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Optimizing the bioenergy industry infrastructure: Transportation networks and bioenergy plant locations

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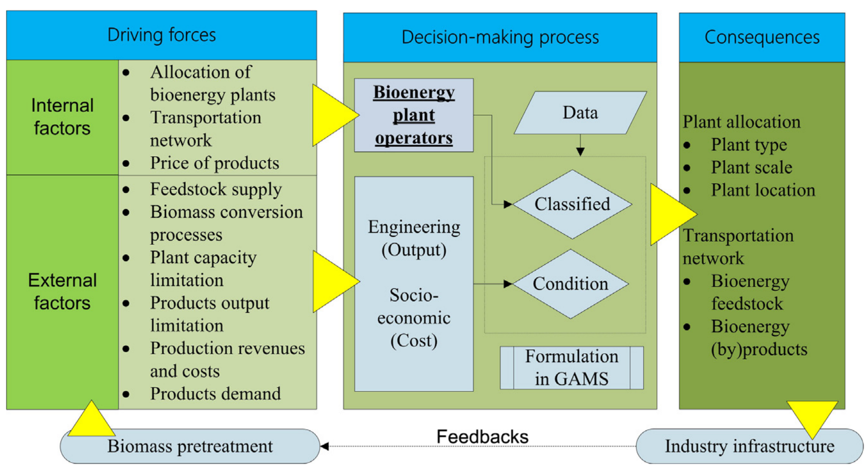
HIGHLIGHTS

- An agent-based model of optimized bioenergy industry infrastructure is developed.
- The new model is applied to emerging economies for the first time.
- Bioenergy plants should be located close to bioenergy feedstock source regions.
- Biomass densification measures are not economically profitable for the case region.
- The benefits of smallholder farmers need to be taken into consideration.

GRAPHICAL ABSTRACT



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ABSTRACT

In the context of combating climate change and maintaining energy security, ambitious bioenergy development projects in emerging economies face considerable challenges, for example an overburdened bioenergy industry infrastructure due to the growing demand for bioenergy products. There are abundant studies on optimizing the bioenergy industry infrastructure. However, they fail to comprehensively simulate the interactions among the predominant actors of the infrastructure, especially the bioenergy plant operators in emerging economies. To fill this research gap, we develop a new dynamic agent-based model of optimized bioenergy industry infrastructure from the perspective of bioenergy plant operators. We then apply the model to Jiangsu Province of China to simulate the coordination of two types of bioenergy plants and project the optimal distribution of these plants and their corresponding transportation networks for the year of 2030. The model results suggest locating bioenergy plants closer to bioenergy feedstock source regions rather than to bioenergy products consumption sites, an answer to the classical facility location problem. A welfare analysis based on the extended model indicates that the biomass densification process aiming at mitigating the growing transport volumes incurred by the delivery of bulky bioenergy feedstock is not economically profitable in our case region. The experiences from this region

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further show that for emerging economies, a successful bioenergy industry infrastructure needs to take the benefits of smallholder farmers into consideration.

1. Introduction

To curb CO_2 emissions and to avert an energy crisis, many countries have increased their efforts to find feasible alternatives to fossil fuels. Bioenergy has rapidly developed in the last decades. In its various forms, it can meet diverse energy demands and play a unique role in promoting rural development. According to the International Energy Agency (IEA), the global supply of bioenergy reached 1381 Million tonnes of oil equivalent (Mtoe) in 2013, ranking fourth after traditional fossil fuels – crude oil (4211 Mtoe), coal (3913 Mtoe) and natural gas (2898 Mtoe) – but leading all renewable energy types [1].

While a rapidly growing bioenergy industry may bring social, economic and environmental benefits, its unprecedented utilization scale provides a challenge to the existing infrastructure. Particularly, bioenergy transportation volumes are likely to exceed the combined capacity of current agricultural and energy supply chains, including grain, petroleum, and coal by mid-century [2]. Kang et al. [3] proposed that a successful bioenergy infrastructure would consist of the following components: (1) a favorable feedstock supply chain tailored to local environmental and economic conditions; (2) a careful choice of bioenergy conversion technologies; and (3) a cost-effective network for the transportation and distribution of bioenergy feedstock and products.

As a classical example in operations research, the facility location problem has been studied for more than half a century. Initially emerging in the food industry [4,5], previous work was first applied to bioenergy research in the 1980s. For the first time, English et al. [6] developed a linear programming model to assess the economic feasibility of using corn residue in coal-fired power plants. In recent years, increased computational resources, improved methods, and better data led to more comprehensive and integrated assessment models representing different structures of the bioenergy supply chain. The methods used in these models can be classified into three types:

(1) Multi-criteria Decision Analysis: For example, Sultana and Kumar [7] analyzed a set of economic, geographical, technological and environmental factors for siting biomass-based facilities to derive a land-suitability model. They applied this model to the province of Alberta, Canada. Sun et al. [8] used spatial analysis technology, economic models and scenario analysis to pick the appropriate development zones for bioelectricity generation in Fujian Province, China.
(2) Heuristic Approaches: Ayoub et al. [9] combined a genetic algorithm with data mining techniques to decide the optimal size of storage and conversion facilities for bioelectricity production from forestry residue in Japan, in which the transportation costs, CO_2 emissions and number of workers were minimized. Izquierdo et al. [10] developed a variant of particle swarm optimization, using an evolutionary stochastic algorithm derived from the social behavior of organisms such as bird flocking and fish schooling [11], to find optimal biomass flows from sources to energy production plants, which took the mountain community of Val Bormida in Italy as a case study.
(3) Mathematical Programming Approaches: This method is well developed in the field of bioenergy systems simulation. Specifically, it can be further divided into four groups: (i) Linear programming (LP), which consists of a linear objective function and linear constraints. For instance, Perpiñá et al. [12] applied the Dijkstra algorithm, which was realized by the closest facility function of Geographical Information Systems (GIS), to the Valencuan Community in Spain to identify the optimal location of bioenergy facilities. Combined with a biophysical and GIS model, Laporte et al. [13] proposed an LP economic model to examine the effects of three different supply chain structures and biomass prices on bioenergy feedstock supply, which took Ontario, Canada as a case study. (ii) Integer programming (IP), meaning all decision variables are restricted to be integers. Höhn et al. [14] combined Kernel Density maps generated on ArcGIS with the p-median model, an IP model, to determine the spatial distribution and amount of potential bioenergy feedstock for biogas production and optimal locations, sizes and number of biogas plants in southern Finland. (iii) Mixed integer linear programming (MILP), in which some decision variables are integers but the objective function, the rest of decision variables and all constraints are linear. For example, Leduc et al. [15] and Petterson et al. [16] developed cost minimization models to separately simulate the productions of lignocellulosic-based methanol via gasification and a variety of biofuels from forest biomass in Sweden. Zhang et al. [17] minimized the cost of the entire switchgrass-based bioethanol supply chain in the U.S., while Cambero and Sowlati [18] considered non-identical social benefits of different new jobs created by a forest-based biorefinery supply chain in the interior region of British Columbia, Canada through a multi-objective MILP model. By contrast, Jonker et al. [19] were more concerned about the optimal location and scale of sugarcane and eucalyptus industrial processing plants for ethanol production. They projected the expansion of biofuel production in the state of Goiás, Brazil between 2012 and 2030. (iv) Non-linear programming (NP), meaning either the objective or some of the constraints contain non-linear functions. Kaylen et al. [20] used this approach to analyze the economic feasibility of producing bioethanol from lignocellulosic biomass in Missouri State, U.S. Shabani and Sowlati [21] developed a mixed integer non-linear programming (MINLP) model to optimize the supply chain of a real biomass-based power plant in Canada by maximizing the chain's overall value.

While considerable research has been conducted to develop and apply optimization models for the analysis of the bioenergy industry infrastructure, there are at least three shortcomings: First, existing studies are mainly conducted in developed countries, although emerging economies (such as China, India, Indonesia, Brazil and the Philippines[1]) are perceived as important booming bioenergy markets for the coming years [22–24]. Second, among the above mentioned optimization models, most are LP, IP or MILP

[1] Although there are multiple lists of emerging and developing economies created by various organizations based on their different interpretations of the term, the countries named here are all included in the lists of the International Monetary Fund (IMF), the Financial Times Stock Exchange (FTSE), Morgan Stanley Capital International (MSCI), The Economist, Standard & Poor and Dow Jones (http://www.economywatch.com/world_economy/emerging-markets). Therefore, they are the most widely recognized emerging economies.