticas foi demostrada a través de um caso hipotético para um número similar de cenários de mudança na política energética.

Com base nos resultados obtidos, os que foram apresentados nos capítulos 2 e 3, chega-se às seguintes conclusões:

1. Existe uma frente de Pareto perfeitamente identificável para cada conjunto de soluções e para cada cenário climático. O conjunto de soluções está conformado pelos resultados, em termos de custos e emissões de CO_2 totais, gerados ao final do período de análise, da aplicação dos diferentes cenários de mudanças das políticas energéticas na expansão da capacidade. As soluções que conformam a frente de Pareto são as soluções não dominadas e as que não o conformam são as soluções dominadas. Este fato, implica que:
    a. Primeiro, que é possível identificar os impactos das mudanças nas políticas através dos diferentes resultados obtidos por cada cenário de mudança da política (custos e emissões CO_2);
    b. Segundo, que é possível classificar as mudanças nas políticas, neste caso em duas: dominadas e não dominadas. Considera-se as que conformam a frente de Pareto como as melhores mudanças.

   Os resultados que sustentam esta conclusão são apresentados nas figuras 5 e 6 do segundo capítulo e nas figuras 7 e 8 do terceiro capítulo. Nestas figuras, fica evidente uma frente de Pareto.

2. O desempenho da política energética é sensível ao cenário climático onde é aplicado, podendo passar de ser uma solução não dominada (Frente de Pareto) num cenário climático, a ser uma solução dominada em outro cenário climático.
   Dos resultados apresentados na figura 8 do terceiro capítulo, evidencia-se que a política B deixa de ser uma solução não dominada, no cenário climático ETA40-CTL, para uma solução dominada, no cenário climático MRCG.

3. As condições climáticas têm influência na incerteza sobre custos e emissões de CO_2. Os cenários climáticos com maior disponibilidade de água apresentam incertezas mais baixas nos trade-off de custos – emissões de CO_2, enquanto que as condições mais secas do cenário geram uma maior incerteza nos trade-off custos – CO2 sendo o maior impacto em termos de emissões de CO_2.
   Nos resultados apresentados na Tabela 6 do terceiro capítulo, fica evidente que, para o cenário climático com melhor disponibilidade hídrica (no caso cenário MPEH), as diferenças dos valores máximo e mínimo, tanto em termos de custos, como de emissões

de CO_2, são os mais baixos. Isto implica uma incerteza menor. No caso que se refere, para as emissões de CO_2 as diferenças encontradas são maiores se comparadas aos custos.

Nos resultados apresentados na Tabela 7 do terceiro capítulo, destaca-se que: os resultados dos custos obtidos para o cenário de mudança da política energética: "1-2-5-8" variam, no máximo 10% em relação ao máximo valor, e em 55% para o caso das emissões de CO_2.

4. Os cenários de política energética caracterizados por mudanças ascendentes (de uma política de baixo custo para uma política energética mais ecológica) são mais susceptíveis a constituir uma solução robusta em termos de custos e emissões de CO_2. Na Tabela 8 do terceiro capítulo, foram analisadas as diferentes configurações das políticas energéticas (cenários, forma como elas podem mudar), identificando-se as robustas, i.e., aquelas que tem um bom desempenho para quaisquer dos cenários climáticos avaliados. Das análises, foi possível identificar, para cada configuração, quantas políticas resultam em robustas. Assim as configurações com mudanças ascendentes apresentam mais políticas robustas do que não robustas.

Finalmente, os resultados confirmam a hipóteses formulada, ao respeito das políticas energéticas: "A configuração das mudanças nas políticas energéticas pode levar a resultados bem diferentes, sendo importante poder identificar também a melhor forma de se executar estas mudanças na expansão de capacidade, de modo a se alcançar o objetivo final".

Efetivamente, os diferentes cenários de mudança das políticas energéticas (14,641), ou seja, a configuração das políticas energéticas, conduziram a diferentes resultados. Estes mesmos resultados modificam-se segundo o cenário climático considerado.

5 RECOMENDAÇÕES

Os objetivos propostos neste trabalho foram atingidos, a metodologia apresentada é promissora para análise das incertezas políticas e climáticas descritas. No entanto, algumas recomendações devem ser consideradas a respeito dos resultados obtidos neste trabalho:

1) As condições de operação do sistema elétrico foram “simplificadas” através da introdução do conceito de “fator de capacidade de utilização”. Assim, para conseguir uma melhor representatividade das condições de operação dos sistemas elétricos a modelar recomenda-se melhorar o sistema de coleta de dados, para incrementar a extensão das informações (maior quantidade de dados) de capacidade instalada e de energia gerada, por tipo de fonte a ser modelada. Alternativamente, fazer uma interface com outro modelo de operação do sistema já comprovado, o que poderia demandar mais tempo para o processamento da informação e para as simulações;

2) Recomenda-se explorar a potencialidade das aplicações da metodologia desenvolvida no presente trabalho, não só para uso como ferramenta para tomada de decisão ou para desenho de políticas, mas também para sua aplicabilidade em outras áreas, como gestão de sistemas de recursos hídricos;

3) Os cenários climáticos empregados no presente trabalho foram utilizados pela facilidade de se acessar esta informação, de modo que, no caso de não se contar com este tipo de informação, deve-se considerar o processo de modelagem climática, ajuste e naturalização das vazões a serem empregadas.

Trabalhos futuros com aplicação desta metodologia poderiam também considerar: as demandas concorrentes pelo recurso hídrico assim como a variação nos custos do investimento para cada estágio.

Finalmente, recomenda-se explorar as vantagens da utilização da combinação da Programação Dinâmica com a Programação Linear Multi-objetivo como técnica para enfrentar o problema da dimensionalidade da Programação Dinâmica.

REFERÊNCIAS BIBLIOGRÁFICAS

AGHAEI, J., AKBARI, M. A., ROOSTA, A., & BAHARVANDI, A. (2013). Multiobjective generation expansion planning considering power system adequacy. *Electric Power Systems Research*(102), 8-19.

AHMED, S., KING, A., & PARIJA, G. (2003). A Multi-Stage Stochastic Integer Programming Approach for Capacity Expansion Under Uncertainty. *Journal of Global Optimization*(26), 3-24.

BBCNEWS. (2015). *BBC News. Business*. de Erlier end to subsidies for new UK onshore wind farms. Disponível em: http://www.bbc.com/news/business-33177025. Acceso em: 22 de jul. 2015.

CARERI, F., GENESI, C., PAOLO, M., MONTAGNA , M., ROSSI, S., E SIVEIRO, I. (Novembro de 2011). Generation expansion planning in the age of green economy. *Transactios on power systems*, págs. 2214-2223.

DAVIS, M., DEMPSTER, M., SETHI, S., & VERMES, D. (1987). Optimal Capacity Expansion under Uncertainty. *Advances in Applied Probability, 19*(1), 156-176.

ELKARMI, F., E ABUSHIKHAH, N. (2012). *Power system planning technologies and applications.Concepts, solutions and management* (1 ed.). (L. Johnston, Ed.) Palmdale: Engineering Science Reference .

FILION, Y. (2000). Climate change: Implicantions for Canadian Water resources and hydropower production. *Canadian Water Resources Journal, 25*, 255-269.

FUSS, S., JOHANSSON, D. J., SZOLGAYOVA, J., E OBERSTEINER, M. (2009). Impact of climate policy uncertainty on the adoption of electricity generating technologies. *Energy Policy*(37), 733-743.

GORENSTIN, B. G., CAMPODONICO, N. M., COSTA, J. P., E PEREIRA, M. V. (fevereiro de 1993). Power system expansion planning under uncertainty. *Transactions on Power Systems, 8*(1), 129-136.

HOUSE, R., E WARFIELD, J. (1969). What is System Planning. *Automatica, 5*, 151-157.

IAEA. (1984). *Expansion planning for electrical generating systems - A Guidebook* (1ra ed.). (I. A. Agency, Ed.) Vienna: International Atomic Energy Agency.

IEA. (2014). *World Energy Outlook. Executive Summary.* Paris: OECD/IEA.

IPCC. (2014). *Climate Change 2014: Synthesis report. Contribution of working groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* (Core Writing Team, R. Pachauri, e L. Meyer, Edits.) Geneva, Switzerland: IPCC.

KAGIANNAS, A. G., ASKOUNIS, D. T., E PSARRAS, J. (2004). Power generation planning: a survey from monopoliy to competition. *Electrical Power and Energy Systems*(26), 413-421.

KURAMOCHI, T. (2015). Review of energy and climate policy developments in Japan be fore and after Fukushima. Renewable and Sustainable Energy Reviews (43), 1320-1332.

LEHNER, B., CZISCH, G., E VASSOLO, S. (2005). The impact of global change on the hydropower potential of Europe: a model-based analysis. *Energy Policy*, 839-855.

LI, S., COIT, D. W., SELCUKLU, S., E FELDER, F. (2014). Electric Power Generation Expansion Planning: Robust Optimization Considering Climate Change. *Proceedings of the 2014 Industrial and Systems Engineering Research Conference* (págs. 1049-1058). Y. Guan and H.Liao.

LI, Y. (18 de September de 2014). The Debate of the Green Paradox. *Review of Environment, Energy and Economics (Re3).*

LIMA, J. M., COLISCHONN, W., E MARENGO, J. (2014). *Efeitos das Mudanças Climáticas na geração de energia elétrica.* São Paulo: Hunter Books.

LUSS, H. (September - October de 1982). Operations research and capacity expansion problems: a survey. *Operations Research, 30*(5), págs. 907 - 947.

PARKER, G., E DOAK, J. (2012). *Key Concepts in Planning* (1 ed.). (R. Kitchin, Ed.) London: SAGE.

PÁSTOR, L., & VERONESI, P. (2012). Uncertainty about Goverment Policy and Stock Prices. *The Journal of Finance, LXVII*(4), 1219-1264.

REBENNACK, S. (2014). Generation expansion planning underuncertainty with emissions. *Electric power systems research*(114), 78-85.

REUTER, W. H., SZOLGAYOVÁ, J., FUSS, S., & OBERSTEINER, M. (2012). Renewable energy investment: Policy and market impacts. *Applied Energy*(97), 249-254.

SAMPLE, J.E., DUNCAN N., FERGUSON, M., COOKSLEY, S. (20115). Scotland׳s hydropower: Current capacity, future potential and the possible impacts of climate change. *Renewable and Sustainable Energy Review* (52), 111–22.

SCHWENKER, B., E WULF, T. (2013). An uncertain World. En B. Schwenker, T. Wulf, B. Schwenker, e T. Wulf (Edits.), *Scenario-based strategic planning. Developing strategies in an uncertain world* (1a ed., págs. 12-14). Springer Gabler.

SEIFI, H., E SEPASIAN, M. (2011). *Electric Power System Planning - Issues, Algorithms and Solutions.* Berlin: Springer.

SCHLANGER, Z. (2015). *Newsweek World*. Acesso em 21 de July de 2015, disponível em http://www.newsweek.com/australia-prime-minister-bans-government-investment-wind-power-352912

TEKINER, H., COIT, D. W., E FELDER, F. A. (July de 2010). Multi-period multi-objective electricity generation expansion planning problem with Monte-Carlo simulation. *Electric Power Systems Research*(80), 1394 - 1405.

TSP. (2017). *The Shift Project Data Portal*. de Breakdown of Electricity Generation by Energy Source. Disponivel em: http://www.bbc.com/news/business-33177025. Acceso em: 12 de fev. 2017.

VITHAYASRICHAREON, P., RIESZ, J., E MACGILL, I. (2015). Using renewables to hedge against future electricity industry uncertainties-An Australian case study. *Energy Policy*(76), 43-56.

YAO Y, HUANG GH, LIN Q. (2012). Climate change impacts on Ontario wind power resource. *Environmental Systems Research*. (1:2), 1-11.

YEPEZ-GARCÍA, R., JOHNSON, T., E ANDRÉS, L. A. (2010). *Meeting the Electricity sypply/demand balance in Latin America E the Caribbean.* (M. t. Caribbean, Ed.) World Bank - ESMAP.