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Benchmarking Material Use Efficiency for Building Projects †

Jiyong Choi *, Myungjin Chae and Namhun Lee

Department of Manufacturing and Construction Management, Central Connecticut State University, 1615 Stanley St., New Britain, CT 06050, USA; chae@ccsu.edu (M.C.); leen@ccsu.edu (N.L.)
* Correspondence: jaychoi@ccsu.edu
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Abstract: Reducing the quantities of engineered materials provides a significant opportunity to mitigate the environmental impacts caused by material production and processing. Although the efficient use of materials in building construction has been emphasized, there has been little attention given to measuring the material use efficiency (MUE) of a project. This research fulfills this gap by using data envelopment analysis (DEA) as a benchmarking tool to generate an overall perspective on the MUE and to further compare its efficiency with that of peer projects, thereby promoting enhanced efficiency through target setting. In this research, MUE was measured by adopting the quantities of a variety of materials consumed during construction as input variables and the floor area of a built facility as an output variable. To generate a reliable MUE performance, a stepwise variable selection process was applied and then the performance was ranked based on evaluating cross-efficiency. In addition, clustering analysis and DEA were fused to enable a more realistic target to be set for each input, thereby determining practical targets for each underperforming project. It is anticipated that the proposed MUE benchmarking model would enable projects to recognize the gap with the best-performing projects and help them determine the targets to focus on to become efficient.

Keywords: material use efficiency; data envelopment analysis; benchmarking; target setting

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1. Introduction

Recent research in the realm of the construction industry proposed possible measures that can generate a quantitative approximation of material use efficiency (MUE) by using efficiency measures that evaluate the ratio of useful input to output. These measures assume that an improved design that optimizes the required building size and functional areas can reduce the amount of building materials needed to construct a building [1]. To this end, some researchers used the quantities of the main building materials consumed for a project as inputs and used the area of floor space generated with the materials as the output. However, a robust approach for assessing the MUE based on factual data was not demonstrated in the study. Moreover, the research lacked a discussion on how to quantitatively assess the MUE at the project level and how to make continuous improvement in the efficiency of a project possible by cross-project comparisons.

One of the identified challenges with quantifying the MUE is that there are various types of materials used for building construction and they are generally quantified in diverse measurement units (e.g., tons for steel, cubic yards for concrete, or square footage for glazing). Moreover, different projects may operate in different environments (e.g., function, location, and size) and accordingly, the level (or degree) of MUE can vary from one project to another. In this regard, it would be desirable if all the materials could be considered together to measure the efficiency while taking into account differences in many project characteristics for credible cross-project comparisons and benchmarking. One modeling methodology that provides a flexible and powerful approach for measuring efficiency while facilitating cross-project comparison is data envelopment analysis (DEA), a linear programming (LP)-based relative efficiency evaluation methodology. Building on the existing body of knowledge on MUE and DEA, this paper proposes a MUE benchmarking model that can generate reliable MUE scores for multiple building projects, thereby allowing the scores to be compared for possible improvements through targeted design.

2. Background

2.1. Material Use Efficiency

Material efficiency includes a broad range of technical strategies aimed at pursuing sustainable building project delivery which are introduced by reducing environmental and economic impacts arising from material production and processing, as well as material consumption. Examples of such efforts include industrialized building construction [2], downsized building design [3], the flexible layout of building space [4], minimum quantity of materials used [5], more intensive use of a building (by reducing per capita floor area), extension of building lifespan, and reuse and recycling of building materials [6].

To alleviate the environmental impacts of construction materials and the consequences of increased material costs, one potential strategy is MUE which is rather focused on reducing the demand for construction materials needed to build the facility. When building designs use only the materials required, in the right place and without excess, the demand for materials is reduced for the same size of the facility which is often represented by the area of floor space or building gross square footage (BGSF) [6]. Likewise, ensuring each structural element is appropriately sized and working efficiently takes some additional design time but can result in substantial material savings during the construction phase.

2.2. Data Envelopment Analysis

DEA is a mathematical procedure that utilizes an LP technique and identifies a set of weights that individually maximizes each DMU's efficiency using the same weights for all DMUs [7]. There are two different types of models in DEA depending on the type of envelopment surface formed by the frontiers; (1) the CCR model developed by Charnes and colleagues and Cooper and Rhodes [8] and (2) the BCC model developed by Banker, Charnes, and Cooper [9]. The first model assumes that the increase in outputs is proportional to the increase of inputs at any scale of operation, and thus it is known as a constant returns-to-scale (CRS) model. The second one, however, allows the production to exhibit increasing or decreasing returns-to-scale so it is called a variable returns-to-scale (VRS) model. Both models are further classified by their orientation which indicates the direction that an inefficient DMU approaches the frontier; either an increase in its output levels while keeping the same level of input (i.e., output-oriented) or a decrease in its input while maintaining the same output level (i.e., input-oriented). In both input- and output-oriented models, the best DMUs are assigned an efficiency score of 1 (or 100%) and those of the others are less than 1. For brevity, the mathematical formulations for other DEA models are not presented here; instead, the reader is referred to a more comprehensive text [10].

3. MUE Benchmarking Model

In this study, an output-oriented CCR model was employed to answer the question; by how much can inputs be proportionally decreased while keeping the level of output constant? This way, the outcomes of the DEA analysis can be used to identify the savings or reductions in inputs and the most suitable direction to enhance inefficient DMUs. However, traditional DEA alone is not enough to set reliable benchmarks for MUE because of some critical limitations that the conventional DEA model exhibits. The MUE benchmarking model was designed to generate reliable benchmarking by improving the three main deficiencies of the traditional DEA model.

First of all, the DEA results depend heavily on the input and output variables used in the analysis, which means attention to variable selection is crucial for obtaining reliable outcomes [11]. This is mainly because the greater the number of input and output variables, the less constrained the model weights assigned to the inputs and outputs, resulting in less discriminating results [12]. In this regard, one of the main challenges in DEA application is to find a parsimonious model using as many variables as required but as few as possible. To address this issue, we employed a formal stepwise approach to prioritizing meaningful inputs. Such an approach involves sequentially minimizing the average change in the efficiencies as inputs are dropped from the analysis.

Moreover, each DMU selects its own most favorable input and output weights for computing its efficiency, instead of using the same weights for all DMUs. This flexibility in choosing the weights prevents DMUs from being compared on a common base. The same issue regarding this weighting scheme can also happen when some DMUs heavily weight a few favorable inputs and outputs while ignoring other variables to achieve a high efficiency score [13]. The MUE benchmarking model overcomes this limitation by evaluating the efficiencies based on a cross-efficiency method (see Table 1), such as a DEA extension tool.

Table 1. Generalized cross-efficiency matrix (CEM).

DMU	**Target DMU**				**Average Cross-Efficiency**
	DMU_1	**DMU_2**	...	**DMU_n**	
DMU_1	E_{11}	E_{12}		E_{1n}	$\sum_{k=1}^{n} E_{1k}/n$
DMU_2	E_{21}	E_{22}		E_{2n}	$\sum_{k=1}^{n} E_{1k}/n$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
DMU_n	E_{n1}	E_{n2}	...	E_{nn}	$\sum_{k=1}^{n} E_{nk}/n$

Lastly, DEA presents the capability of determining a specific reference set for inefficient DMUs and deriving their potential improvements (or targets). Although this is a remarkable feature of DEA, the limitation of this feature is that an inefficient DMU and the corresponding reference set of the DMU may not be inherently similar in their operations or practices. This is because DEA assumes that DMUs are homogeneous and identical in operations or practices. Accordingly, the efficiency scores obtained from the DEA may cause the degree of improvement to become unattainable for an inefficient unit. To solve this problem, in the MUE benchmarking model, clustering analysis was adopted to cluster DMUs into a set of groups so that the best performing DMU in each cluster is utilized as the benchmark (or target) for other DMUs in the same cluster.

4. Summary and Conclusions

This study introduced a MUE benchmarking model that leverages the capability of DEA to measure the MUE performance and to identify useful benchmarks enabling inefficient projects to set potential improvement paths. To accomplish the goal, the model was designed to overcome the conventional application of DEA by selecting meaningful variables before running DEA analysis, ranking the efficiency scores on a common basis by measuring cross-efficiency, and integrating DEA with clustering analyses to determine practical references or targets from which inefficient DMUs can learn from. As a future direction, qualitative research will be conducted to validate the proposed model. With continuous data collection, it will be possible to conduct rigorous analyses to examine the relationship between a host of construction materials and different parameters of building products, which will help the authors update the model by including various input and output variables.

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References

1. Ruuska, A.; Häkkinen, T. Material Efficiency of Building Construction. *Buildings* **2014**, *4*, 266–294. [CrossRef]
2. Kedir, F.; Hall, D.M. Resource Efficiency in Industrialized Housing Construction—A Systematic Review of Current Performance and Future Opportunities. *J. Clean. Prod.* **2021**, *286*, 125443. [CrossRef]
3. Wilson, A.; Boehland, J. Small Is Beautiful. *J. Def. Model. Simul.* **2005**, *9*, 277–287. [CrossRef]
4. Kumar Dhar, T.; Sk. Maruf Hossain, M.; Rubayet Rahaman, K. How Does Flexible Design Promote Resource Efficiency for Housing? A Study of Khulna, Bangladesh. *Smart Sustain. Built Environ.* **2013**, *2*, 140–157. [CrossRef]
5. Wu, G. A Multi-Objective Trade-off Model in Sustainable Construction Projects. *Sustainability* **2017**, *9*, 1929. [CrossRef]
6. Hertwich, E.G.; Ali, S.; Ciacci, L.; Fishman, T.; Heeren, N.; Masanet, E.; Asghari, F.N.; Olivetti, E.; Pauliuk, S.; Tu, Q.; et al. Material Efficiency Strategies to Reducing Greenhouse Gas Emissions Associated with Buildings, Vehicles, and Electronics—A Review. *Environ. Res. Lett.* **2019**, *14*, 043004. [CrossRef]
7. Sharma, M.J.; Yu, S.J. Performance Based Stratification and Clustering for Benchmarking of Container Terminals. *Expert Syst. Appl.* **2009**, *36*, 5016–5022. [CrossRef]
8. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the Efficiency of Decision Making Units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
9. Banker, R.D.; Charnes, A.; Cooper, W.W. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Manage. Sci.* **1984**, *30*, 1078–1092. [CrossRef]
10. Charnes, A.; Cooper, W.W.; Lewin, A.Y.; Seiford, L.M. *Data Envelopment Analysis: Theory, Methodology, and Applications*; Kluwer Academic: Dordrecht, the Netherlands, 1994.
11. Wagner, J.M.; Shimshak, D.G. Stepwise Selection of Variables in Data Envelopment Analysis: Procedures and Managerial Perspectives. *Eur. J. Oper. Res.* **2007**, *180*, 57–67. [CrossRef]
12. Jenkins, L.; Anderson, M. A Multivariate Statistical Approach to Reducing the Number of Variables in Data Envelopment Analysis. *Eur. J. Oper. Res.* **2003**, *147*, 51–61. [CrossRef]
13. Sexton, T.R.; Silkman, R.H.; Hogan, A.J. Data Envelopment Analysis: Critique and Extensions. *New Dir. Progr. Eval.* **1986**, *32*, 73–105. [CrossRef]