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Designing a sustainable stochastic electricity generation network with hybrid production strategies

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This paper aims to design a sustainable stochastic electricity production network where fossil fuels-based, biomass-based, and co-firing-based production strategies are simultaneously considered in order to take advantage of all the three production strategies. A multi-objective stochastic mixed integer linear programming model is proposed to achieve economic feasibility, as well as environmental and social benefits under multiple uncertainties. The model is solved by using the improved augmented epsilon constraint method. A case study is used to illustrate the effectiveness of the proposed model. Pareto optimal analysis is conducted to understand the trade-off between economic, environmental, and social aspects of sustainability.

Keywords: Hybrid production strategy; electricity generation network; sustainability; multi-objective stochastic mixed integer linear programming; improved augmented ε–constraint method

1. Introduction

The demand for electricity has increased significantly due to the growing global population, urbanisation, and industrialisation (Evans, Strezov, and Evans 2010). In the past 50 years, fossil fuels such as coal, natural gas, and crude oil have been considered as the primary source of energy for generating electricity as they provide significant economic benefits. However, fossil fuels are non-renewable and have raised energy security concerns. In addition, the excessive use of fossil fuels has raised environmental issues due to the high greenhouse gas (GHG) emissions. In fact, the environmental protection agency (EPA) reports that 37% of the GHG emissions in the US are contributed by the combustion of fossil fuels for electricity generation (USEPA 2011). As a result, it is necessary to look for alternative energy sources that are both renewable and sustainable to generate electricity. Therefore, new renewable energy policies have been developed by various government agencies. For example, the US Federal Government's Green Power Purchasing Incentive (GPPI) initiative stipulates that 20% of electricity should be generated from renewable energy by the fiscal years 2020–2021 (DSIRE 2016).

Biomass is considered as one of the alternatives for generating electricity because it is both renewable and sustainable. While there are several biomass types, the use of lignocellulosic biomass for electricity purposes has been emphasised because it is non-edible (Akgul et al. 2014). Lignocellulosic biomasses are of two types: (1) dedicated energy crops such as switchgrass and miscanthus that can be produced through agricultural methods and (2) waste biomass such as woody materials, crop residues which are the remnants of forestry, woodwork, and agriculture (Cuellar 2012). These biomasses are perennial and are considered carbon neutral as they sequester GHG from the atmosphere during the growth process (Zhang et al. 2010). Consequently, biomass-based power plants (BBPs) have been operating in several areas in order to reduce the GHG emission (Yue et al. 2014). However, the cost of BPPs is higher compared to fossil fuel-based power plants (FPPs). Therefore, co-firing-based power plants (CFPPs) have been established in order to reduce the cost and improve environmental benefits, since the co-firing strategy does not require a new infrastructure (Roni et al. 2017).

From a long-term sustainability perspective, an electricity generation network should be designed by considering not only the economic performance but also environmental and social performance. Since the three electricity generation strategies (fossil fuel-based, biomass-based, and co-firing-based) perform differently in terms of economic, environmental, and social benefits, there is not a single optimal strategy that can satisfy all the sustainability measures simultaneously. Therefore, it is necessary to design a sustainable electricity generation network with hybrid production strategies (EGN-HPS) that consists of FPPs, BPPs, and CFPPs by considering economic, environmental, and social performance simultaneously. In

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Table 1. Acronyms used in this paper.

Acronym	Description
AUGMECON 2	Improved augmented epsilon constraint
BEGN	Biomass-based electricity generation network
BPP	Biomass-based electricity power plant
CFEGN	Co-firing-based electricity generation network
CFPP	Co-firing-based power plant
FEGN	Fossil fuel-based electricity generation network
FPP	Fossil fuel-based power plant
GHG	Greenhouse gas
GPPI	Green power purchasing Incentive
EGN-HPS	Electricity generation network with hybrid production strategy
Mo-SMILP	Multi-objective stochastic mixed integer linear programming

addition, the EGN-HPS is exposed to several uncertainties such as electricity conversion rate, biomass yield, and coal excavation rate. Therefore, this paper aims to design a sustainable EGN-HPS that aims to simultaneously improve the economic, environmental, and social aspects of sustainability under various uncertainties. Review of the literature suggests that none of the up-to-date literature have considered all the three electricity production strategies and all the three sustainability aspects together in the electricity generation network. Therefore, the unique contribution of the paper is to design an EGN-HPS that simultaneously consists of fossil fuels-based, co-firing-based, and biomass-based production strategies in a single electricity generation network under uncertainties by considering economic, environmental, and social aspects of sustainability.

A multi-objective stochastic mixed integer linear programming (Mo-SMILP) model is proposed to determine a sustainable EGN-HPS under uncertainties. The proposed model is solved by using the improved augmented ε–constraint method (AUGMECON 2). Table 1 provides the acronyms used in the paper.

The following outlines the remaining sections of the paper: Section 2 provides the related literature review; Section 3 presents the problem statement; Section 4 proposes the Mo-SMILP model and the solution technology; Section 5 discusses the case study set in the state of North Dakota (ND) in the US; Section 6 presents the results and sensitivity analysis; and finally, Section 7 provides the conclusions and future research.

2. Literature

Since the paper focuses on the electricity generation network design, the literature reviews are only conducted in four areas: (1) electricity production strategies, (2) analytical approaches, (3) sustainability performance metrics, and (4) solution methods for the multi-objective program. The literature review is summarised in Table 2.

2.1. Electricity production strategies

There are three electricity production strategies: (1) fossil fuel-based electricity production, (2) biomass-based electricity production, and (3) co-firing-based electricity production. Fossil fuel-based electricity production uses fossil fuels such as coal, natural gas, and crude oil to generate electricity (Koornneef et al. 2008; Van der Wijk et al. 2014). The literature suggests that fossil fuel-based electricity production provides economic benefits (Weldu and Assefa 2017). However, the GHG emissions are significantly high (Han, Ahn, and Lee 2012; Van der Wijk et al. 2014). In order to overcome the environmental disadvantage of fossil fuel-based electricity production, biomass-based electricity production has been studied by researchers. Biomass-based electricity production uses biomass such as switchgrass, miscanthus, and wood waste to generate electricity (Yue et al. 2014; Shabani and Sowlati 2016; Gutiérrez et al. 2017). The literature indicates that biomass-based electricity production can significantly reduce GHG emissions (Röder, Whittaker, and Thornley 2015; Shabani and Sowlati 2016; Weldu and Assefa 2017). However, the cost of the biomass-based electricity production is significantly high. Consequently, co-firing-based electricity production is implemented at many FPPs. Co-firing-based electricity production uses both fossil fuel and biomass for electricity generation (Basu, Butler, and Leon 2011; Akgul et al. 2014). The literature indicates that co-firing-based electricity production can balance the benefits of both fossil fuel-based electricity production and biomass-based electricity production by simultaneously reducing the cost and increasing the environmental benefits, since the co-firing strategy does not require a new infrastructure (Roni et al. 2014). Since different electricity generation strategies provide different sustainability benefits, it is necessary to consider all the three fossil fuels, biomass, and co-firing strategies while designing an electricity generation network.

Table 2. Literature review summary on electricity supply chain design.

Author	Electricity generation strategy: Fossil fuel	Biomass	Co-firing	Analytical approach	Sustainability performance metric: Economic	Environmental	Social	Result
Qin et al. (2006)		×	×	LCA	×	×		The results indicate a significant decrease in GHG in biomass alone electricity plant compared to co-firing.
Gan and Smith (2007)		×		Data analysis	×	×	×	The data analysis suggests that using logging residues can displace around 2.44 Metric ton (Mt) of CO_2, create 1340 new jobs every year.
Koornneef et al. (2008)	×			LCA		×		The result indicates a significant decrease in GHG emissions/kWh when CCS technology is used.
Basu, Butler, and Leon (2011)			×	Economic analysis	×	×		The result indicates that co-firing significantly reduce cost and GHG emissions.
Akgul et al. (2012)			×	Stochastic	×	×		The results provide strategic decisions to design a sustainable co-firing-based electricity supply chain.
Han, Ahn, and Lee (2012)	×			Stochastic	×	×		The results provide optimal CO_2 capture, sequestration and transportation activities.
Steinmann et al. (2012)	×			LCA		×		The results indicate that carbon footprint for coal-fired power ranges from 0.97 to 1.69 kg CO_2 eq/kWh.
Vance et al. (2012)	×	×	×	Deterministic	×	×		The results indicate that renewable energy can reduce cost by 5% and GHG emissions by 77%.
Roni et al. (2014)			×	Deterministic	×	×		The result provides optimal supply chain network for waste biomass co-firing in coal-fired electricity plants.
Van der Wijk et al. (2014)	×			Simulation	×	×		The results indicate that CCS becomes extremely unattractive at higher costs.
Yue et al. (2014)		×		Deterministic	×	×	×	The results provide a Pareto optimal curve indicating the trade-off between economic, environmental and social aspects of sustainability for biomass-based supply chain.

(*Continued*)

Table 2. Continued.

Author	Electricity generation strategy: Fossil fuel	Biomass	Co-firing	Analytical approach	Sustainability performance metric: Economic	Environmental	Social	Result
Cinar, Pardalos, and Rebennack (2015)			×	Stochastic	×			The result provides optimal co-firing electricity supply chain configuration.
Röder, Whittaker, and Thornley (2015)		×		LCA		×		The results indicate a significant reduction in GHG emissions and stronger variation in GHG emissions under different scenarios.
Cambero and Sowlati (2016)		×		Deterministic	×	×	×	A positive correlation has been observed between the number of jobs created and GHG emissions.
Ekşioğlu, Karimi, and Ekşioğlu (2016)				Stochastic	×			The results provide optimal co-firing-based electricity supply chain.
Nian (2016)	×	×		LCA		×		The result indicates coal is more carbon neutral compared to woody biomass when biogenic forest system is considered in system boundary of LCA.
Shabani and Sowlati (2016)		×		Stochastic	×			The results indicate a significant trade-off between profit and range of biomass quality.
Xu et al. (2016)	×	×		LCA		×		The result indicates that biomass is not unconditionally cleaner than fossil fuel. Compared with corn straw based electricity generation, coal-based electricity generation is better in most the environmental categories except climate change and human toxicity.
Gutiérrez et al. (2017)		×		Optimisation	×	×		The results indicate sugar based electricity production has a potential of producing 1150 GWh of electricity for the province of Cienfuegos, Cuba.
Weldu and Assefa (2017)	×	×		LCA	×	×		The result indicates that coal-fired electricity generation demonstrated 63–83% lower cost compared to biomass alternatives. Similarly, biomass-based electricity generation showed improvement in environmental impacts by 47–92% compared to coal.
This paper	×	×	×	Stochastic	×	×	×	

2.2. Analytical approaches

In analysing the electricity power plant/ generation network, the common approaches are (1) life cycle assessment (LCA), (2) data analysis, (3) simulation, and (4) mathematical modelling (deterministic/stochastic model). LCA and data analysis approaches are good at analysing the performance of the pre-determined electricity plant/supply chain (Qin et al. 2006; Gan and Smith 2007; Steinmann et al. 2014; Röder, Whittaker, and Thornley 2015; Nian 2016; Xu et al. 2016). This approach alone cannot be used to design a complex electricity generation network. Simulation is another tool that has been used to analyse supply chain performance. However, this approach cannot generate an optimal solution (Van der Wijk et al. 2014). Mathematical modelling such as deterministic optimisation models have been commonly used to design the electricity generation network as they provide optimal solutions (Roni et al. 2014; Yue et al. 2014). However, the electricity generation networks are exposed to a number of uncertainties that need to be considered while modelling (Ekşioğlu, Karimi, and Ekşioğlu 2016; Shabani and Sowlati 2016). Therefore, the stochastic mathematical modelling approach that considers uncertainties is necessary while designing a robust electricity generation network.

2.3. Sustainability performance metric

The literature (Table 2) suggests there are three common metrics used to measure sustainability. They are as follows: (1) economic performance, (2) environmental performance, and (3) social performance (Yue et al. 2014). Economic performance is commonly measured by the total annualised electricity generation network cost (Akgul et al. 2012). Environmental performance is commonly measured by the total annualised electricity generation network GHG emissions (Han, Ahn, and Lee 2012; Roni et al. 2014). Social performance is commonly measured by the total annualised electricity generation network job creation (Gan and Smith 2007; Yue et al. 2014; Cambero and Sowlati 2016). In order for the electricity generation network to be sustainable, it is necessary to improve all three, economic, environmental, and social performance while designing the electricity generation network.

2.4. Solution methods for the multi-objective program

There are several solution methods that have been used for multi-objective programming. These include, but not limited to: (1) the weighted method; (2) the epsilon constraint method; (3) the augmented epsilon constraint method; and (4) the improved augmented epsilon constraint method. The weighted method is a well-known method for solving multi-objective problems (Marler and Arora 2010). However, the weighted method cannot provide solutions to the non-convex set and solutions do not necessarily reflect the decision maker's preferences (Marler and Arora 2010). The epsilon constraint method has also been used intensively in solving multi-objective problems (Laumanns, Thiele, and Zitzler 2006; Cortés, García, and Hernández 2012; Yadollahi et al. 2014; Amirian and Sahraeian 2015). However, it is difficult to choose bounds as the bounds may not necessarily give feasible solutions and might generate weakly efficient solutions (Laumanns, Thiele, and Zitzler 2006). Consequently, the augmented epsilon constraint method (AUGMECON) is developed by Mavrotas (2009) which uses a combination of the epsilon constraint method and the lexicographic method. This method enables one to obtain efficient Pareto solutions (Cortés, García, and Hernández 2012; Yadollahi et al. 2014; Amirian and Sahraeian 2015). However, the slack variables for each are treated equally, resulting in increased computational time due to redundant iterations (Mavrotas and Florios 2013). Consequently, Mavrotas and Florios (2013) developed the improved augmented epsilon constraint method (AUGMECON 2) which considers the information from slack variables and reduces the redundant iterations (by skipping redundant steps) resulting in reduced computational time. Therefore, in this study, AUGMECON 2 is selected to solve the multi-objective program.

2.5. Summary

Based on the literature review (Table 2), it is evident that none of the recent literature has considered designing an electricity generation network that incorporates all three production strategies (fossil fuel-based, biomass-based and co-firing-based strategies) and all three sustainability measures (economic, environmental, and social) under stochastic conditions. The literature (Vance et al. 2012) have considered all the three electricity production strategies under economic and environmental aspects of sustainability. However, the study fails to consider the social aspect of sustainability. Qin et al. (2006) have evaluated two electricity production strategies – specifically, biomass-based electricity generation and co-firing-based electricity generation under economic, environmental, and social aspects of sustainability. However, their study only compares the sustainability performance of the pre-determined stand-alone power plants without considering the design of the network. Other studies focusing on designing an electricity supply chain network have considered only one of the three electricity production strategies (Akgul et al. 2012; Han, Ahn, and Lee 2012; Roni et al. 2014; Yue et al. 2014; Cinar, Pardalos, and

Rebennack 2015; Ekşioğlu, Karimi, and Ekşioğlu 2016; Cambero and Sowlati 2016 ; Shabani and Sowlati 2016; Gutiérrez et al. 2017). The literature indicates that each of the strategies performs differently under different sustainability measures. For instance, FPP can operate at low cost, and BPP leads to less GHG emission. CFPP can balance cost and GHG emissions. In order for an electricity generation network to be sustainable, it should be economically feasible, environmentally friendly, and socially beneficial. In addition, the supply chain should be robust to uncertainties such as the electricity conversion rate, biomass yield rate, and coal excavation rate. Therefore, it is beneficial to design a framework that consists of all the three strategies in an electricity supply chain to reach a desired sustainability level by considering various uncertainties. Consequently, the paper bridges the gap in the literature and is the first paper that focuses on taking advantage of each of the production strategies and design optimal electricity generation with hybrid production strategies (EGN-HPS) that may consist of a combination of fossil fuel, co-firing, and biomass production strategies in order to simultaneously meet economic, environmental, and social sustainability requirements under multiple uncertainties. A stochastic mathematical model is proposed and solved using AUGMECON 2 to accomplish the design process.

3. Problem statement

This study focuses on designing a sustainable EGN-HPS that simultaneously considers fossil fuel-based, co-firing-based, and biomass-based strategies for electricity generation under uncertainties. Three sustainability dimensions, minimising total annualised electricity generation network cost, minimising total annualised GHG emission, and maximising total annualised job creation are considered. In addition, uncertainties such as electricity conversion rate, biomass yield, and coal excavation rate are considered in order to design a robust EGN-HPS.

Figure 1 presents the proposed structure of the EGN-HPS. Let U be the set of fossil fuel excavation sites, indexed by u where the fossil fuels are excavated. Let F be the set of fossil fuels indexed by f. Let C be the set of biomass supply zones, indexed by c. Let B be the set of biomass, indexed by b. It should be noted that dedicated crops (switchgrass and miscanthus) are cultivated and waste biomass (woody materials; crop residues, which are the remnants of forestry; woodwork; and agriculture) are collected. The cultivated or collected biomasses are then stored at the collection centre which is also located in the same supply zone. The biomass from the supply zones and the fossil fuels from the excavation sites are then shipped

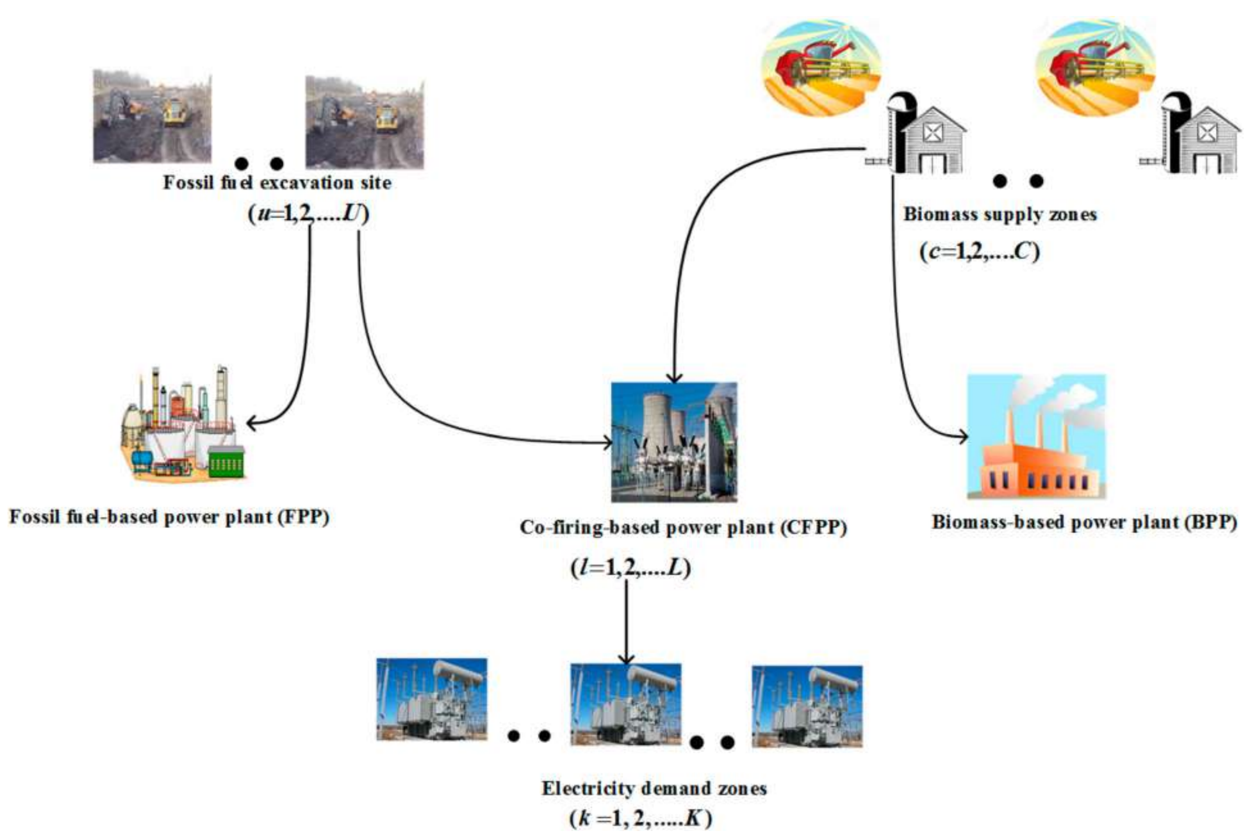

Figure 1. Proposed EGN-HPS structure.

to the electricity plant for electricity generation. Let L be the set of electricity plant locations, indexed by l. Three electricity plant strategies are considered. Let E be the set of electricity plant production strategies, indexed by e. The three electricity plant production strategies are as follows: (1) fossil fuel-based power plant (FPP), indexed by $e = 1$; (2) co-firing-based power plant (CFPP), indexed by $e = 2$; and (3) biomass-based power plant (BPP) indexed by $e = 3$. In addition, let Q be the capacity level for each electricity plant indexed by q. It should be noted that at each location, an electricity plant with only one electricity production strategy and one capacity level can be opened. The electricity generated at the electricity plant is then transmitted to the electricity demand zones. Let K be the set of electricity demand zones, indexed by k. Let T be the time horizon, indexed by t. Let S be the set of uncertain scenarios such as electricity conversion rate, biomass yield, and coal excavation rate, indexed by ξ.

Given such a structure, an Mo-SMILP model is developed to determine the following strategic decisions: (1) an optimal electricity generation network with different types of power plants and their capacity levels; (2) optimal power plant locations; (3) optimal fossil fuel excavation sites, if any; and (4) optimal biomass supply zones, if any.

4. Methodology and solution procedure

This section presents the mathematical formulation for the proposed Mo-SMILP model. The proposed model aims to design an optimal EGN-HPS that accounts for economic, environmental, and social aspects of sustainability. In addition, uncertainties such as electricity conversion rate, biomass yield rate, and excavation rate are considered. The notations for the proposed Mo-SMILP model are presented in Appendix 1. The proposed model is solved by using the AUGMECON 2 method (Mavrotas and Florios 2013).

4.1. Objective functions

The proposed Mo-SMILP has three distinct objective functions: (1) costs, (2) GHG emissions, and (3) job creation. Objective function (1) focuses on minimising the total annualised cost of an EGN-HPS.

$$TC = \left[\begin{array}{l} \sum_{e=1}^{3}\sum_{q=1}^{Q}\sum_{l=1}^{L} CC_{eq}\cdot Y_{eql} + \sum_{c=1}^{C} CCS_c\cdot Y_c + \sum_{f=1}^{F}\sum_{u=1}^{U} R_{fu}\cdot LF_{fu} + \sum_{b=1}^{B}\sum_{c=1}^{C} R_{bc}\cdot LB_{bc} \\ + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot(tr + t\bar{r}\cdot d_{lk})\cdot s_{lk}^{t\xi} + \sum_{e=1}^{3}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot P_e\cdot Z_{el}^{t\xi} + \sum_{f=1}^{F}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot H_f\cdot IP_{fl}^{t\xi} \\ + \sum_{f=1}^{F}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot B_f\cdot IM_{fl}^{t\xi} + \sum_{b=1}^{B}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot H_b\cdot IP_{bl}^{t\xi} + \sum_{b=1}^{B}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot B_b\cdot IM_{bl}^{t\xi} \\ + \sum_{f=1}^{f}\sum_{u=1}^{U}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot(tc_f + t\bar{c}_f\cdot d_{ul})\cdot xf_{ful}^{t\xi} + \sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot(tc_b + t\bar{c}_b\cdot d_{cl})\cdot xb_{bcl}^{t\xi} \\ + \sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot H_b\cdot ISP_{bc}^{t\xi} + \sum_{b=1}^{B}\sum_{c=1}^{c}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot B_b\cdot ISM_{bc}^{t\xi} + \sum_{f=1}^{F}\sum_{u=1}^{U}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot DG_{fu}\cdot xu_{fu}^{t\xi} \\ + \sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{\xi=1}^{S} \vartheta_\xi\cdot HT_{bc}\cdot bc_{bc}^{t\xi} + \sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{\xi=1}^{S} \vartheta_\xi\cdot CT_{bc}\cdot bc_{bc}^{t\xi} + \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot SC_k\cdot SL_k^{t\xi} \end{array}\right] \tag{1}$$

Objective function (2) focuses on minimising the total expected GHG emissions of the entire EGN-HPS. It should be noted that as biomass absorbs GHG while growing, the amount of GHG neutralised by the biomass is subtracted from the GHG emissions.

$$G = \left[\begin{array}{l} \sum_{e=1}^{3}\sum_{q=1}^{Q}\sum_{l=1}^{L} g_{eq}\cdot Y_{eql} + \sum_{c=1}^{C} g_c\cdot Y_c + \sum_{e=1}^{3}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot g_e\cdot Z_{el}^{t\xi} + \sum_{f=1}^{F}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot gt_f\cdot d_{cl}\cdot xf_{ful}^{t\xi} \\ + \sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot gt_b\cdot d_{cl}\cdot xb_{bcl}^{t\xi} + \sum_{f=1}^{F}\sum_{u=1}^{U}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot gc_f\cdot xu_{fu}^{t\xi} + \sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot gc_b\cdot bc_{bc}^{t\xi} \\ + \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot gs_k\cdot SL_k^{t\xi} - \sum_{e=1}^{E}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S} \vartheta_\xi\cdot g_r\cdot Z_{el}^{t\xi} \end{array}\right] \tag{2}$$

Objective function (3) focuses on maximising the total expected number of jobs created by the EGN-HPS. It should be noted that jobs are measured in person-hours because the problem is annualised and includes both direct and indirect jobs

(Dutta 2012).

$$J=\begin{bmatrix} -\sum_{e=1}^{3}\sum_{q=1}^{Q}\sum_{l=1}^{L} j_{eq}\cdot Y_{eql}-\sum_{c=1}^{C} j_c\cdot Y_c+\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S}\vartheta_\xi\cdot je\cdot s_{kl}^{t\xi}+\sum_{e=1}^{3}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S}\vartheta_\xi\cdot jp_e\cdot Z_{el}^{t\xi} \\ +\sum_{f=1}^{F}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S}\vartheta_\xi\cdot jt_f\cdot xf_{ful}^{t\xi}+\sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{\xi=1}^{S}\vartheta_\xi\cdot jt_b\cdot xb_{bcl}^{t\xi}+\sum_{f=1}^{F}\sum_{u=1}^{U}\sum_{t=1}^{T}\sum_{\xi=1}^{S}\vartheta_\xi . jc_f\cdot xu_{fu}^{t\xi} \\ +\sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{t=1}^{T}\sum_{\xi=1}^{S}\vartheta_\xi\cdot j_{bc}\cdot bc_{bc}^{t\xi}+\sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{t=1}^{T}\sum_{\xi=1}^{S}\vartheta_\xi\cdot jc_b\cdot bc_{bc}^{t\xi} \end{bmatrix} \tag{3}$$

4.2. Constraints

4.2.1. Electricity demand and supply constraints

Constraint (4) ensures that the electricity demand at each demand zone is met by a combination of in-state and out-of-state electricity generation.

$$s_k^{t\xi}+SL_k^{t\xi}=D_k^t\forall k,\forall t,\forall\xi \tag{4}$$

Constraints (5) and (6) ensure that the electricity transmitted from the electricity plants is equal to the electricity obtained at the demand zones and power lost during transmission.

$$s_k^{t\xi}=(1-PL)\cdot\sum_{l=1}^{L}s_{lk}^{t\xi}\forall k,\forall t,\forall\xi \tag{5}$$

$$s_l^{t\xi}=\sum_{k=1}^{K}s_{lk}^{t\xi}\forall l,\forall t,\forall\xi \tag{6}$$

4.2.2. Electricity production strategy and capacity constraints

Constraints (7)–(9) ensure that only one electricity generation strategy with one capacity level is opened at a given location. The amount of electricity transmitted from an electricity plant should be equal to the electricity produced. In addition, the electricity produced at each electricity plant should be less than maximum allowable capacities for the electricity plant.

$$\sum_{e=1}^{E=3}\sum_{q=1}^{Q}Y_{eql}\le 1\forall l \tag{7}$$

$$s_l^{t\xi}=\sum_{e=1}^{E=3}Z_{le}^{t\xi}\forall l,\forall t,\forall\xi \tag{8}$$

$$Z_{el}^{t\xi}\le\sum_{q=1}^{Q}\bar{\rho}_{lq}\cdot Y_{eql}\forall l,\forall e,\forall t,\forall\xi \tag{9}$$

4.2.3. Electricity conversion constraints

Constraints (10)–(13) indicate the amount of electricity produced at an electricity plant based on the electricity generation strategy. Since different inputs are used for combustion, all the inputs are converted to energy content. Constraint (10) indicates that the amount of electricity produced at the FPP depends on the amount of fossil fuel used, the efficiency of the FPP, quality of the fossil fuel mixture, and energy content in each fossil fuel. Constraint (11) represents the amount of electricity produced at the CFPP which depends on the biomass and fossil fuel used, efficiency of the CFPP, quality of the biomass and fossil mixtures, and energy content in the biomass and fossil fuel. Constraint (12) ensures that a certain amount of electricity should be produced by using biomass at CFPP. Constraint (13) indicates that the amount of electricity produced at the BPP depends on the amount of biomass used, efficiency of the BPP, quality of the biomass mixture, and energy content in each biomass.

$$Z_{el}^{t\xi} = (1 - QRF_e) \cdot ef_e \cdot \omega \cdot \sum_{f=1}^{F} \eta_{f\xi} \cdot X_{fl}^{t\xi} e = 1, \forall l, \forall t, \forall \xi \tag{10}$$

$$Z_{el}^{t\xi} = (1 - QRF_e) \cdot ef_e \cdot \omega \cdot \left(\sum_{b=1}^{B} \eta_{b\xi} \cdot X_{bl}^{t\xi} + \sum_{f=1}^{F} \eta_{f\xi} \cdot X_{fl}^{t\xi} \right) e = 2, \forall l, \forall t, \forall \xi \tag{11}$$

$$(1 - QRF_e) \cdot ef_e \cdot \omega \cdot \sum_{b=1}^{B} \eta_{b\xi} \cdot X_{bl}^{t\xi} = w \cdot Z_{el}^{t\xi} e = 2, \forall l, \forall t, \forall \xi \text{ where } w \in [0, 1] \tag{12}$$

$$Z_{el}^{t\xi} = (1 - QRF_e) \cdot ef_e \cdot \omega \cdot \sum_{b=1}^{B} \eta_{b\xi} \cdot X_{bl}^{t\xi} e = 3, \forall l, \forall t, \forall \xi \tag{13}$$

4.2.4. Fossil fuel material balance constraints

Constraints (14)–(16) represent the material balance, inventory level, and inventory holding capacity for fossil fuel at the electricity plant.

$$\sum_{u=1}^{U} xf_{ful}^{t\xi} + I_{fl}^{t-1\xi} = X_{fl}^{t\xi} + I_{fl}^{t\xi} \forall f, \forall l, \forall t, \forall \xi \tag{14}$$

$$I_{fl}^{t\xi} = IP_{fl}^{t\xi} - IM_{fl}^{t\xi} \forall f, \forall l, \forall t, \forall \xi \tag{15}$$

$$IP_{fl}^{t\xi} \leq IC_{fl} \cdot Y_{eql} \forall f, \forall e, \forall q, \forall l, \forall t, \forall \xi \tag{16}$$

4.2.5. Biomass material balance constraints

Constraints (17)–(19) represent the material balance, inventory level, and inventory holding capacity for the biomass at the electricity plant.

$$\sum_{c=1}^{C} xb_{bcl}^{t\xi} + I_{bl}^{t-1\xi} = X_{bl}^{t\xi} + I_{bl}^{t\xi} \forall b, \forall l, \forall t, \forall \xi \tag{17}$$

$$I_{bl}^{t\xi} = IP_{bl}^{t\xi} - IM_{bl}^{t\xi} \forall b, \forall l, \forall t, \forall \xi \tag{18}$$

$$IP_{bl}^{t\xi} \leq IC_{bl} \cdot Y_{eql} \forall b, \forall e, \forall q, \forall l, \forall t, \forall \xi \tag{19}$$

4.2.6. Biomass collection centre material balance constraints

Constraints (20)–(22) represent the material balance, inventory level, and inventory holding capacity for biomass collection centre at the supply zone.

$$bc_{bc}^{t\xi} + IS_{bc}^{t-1\xi} = \sum_{l=1}^{L} xb_{bcl}^{t\xi} + IS_{bc}^{t\xi} \forall b, \forall c, \forall t, \forall \xi \tag{20}$$

$$IS_{bc}^{t\xi} = ISP_{bc}^{t\xi} - ISM_{bc}^{t\xi} \forall b, \forall c, \forall t, \forall \xi \tag{21}$$

$$ISP_{bc}^{t\xi} \leq IC_{bc} \cdot Y_c \forall b, \forall c, \forall t, \forall \xi \tag{22}$$

4.2.7. Fossil fuel excavation constraints

Constraints (23)–(25) are constraints for fossil fuel excavation sites. The total amount of fossil fuel shipped to electricity plants should be equal to the amount excavated. In addition, the amount of fossil fuel excavated depends on the excavation rate and the amount of land used. The amount of land used should be less than the maximum allowable land.

$$xu_{fu}^{t\xi} = \sum_{l=1}^{L} xf_{ful}^{t\xi} \forall f, \forall u, \forall t, \forall \xi \tag{23}$$

$$xu_{fu}^{t\xi} = \lambda_{fu}^{\xi}.LF_{fu} \forall f, \forall u, \forall t, \forall \xi \tag{24}$$

$$LF_{fu} \leq FCAP_{fu} \forall f, \forall u \tag{25}$$

4.2.8. Biomass cultivation or collection constraints

Constraints (26) and (27) are the biomass cultivation/collection and harvest constraints. The amount of biomass collected by collection centre depends on the yield rate and the amount of land used. In addition, the amount of land used for a particular type of biomass should be less than the maximum allowable land.

$$bc_{bc}^{t\xi} = \lambda_{bc}^{\xi} \cdot LB_{bc} \forall b, \forall c, \forall t, \forall \xi \tag{26}$$

$$LB_{bc} \leq BCAP_{bc} \forall b, \forall C \tag{27}$$

4.2.9. Renewable energy based electricity generation constraint

Constraint (28) controls the amount of biomass and fossil fuels to be used in the electricity supply chain in order to meet various government policies such as the GPPI initiative. It indicates that the electricity generated from biomass should be greater than a certain level in the EGN-HPS.

$$\sum_{e=1}^{E} \sum_{b=1}^{B} (1 - QRF_e) \cdot ef_e \cdot \omega \cdot \eta_{b\xi} X_{bl}^{t\xi} \geq \pi \sum_{e=1}^{E} \sum_{l=1}^{L} Z_{el}^{t\xi} \forall t, \forall \xi \text{ where } \pi \in [0, 1] \tag{28}$$

4.3. Solution procedure

Since the proposed Mo-SMILP consists of three objectives: (1) economic (cost), (2) environmental (GHG emissions), and (3) social (jobs creation), there exists no single solution that can simultaneously optimise all the objectives. Therefore, it is necessary to obtain Pareto optimal solutions that can provide trade-offs between the three competing objectives. In order to simultaneously obtain efficient solutions and reduce the computational time, an improved augmented–constraint method, also known as AUGMECON 2, is applied to the Mo-SMILP. This section describes the AUGMECON 2 method as applied to (1)–(28). The solution procedure is adopted from Mavrotas and Florios (2013).

The generic form of the proposed Mo-SMILP ((1)–(28)) is given by (29), where x is the vector for decision variables, $f_1(x)$, $f_2(x)$, $f_3(x)$ are the cost, GHG emissions, and job creation objective functions, respectively. S is the feasible region. It should be noted that cost and environmental objectives are minimisation problems which are converted to maximisation problems by using a negative value.

Maximise $f_1(x)$, $f_2(x)$, $f_3(x)$

$$\text{s.t.} \quad x \in S \tag{29}$$

Firstly, a lexicographic optimisation method is used to obtain ranges for the three objective functions. While the best value for each objective is easily attained through individual optimisation, a lexicographic optimisation method is used to completely eliminate the difficulty of estimating the worst value (nadir value). Using the lexicographic optimisation method, reservation values are set which act as lower bounds for each objective. These reservation values are obtained by optimising the first cost objective $f_1(x)$ resulting in max $f_1 = z_1^*$. Then, the second environmental objective is optimised by adding $f_1 = z_1^*$ as a constraint to ensure efficient solutions. Suppose that the optimal max $f_2 = z_2^*$. Then the third job creation objective is optimised by adding constraints $f_1 = z_1^*$ and $f_2 = z_2^*$ such that the optimal solutions for f_1 and f_2 are retained.

Note that the preferences for objectives can be varied based on decision maker preferences or sustainability requirements. The optimal solution ranges obtained through lexicographic optimisation provides the ranges over the efficient set. Let r_1, r_2, r_3 be the ranges for the f_1, f_2, f_3 respectively. The ranges for each objective function can be obtained by the absolute difference between best and reservation values.

Secondly, (29) is reformulated to (30) in order to simultaneously obtain efficient solutions and reduce the computational time. The ranges r_2 and r_3 for GHG emissions and job creation objective functions are divided into q equal intervals. Thus, we have $q + 1$ grid points that are used to parametrically vary the RHS of each objective function. The RHS for the specific iteration drawn from the grid points of the objective functions are given by the parameters e_2 and e_3. In addition, slack or surplus variables s_2, s_3 are introduced for GHG emission and job creation objective function constraints, respectively. A solution is guaranteed to be efficient if the objective function constraints are binding (in other words, when $s_2 = 0$ and $s_3 = 0$). In addition, these slack variables are used as a second term in the objective function with lower priority (eps $\in [10^{-6}, 10^{-3}]$) in a lexicographic manner where the objective constraints are forced to sequential optimisation where the solver will find optimum for f_1 first, then the solver will try to optimise f_2, followed by f_3 resulting in reduced computational time.

$$\begin{aligned} &\text{Maximize} \quad && f_1(x) + \text{eps}\left(\frac{s_2}{r_2} + 10^{-1}\frac{s_3}{r_3}\right) \\ &\text{s.t.} && f_2(x) - s_2 = e_2 \\ &&& f_3(x) - s_3 = e_3 \\ &&& x \in S. \end{aligned} \tag{30}$$

In order to parametrically vary e_2 and e_3, the discretised step size for each of the constrained GHG emissions and job creation objective functions is given by (31) and (32), respectively. Note that the equal number of grid intervals is considered for both the objectives.

$$step_2 = \frac{r_2}{q} \tag{31}$$

$$step_3 = \frac{r_3}{q} \tag{32}$$

The RHS of the constrained GHG emission and job creation objective functions in the tth iteration is given by (33) and (34), where $f\min_2$ and $f\min_3$ are the minimum reservation payoff values obtained by the lexicographic optimisation method.

$$e_2 = f\min_2 + t \times step_2 \tag{33}$$

$$e_3 = f\min_3 + t \times step_3 \tag{34}$$

In each iteration, the surplus corresponding to the innermost objective function, which is f_2 is checked. Then a bypass coefficient (b) is calculated as (35), where int () is the integer value of a real number. Note that if s_2 is greater than $step_2$, the next iteration will have the same solution with the only difference being the surplus variable which will have the value $s_2 - step_2$.. This results in redundant iteration and hence can be bypassed as no new Pareto solution is generated resulting in reduced computational time.

$$b = \text{int}\left(\frac{s_2}{step_2}\right) \tag{35}$$

4.3.1. AUGMECON 2 algorithm

The AUGMECON 2 algorithm which is applied to the proposed Mo-SMILP problem (Mavrotas and Florios 2013) is summarised in the following steps.

Input: Problem S $=$ *Maximize* $f_1(x) + eps\left(\frac{s_2}{r_2} + 10^{-1}\frac{s_3}{r_3}\right)$

$$f_k(x) - s_k = e_k \quad \text{where } k = 2,3 \quad e_k = lb_k + i_k \times \left(\frac{r_k}{q_k}\right) \tag{36}$$

$x \in S$

Step 1: Create Payoff table $\{$*lexicographic maximization* $f_k(x),\ k = 1,2,3.\}$

Step 2: Set lower bounds (lb_k) *for* $k = 2, 3$.
Step 3: Calculate ranges (r_k) *for* $k = 2, 3$.
Step 4: Divide $r_{k.}$ *into* $q_{k.}$ q_k *grid intervals (Set number of grid points* $= q_k + 1$
Step 5: Initialize counters: $i_k = 0$ *for* $k = 2, 3$; *Number of Pareto solutions* $(n_p) = 0$
Step 6: $i_3 = i_3 + 1$
Step 7: $i_2 = i_2 + 1$
Step 8: Solve problem S
Step 9: If feasible then go to Step 11 else go to Step 10
Step 10: $i_2 = q_2$; *go to Step 12*
Step 11: $n_p = n_p + 1$; *Calculate* $b = int\,(s_2/step_2)$; $i_2 = i_2 + b$.
Step 12: If $i_2 < q_2$ *then go to Step 7 else go to Step 13*
Step 13: $i_2 = 0$
Step 14: If $i_3 < q_3$ *then go to Step 6 else STOP*

5. Case study

A case study set in the state of North Dakota (ND) within the US is used as an application of the proposed model. ND is used as a case study because of the availability of fossil fuels (coal), dedicated biomass (switchgrass), and waste biomass (corn stover). Figure 2 presents the agricultural statistical district (ASD) and coal mine configuration of ND. There are nine ASDs in the state of ND: (1) North West (NW), (2) North Central (NC), (3) North East (NE), (4) West Central (WC), (5) Central (C), (6) East Central (EC), (7) South West (SW), (8) South Central (SC), and (9) South East (SE). The potential locations for the electricity plant are considered to be the largest city in each ASD to avail easy access to supply zones and demand zones. At each electricity plant location, three electricity plant strategies are considered: (1) fossil fuel-based power plant (FPP), (2) co-firing-based power plant (CFPP), and (3) biomass-based power plant (BPP). The FPP uses coal for electricity generation. The CFPP uses switchgrass, corn stover, and coal for electricity generation. The CFPP generates electricity by using 80% coal and 20% biomass (switchgrass and corn stover) due to the technical constraints (Cuellar 2012). The BPP uses switchgrass and corn stover for electricity generation.

Four capacity levels are considered for each electricity plant. The capacity levels ($\bar{\rho}_{lq}$) considered for all electricity plant strategies are 50, 100, 150, and 200 MW. Coal is considered the fossil fuel for electricity generation because of high availability. Figure 2 indicates that coal mines are located in the WC ASD. Switchgrass is considered for electricity generation because ND soil and environmental conditions are highly suitable for the switchgrass cultivation (Zhang et al. 2013). It should be noted that switchgrass is cultivated through agricultural methods. Corn stover is considered the biomass because of the high cultivation rate of corn in ND (Gonela et al. 2015a; Gonela et al. 2015b). Switchgrass can be cultivated in all the ASDs and corn stover (which is an agricultural residue) can also be collected from all the ASDs. It is assumed that the cultivated switchgrass or collected corn stover at a particular supply zone is stored at a collection centre in the same supply zone. The inventory holding capacity for biomass at the collection centre (IC_{bc}) and electricity plant (IC_{bl}) is assumed to be 60 days. The inventory holding capacity for coal at the electricity plant is assumed to be 60 days (IC_{fl}).

The study is conducted for one year, with 12-month periods. The uncertainties considered in the study are as follows: (1) electricity conversion rate for switchgrass, corn stover, and coal, respectively (3 uncertainties); (2) the biomass yield rate

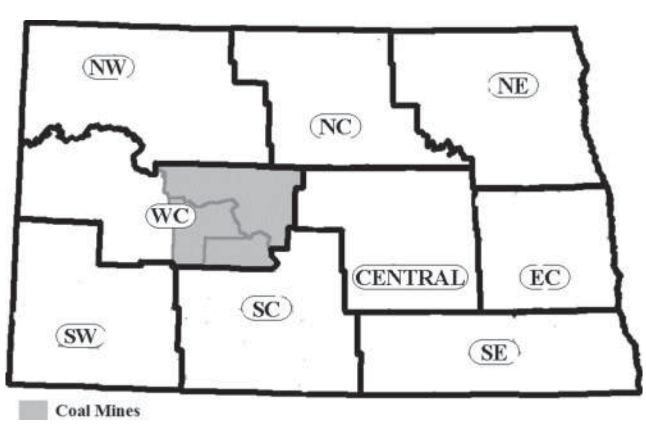

Figure 2. Agricultural statistical district (ASD) map of ND.

Table 3. EGN-HPS performance when different objectives are optimised.

	Performance measures		
Optimisation objective	Cost ($ billion)	GHG emissions (Million tons)	Job creation (Million person-hours)
Minimise cost	0.235[a]	1.184	0.584
Minimise GHG emissions	0.487	0.154[a]	1.199
Maximise job creation	0.656	1.564	2.994[a]

[a]Optimal values.

for switchgrass and corn stover (2 uncertainties) at the cultivation site; and (3) the coal excavation rate (1 uncertainty) at the coal mine. The scenarios are generated by discretising each uncertainty into three levels. These levels are low level (LL), average level (AL), and high level (HL), which results in 729 scenarios. Each of the scenarios is assumed to be equally likely and hence the probability of occurrence of each scenario is 1/729 (ϑ_ξ). For each parameter, the LL is 25% below the AL and the HL is 25% above the AL. It is estimated that the electricity demand will increase by 20% compared to the current annual electricity demand (USDOE 2014). Therefore, the demand is considered to be 120% of the current demand. In addition, it is considered that at least 20% of the electricity demand should be met by biomass in order to meet the GPPI initiative. The supplemental material presents the input parameters used in this study. Tables S1 and S2 present the stochastic input parameters. Tables S3–S5 present the deterministic input parameters.

6. Results

The proposed model and the AUGMECON 2 are coded in General Arithmetic Modeling Software (GAMS). The model has 117 integer variables and 570,943 continuous variables. The model is run 9 times for the entire study. The average model execution time is 0.316 seconds and the standard deviation is 0.006 seconds. Firstly, Section 6.1 presents the EGN-HPS performance when each of the sustainability objectives is optimised. Secondly, 6.2 presents the EGN-HPS performance when all the sustainability objectives are optimised simultaneously. Finally, Section 6.3 presents the EGN-HPS performance when renewable energy based electricity generation is increased. It should be noted that the GHG emissions throughout this paper are presented in tons which are equivalent to 907.185 kg.

6.1. EGN-HPS configuration under individual sustainability objective optimisation

In this section, an optimal EGN-HPS configuration is designed by optimising only one of the three distinct objectives to understand the trade-off among different objectives. It should be noted that any of the three FPP, CFPP and BPP strategies can be selected in the EGN-HPS design. In addition, the GPPI policy (Equation (28)) is considered while designing the optimal EGN-HPS configuration. The GPPI policy stipulates that 20% of the electricity demand should be met from renewable energy by 2020–2021. Table 3 presents the EGN-HPS performance when each of the different objectives is optimised. It should be noted that when one of the objectives is optimised, the resultant performance is indicated by *, and the other performance measures can be obtained by entering the decisions into the corresponding objective functions. The results show that there is always a trade-off among three objectives. For example, cost increases when GHG emission is reduced and job creation is increased. However, when job creation increases, GHG emissions first decrease and then increase.

6.1.1. Optimise economic performance

Figure 3 presents the optimal EGN-HPS configuration when the total cost is minimised. There are three 50 MW CFPP and one 100 MW CFPP that are opened. This indicates that CFPP reduces the cost compared to an FPP and a BPP when the GPPI policy is applied. It should be noted that the CFPP configuration uses 80% coal and 20% biomass. This indicates that the EGN-HPS relies heavily on coal when cost is minimised. Within biomass, switchgrass is preferred compared to corn stover. This is because that corn stover has a low yield as the majority of corn stover is left on the cultivation land to retain nitrogen content. Therefore, corn stover will be required to collect from a larger geographical area resulting in increased collection cost compared to switchgrass cultivation. The CFPP plants in NW and SC are opened to reduce the transportation cost of coal. The CFPP plants in NE and EC are opened in order to reduce electricity transmission cost. The demand for electricity in these ASDs is high due to the increasing population.

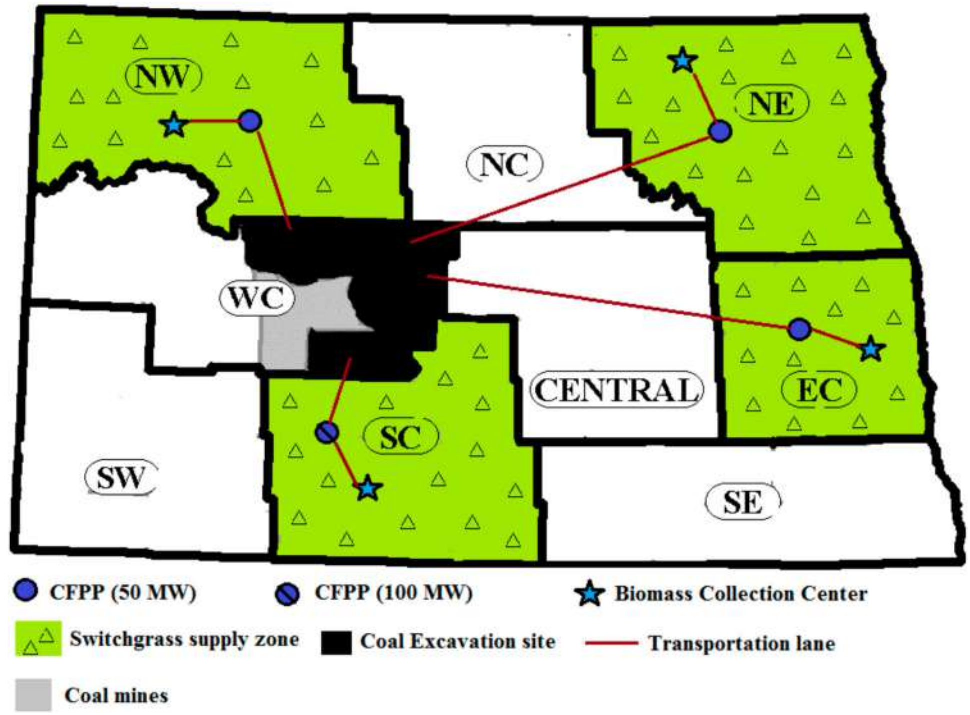

Figure 3. EGN-HPS configuration when economic performance is optimised.

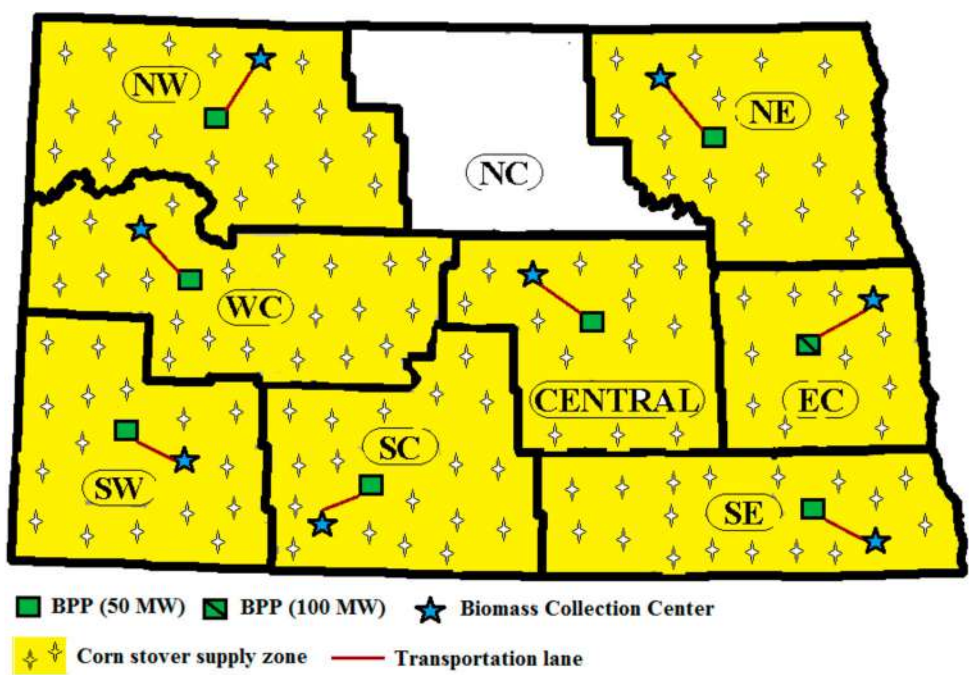

Figure 4. EGN-HPS configuration when environmental performance is optimised.

6.1.2. Optimise environmental performance

Figure 4 presents the optimal EGN-HPS configuration when environmental performance is optimised. There are seven 50 MW BPP and one 100 MW BPP opened. The result also shows that all the BPPs operate with corn stover. This indicates that corn stover can significantly reduce GHG emissions. In addition, a distributed network is preferred in which several small-scale BPPs (50 MW) are opened with shorter transportation distances resulting in reduced GHG emissions.

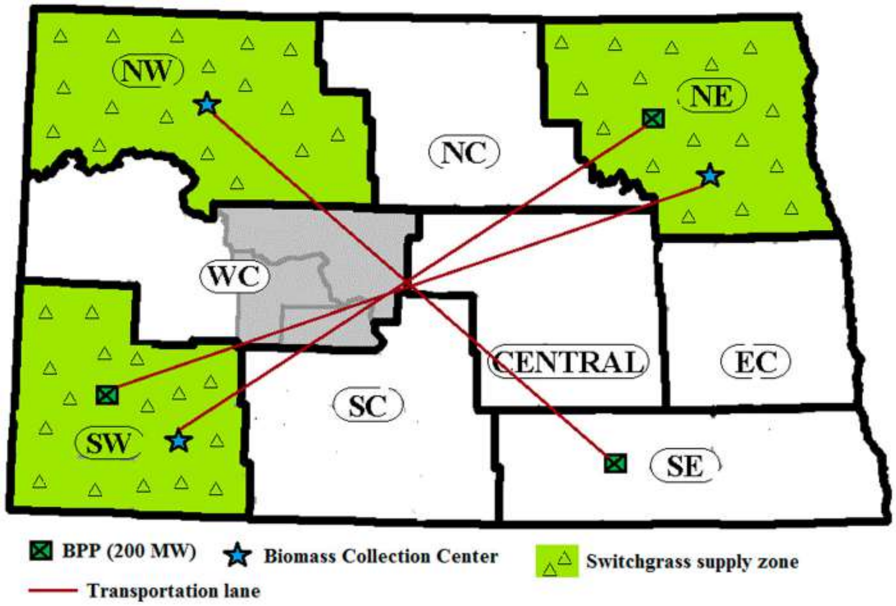

Figure 5. EGN-HPS configuration when social performance is optimised.

6.1.3. Optimise social performance

Figure 5 presents the optimal EGN-HPS configuration when social performance is optimised. There are three large-scale 200 MW BPPs opened. This indicates that large-scale plants can increase the number of jobs. All the BPPs use switchgrass. Switchgrass is preferred compared to corn stover because it generates more jobs through cultivation. In addition, longer biomass transportation routes are preferred in order to increase the number of transportation jobs.

6.2. EGN-HPS configuration under all sustainability objectives optimisation

Section 6.1 shows that different objectives will lead to different optimal network designs and the objectives' conflict with each other. This section presents the EGN-HPS performance when all three economic, environmental, and social aspects of sustainability are considered simultaneously. Pareto analysis is conducted to obtain the trade-off between the three competing objectives. In order to obtain the 3D-Pareto optimal curve, the proposed model is solved by using AUGMECON 2. It should be noted that the GPPI policy, which is a minimum of 20% of electricity should be generated from biomass, needs to be considered. Figure 6 presents the 3D-Pareto optimal curve showing the trade-off between total cost, GHG emissions, and job creation. Ninety Pareto optimal solutions are obtained from 441 points (21 grid points for GHG emissions multiplied by 21 grid points for job creation). Any solution above the curve is a sub-optimal solution and below the curve is infeasible. The 3D-Pareto curve shows that as GHG emissions reduce, the cost of the EGN-HPS increases. In addition, as job creation increases, the cost of the EGN-HPS increases. The cost of EGN-HPS increases significantly when GHG emissions need to be reduced and the job creation needs to be increased simultaneously. In the 3D-Pareto curve, each of the points provides different sustainability benefits and compromises. Therefore, no point is better or worse than the other. For example, 'A' is a trade-off state where the cost is low. However, the GHG emissions are significantly high and job creation is significantly low. 'B' is a trade-off state where GHG emissions are less. However, the cost is significantly high. In addition, an insignificant number of jobs are compromised to achieve the optimal GHG level. 'C' is a trade-off state where the job creation is high. However, the cost is significantly high. In addition, an insignificant amount of GHG emissions are compromised to achieve the optimal level of job creation. It has been observed that different combinations of production strategies are selected for different sustainability levels. However, a combination of only two production strategies or less are selected in each of the Pareto solution. In 90 Pareto solutions, 36% of the Pareto solutions, where the GHG emissions are allowed to be high and job requirements are low, prefer the co-firing-based electricity production strategy. It has also been noted that the capacity of the co-firing strategy decreases as the sustainability requirements increase. One hundred per cent of the Pareto solutions contained biomass-based production capacities with less capacity at low GHG emissions and job creation sustainability levels and high capacity at high GHG and job creation sustainability levels. In fact, when GHG emissions are required to be less and job creation is required to be high, biomass-based electricity production is preferred. Since the

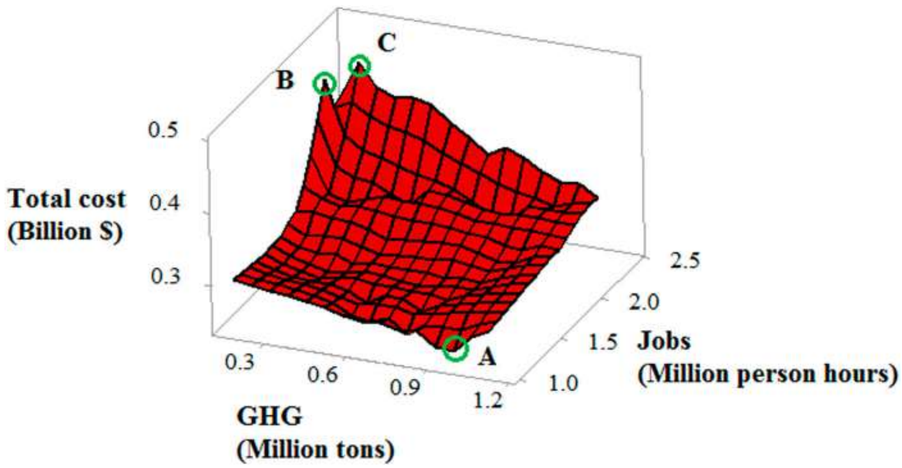

Figure 6. 3D-Pareto optimal curve showing the trade-off between economic, environmental and social performance.

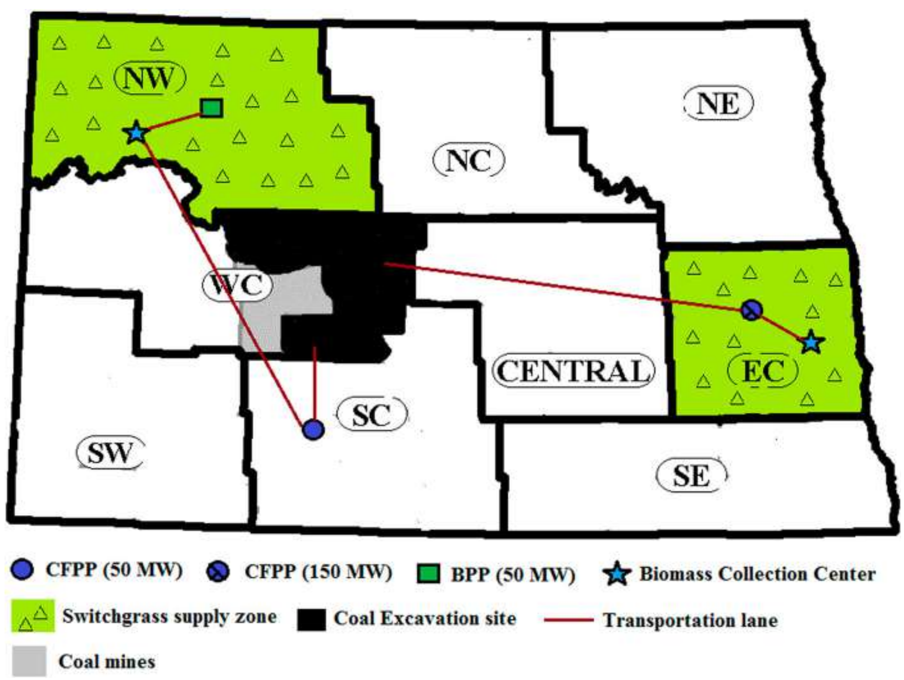

Figure 7. EGN-HPS configuration for A.

GPPI policy requires that 20% of the electricity should be produced from biomass, the co-firing-based production strategy is preferred under the GPPI policy compared to the fossil fuel-based production strategy.

The 3D-Pareto optimal curve can be used to determine the cost between two states of sustainability. For example, consider sustainability states A and B. The total cost, GHG emissions, and job creation of the optimal EGN-HPS at ‘A’ are 0.245 billion, 0.94 million tons, and 1.03 million person-hours, respectively. The total cost, GHG emissions, and job creation at ‘B’ are 0.463 billion, 0.17 million tons, and 2.18 million person-hours, respectively. Therefore, a cost of $0.218 billion can reduce GHG emissions by 0.77 million tons and increase job creation by 1.15 million person-hours.

Based on the 90 Pareto optimal solutions, a regression model is developed for policy makers and decision makers to estimate the total cost for a given level GHG emissions and job creation. Equation (36) presents the regression model in which the response variable is the expected total cost and the predictors are GHG emissions and job creation. The regression model has an $R^2 = 0.84$ and the P-value $< .05$ for all the coefficients. The range for GHG emissions is 0.1731–1.1049 million tons. The range for job creation is 1.0274–2.3585 million person-hours. The regression model is a quadratic equation with an interaction between GHG emissions and jobs. The interaction between GHG emissions and job creation is due to

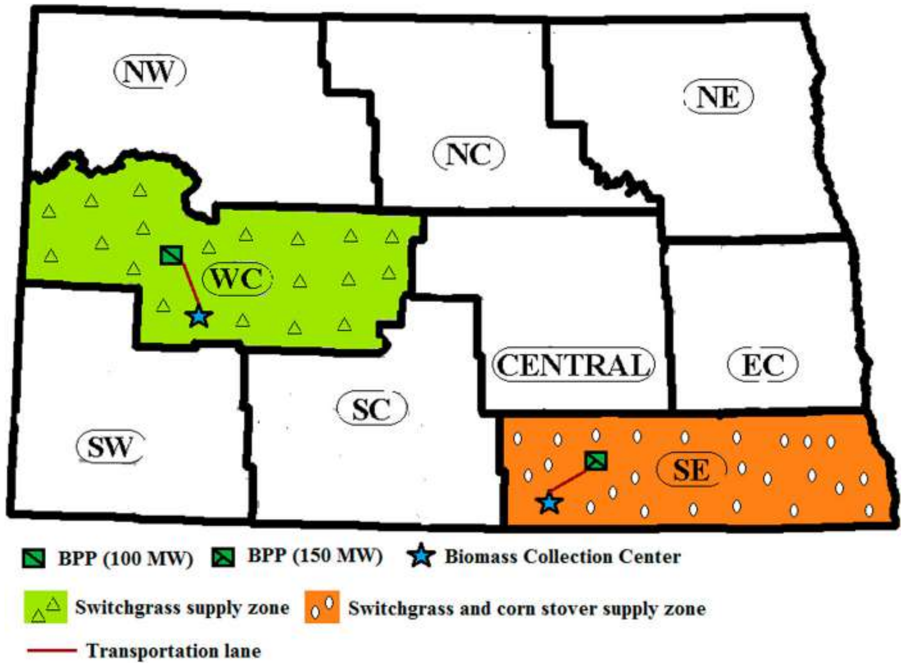

Figure 8. EGN-HPS configuration for B.

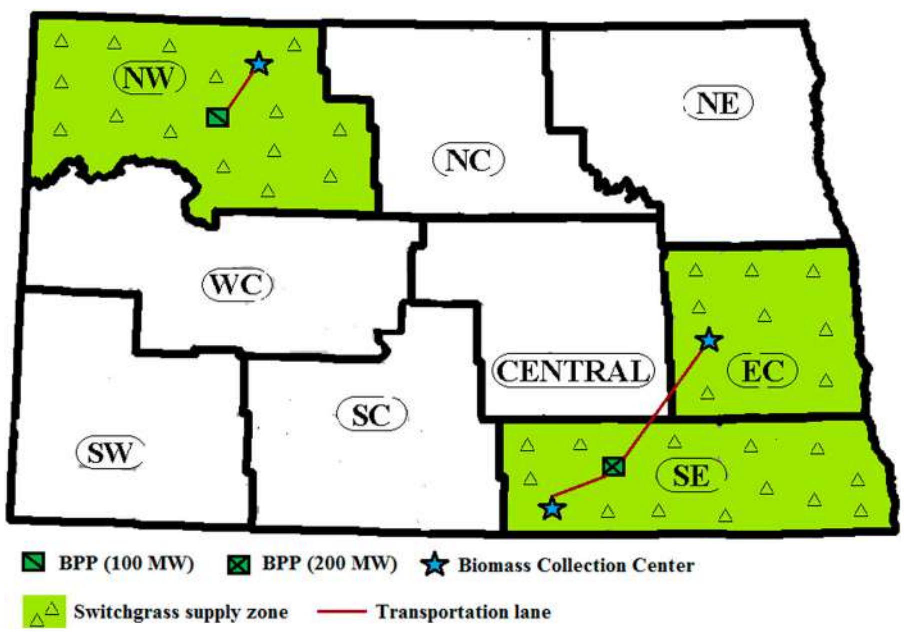

Figure 9. EGN-HPS configuration for C.

the biomass, as the biomass shows the potential to reduce GHG emissions and increase jobs simultaneously.

$$\textit{Total Cost} = 0.19515 - 0.1328\,\textit{GHG emissions} \times \textit{Job creation} + 0.1545\,\textit{GHG emissions}^2 + 0.05476\,\textit{Job creation}^2 \quad (37)$$

Figures 7–9 present the EGN-HPS configuration for A, B, and C, respectively, in which different sustainability objectives are compromised. In A, which is an economically better solution, the EGN-HPS configuration consists of a combination of CFPPs and BPP. It should be noted that CFPP uses 80% coal and 20% biomass. This indicates that the majority of electricity is produced by coal. Within biomasses, switchgrass is preferred compared to corn stover. In B, which is environmentally best and socially a better solution, EGN-HPS consists of BPPs. In this configuration, medium range BPPs are preferred and short transportation routes are preferred in order to reduce GHG emissions. In addition, a combination of switchgrass and

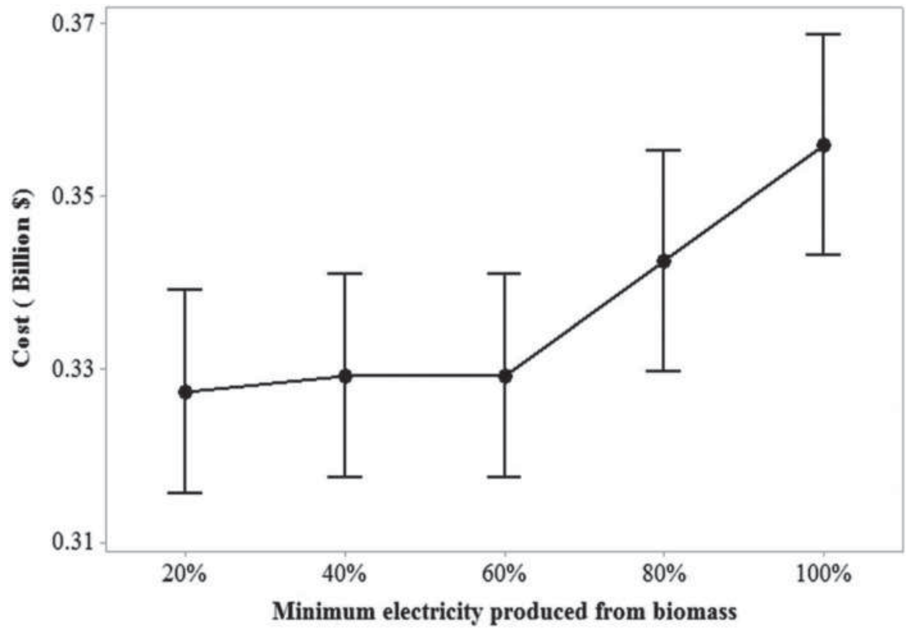

Figure 10. 95% confidence interval for cost when electricity production from biomass is increased.

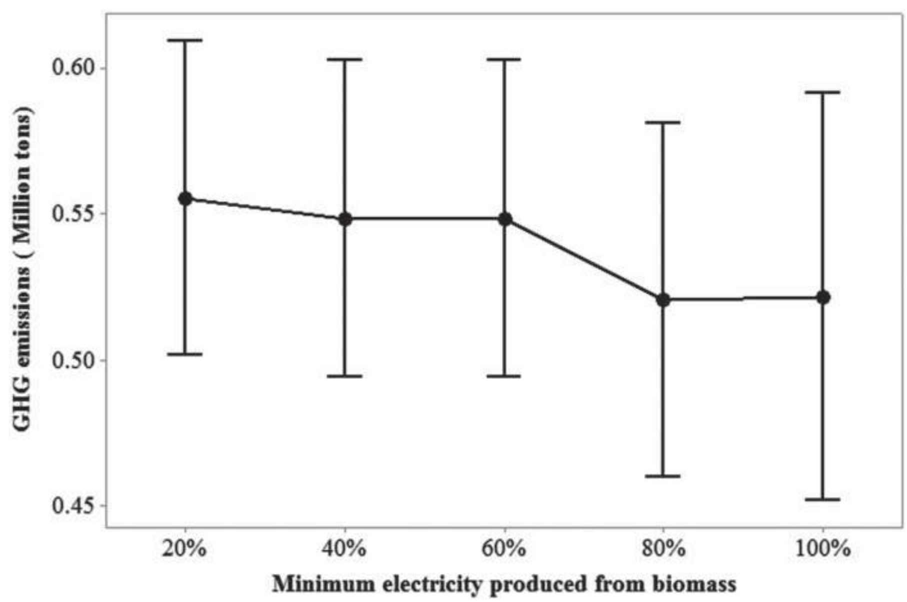

Figure 11. 95% confidence interval for GHG emissions when electricity production from biomass is increased.

corn stover is used for electricity production. In C, which is a socially best solution and environmentally better solution, BPPs are preferred. One large-scale BPP and switchgrass are preferred in order to improve job creation.

Based on the electricity generation networks, it can be observed electricity production strategies, size of the plant, transportation distances, energy sources (coal, switchgrass, and corn stover) differ for different sustainability levels.

6.2.1. *EGN-HPS performance when increasing electricity production from renewable source*

The current GPPI policy stipulates that 20% of the electricity demand should be met from renewable energy by 2020–2021. This section studies the performance of EGN-HPS when the percentage of electricity generation varies from the renewable source. Figures 10–12 provide the 95% confidence intervals for cost, GHG emissions, and job creation performances,

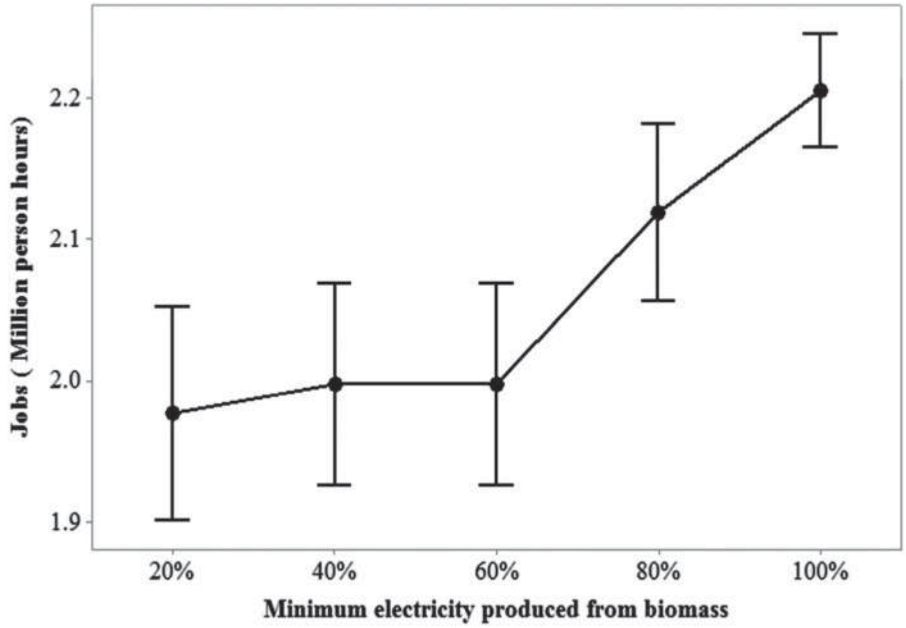

Figure 12. 95% confidence interval for jobs when electricity production from biomass is increased.

respectively, when the electricity from biomass increases from 20% to 100%. The results indicate that the cost increases, GHG emissions decrease (insignificantly), and job creation increases as the electricity generation from biomass increases.

The results indicate that for 20–60% of electricity produced from biomass, the Pareto solutions with lower GHG emissions and job creation requirements are preferred to the co-firing-based electricity production strategy and higher GHG emissions and job creation requirements are preferred to the biomass-based electricity production strategy. In fact, 36%, 34% and 33% of the Pareto solutions in 20%, 40%, and 60% of electricity generation from biomass contained the co-firing-based electricity production strategy. However, in all the cases 100% of the Pareto solutions contained the biomass-based production strategy. For 80% electricity generation from biomass, 12% of the Pareto solutions contained the co-firing-based production strategy and 100% of the Pareto solutions contained the biomass-based production strategy. For 100% electricity generation, all the Pareto solutions contained only the biomass-based electricity generation strategy for all sustainability levels. Therefore, it can be concluded as the electricity required to be generated from renewable energy increases, the co-firing production strategy is less preferred and the biomass production strategy is highly preferred.

In Figure 11, the variability for GHG emissions increases at higher electricity generation from biomass as the EGN-HPS relies heavily on biomass requiring the biomass to be collected from wider geographical areas which has significantly different biomass yield rates. The job creation in Figure 12 has less variability because all the Pareto solutions have the same capacity of electricity produced from the biomass-based electricity generation strategy resulting in an almost same number of jobs for most of the Pareto solutions.

7. Conclusions and future research

This paper focuses on designing a sustainable electricity generation network with the hybrid production strategy (EGN-HPS) where fossil fuel-based, biomass-based, and co-firing-based production strategies are considered for electricity generation simultaneously. Three sustainable performances, economic, environmental, and social performances, are considered. In addition, uncertainties such as electricity conversion rate, biomass yield, and coal excavation rate are modelled in the decision process. A multi-objective stochastic mixed integer linear programming (Mo-SMILP) model is developed and solved by using the improved augmented–constraint (AUGMECON 2) method. The proposed model can be applied to solve any practical problem in a given geographical area whenever the decision maker is seeking to simultaneously take the advantages of fossil fuel-based power plant, co-firing-based power plant, and biomass-based power plant. In practice, the results of the proposed model can help policy makers and investors make synchronised decisions. The proposed model can help policy makers determine and promote appropriate production strategy to reach the desired sustainability requirements. The investors can then invest in appropriate production strategies in order to realise long-term sustainability benefits.

A case study of North Dakota (ND) state in the US is used to illustrate the effectiveness of the proposed model and provide managerial insights. The 3D-Pareto optimal curve is obtained to show the trade-off among three performance measures. Some of the important managerial insights are as follows: (1) when GHG emission is allowed to be high and job creation is allowed to be low, the EGN-HPS configuration consists of both co-firing-based production strategy and biomass-based production strategy. Therefore, co-firing and biomass-based production strategies should be promoted; (2) When GHG emissions are required to be low and job creation is required to be high, EGN-HPS consists of only the biomass-based production strategy. Therefore, incentives need to be provided to promote the biomass-based production strategy. (3) Co-firing-based production strategy is the best strategy under the GPPI policy when the total cost is minimised. Therefore, the co-firing strategy should be promoted under the GPPI policy in order to improve economic benefits. (4) Switchgrass is preferred to co-firing compared to corn stover when the total cost is minimised. (5) Biomass-based production strategy is the best strategy when GHG emissions is minimised. (6) Small-scale BPP’s and shorter transportation distances decrease GHG emissions. (7) Corn stover reduces GHG emissions compared to switchgrass. (8) The biomass-based production strategy improves job creation. (9) Large-scale BPP’s and longer transportation routes increase the number of jobs created. (10) Switchgrass grass increases the number of jobs created compared to corn stover. (11) The fossil fuel-based production strategy is not selected under the GPPI policy; (12) when higher levels of electricity is required to be generated from renewable source, the economic performance decreases; environmental performance increases; and social performance increase as well.

Future research can consider including carbon capture and storage for the fossil fuel-based electricity generation strategy in order to make the strategy environmentally competitive. In addition, more traditional and renewable energy sources can be integrated into the generation network framework to investigate the optimal sustainable energy profile under uncertainties.

Disclosure statement

No potential conflict of interest was reported by the authors.

Supplemental data

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Appendix 1: Notations

Indices/Sets

k	Electricity demand zones ($k = 1, 2, \ldots .K$)
l	Potential electricity plant locations ($l = 1, 2, \ldots ..L$)
e	Electricity plant strategy $e = 1$ (BPP); $e = 2$ (CFPP); $e = 3$ (FPP)
q	Capacity levels of electricity plants ($q = 1, 2, \ldots \ldots Q$)
u	Fossil fuel excavation site ($u = 1, 2, \ldots .U$)
c	Biomass supply zones ($c = 1, 2, \ldots$ ..C)
f	Fossil fuel type ($f = 1, 2, \ldots .F$)
b	Biomass type ($b = 1, 2, \ldots \ldots B$)
t	Time period horizon ($t = 1, 2, \ldots ..T$)
ξ	Uncertain scenarios ($\xi = 1, 2, \ldots \ldots S$)

Stochastic Parameters

$\eta_{f\xi}$	The energy value in fossil fuel of type f under scenario ξ
$\eta_{b\xi}$	The energy value in biomass of type b under scenario ξ
λ_{fu}^{ξ}	Excavation rate of fossil fuel of type f at excavation site u under scenario ξ
λ_{bc}^{ξ}	Yield rate of biomass b at biomass supply zone c under scenario ξ

Deterministic Parameters

CC_{eq}	Annualised capital cost of opening electricity plant of type e with capacity level q
CCS_c	Annualised capital cost of opening collection centre at supply zone c
R_{fu}	The annualised fixed cost of excavation site u for fossil fuel f
R_{bc}	The annualised cost of renting cultivation site at supply zone c for biomass b.
tr	Fixed electricity transmission cost
$t\bar{r}$	Variable electricity transmission cost
tc_f	Fixed cost of transporting fossil fuel of type f
$t\bar{c}_f$	Variable cost of transporting fossil fuel of type f
t_b	Fixed cost of transporting biomass of type b
$t\bar{c}_b$	Variable cost of transporting biomass of type b
P_e	Electricity production cost at electricity plant type e
H_f	The inventory holding cost of fossil fuel of type f
B_f	The inventory backorder cost of fossil fuel of type f
H_b	The inventory holding cost of biomass of type b
B_b	The inventory backorder cost of biomass of type b
DG_{fu}	The cost of excavating fossil fuel f at the excavation site u
HT_{bc}	The cost of harvesting or collecting biomass b at biomass supply zone c
CT_{bc}	The cost of cultivating biomass b at biomass supply zone c. If biomass is collected, $CT_{bv} = 0$
SC_k	The cost of obtaining electricity from out-of-state by demand zone k
g_{eq}	Fixed GHG emission at electricity plant of type e with capacity level q. Very small value of the order 10^{-3} is assigned to avoid unnecessary opening of electricity plants.
g_c	Fixed GHG emission for biomass collection centre at supply zone c. Very small value of the order 10^{-3} is assigned to avoid unnecessary opening of collection centres.
g_e	The amount of GHG emitted in producing electricity by electricity plant type e
gt_f	The amount of GHG emitted while transporting fossil fuel of type f
gt_b	The amount of GHG emitted while transporting biomass of type b
gc_f	The amount of GHG emitted while excavating fossil fuel of type f
gc_b	The amount of GHG emitted while cultivating or collecting biomass of type b
gs_k	The amount of GHG emitted when electricity is obtained from out-state at the electricity demand zone k
g_r	The amount of GHG neutralised in regrowth of biomass of type b
j_{eq}	The minimum fixed number of jobs created at the electricity plant of type e with capacity level q. Very small value of the order 10^{-3} is assigned to avoid unnecessary opening of electricity plants.
j_c	The minimum number of jobs created at the biomass supply zone c. Very small value of the order $10 - 3$ is assigned to avoid unnecessary opening of collection centres.
je	The number of jobs created in electricity transmission
jp_e	The number of jobs created at electricity plant of type e
jt_f	The number of jobs created while transporting fossil fuels of type f
jt_b	The number of jobs created while transporting biomass of type b
jc_f	The number of jobs created while excavating fossil fuel of type f
j_{bc}	The number of jobs created in storing biomass at the collection centre c
jc_b	The number of jobs created while cultivating or collecting biomass of type b

D_k^t	The demand for electricity at electricity demand zone k in time period t
$\bar{\rho}_{lq}$	Maximum allowable electricity production volume at electricity plant location l with capacity level q
IC_{fl}	Maximum inventory that can be held for fossil fuel of type f at electricity plant location l
IC_{bl}	Maximum inventory that can be held for biomass of type b at electricity plant location l
IC_{bc}	Maximum inventory that can be held for biomass of type b at supply zone c
PL	Power loss during transmission
QRF_e	Quality reduction factor for electricity plant type e based on the input product mixture
ef_e	Efficiency of plant type e
w	Weight for biomass usage at CFPP
π	Minimum percentage of electricity to be produced by biomass
ω	The amount of electricity produced per unit of energy
d_{lk}	Distance between the electricity plant l and the electricity demand zone k
d_{ul}	Distance between the excavation site u and electricity plant l
d_{cl}	Distance between the collection centre c and the electricity plant l
ϑ_ξ	Probability of occurrence of scenario ξ

Decision Variables

Unrestricted Variables

TC	Total expected cost of EGN-HPS
G	Total expected GHG emitted by EGN-HPS
J	Total expected jobs created by EGN-HPS
$I_{fl}^{t\xi}$	Inventory level for fossil fuel of type f at electricity plant location l in time period t under scenario ξ
$I_{bl}^{t\xi}$	Inventory level for biomass type of b at electricity plant location l in time period t under scenario ξ
$IS_{bc}^{t\xi}$	Inventory level for biomass type of b at supply zone c in time period t under scenario ξ

Binary Variable

Y_{eql}	{1, if electricity plant of type e with capacity level q is opened at the location l; else 0}
Y_c	{1, if collection centre is opened at supply zone c; else 0}

Positive Variables

$s_k^{t\xi}$	The amount of electricity obtained from in-state at demand zone k in time period t under scenario ξ
$s_l^{t\xi}$	The amount of electricity transmitted by electricity plant at location l in time period t under scenario ξ
$s_{lk}^{t\xi}$	The amount of electricity transmitted by electricity plant at location l to demand zone k in time period t under scenario ξ
$Z_{el}^{t\xi}$	The amount of electricity produced by electricity plant type e at electricity plant location l in time period t under scenario ξ
$X_{fl}^{t\xi}$	The amount of fossil fuel of type f used at electricity plant location l in time period t under scenario ξ
$X_{bl}^{t\xi}$	The amount of biomass of type b used at electricity plant location l in time period t under scenario ξ
$xf_{ful}^{t\xi}$	The amount of fossil fuel of type f shipped from excavation site u to electricity plant location l in time period t under scenario ξ
$xb_{bcl}^{t\xi}$	The amount of biomass of type b shipped from biomass supply zone c to electricity plant at location l in time period t under scenario ξ
$xu_{fu}^{t\xi}$	Amount of fossil fuel of type f excavated at excavation site u in time period t under scenario ξ
$bc_{bc}^{t\xi}$	The amount of biomass of type b collected at supply zone c in time period t under scenario ξ
$IP_{fl}^{t\xi}$	The amount of fossil fuel of type f held at electricity plant location l in time period t under scenario ξ
$IM_{fl}^{t\xi}$	The amount of fossil fuel of type f back ordered at electricity plant location l in time period t under scenario ξ
$IP_{bl}^{t\xi}$	The amount of biomass of type b held at electricity plant location l in time period t under scenario ξ
$IM_{bl}^{t\xi}$	The amount of biomass of type b back ordered at electricity plant location l in time period t under scenario ξ
$ISP_{bc}^{t\xi}$	The amount of biomass of type b held at supply zone c in time period t under scenario ξ
$ISM_{bc}^{t\xi}$	The amount of biomass of type b back ordered at supply zone c in time period t under scenario ξ
LF_{fu}	Land used for excavating fossil fuel of type f at excavation site u
LB_{bc}	Land used for cultivating biomass of type b at biomass supply zone c
$SL_k^{t\xi}$	The amount of electricity obtained from out-state at demand zone k in time period t under scenario ξ