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Mergers as an alternative for energy use optimization: evidence from the cucumber greenhouse production using the Inverse DEA approach

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Abstract
This paper investigates the merits of Mergers & Acquisitions (M&A), as strategic decisions, in optimizing energy use. The impact of M&A decisions on reducing energy consumption and, as a result, GHG emissions, are evaluated through the inverse data envelopment analysis (DEA) approach. Moreover, a new index, identified as synergy merge index (SMI), is developed to measure the merger's synergetic effect and determine accordingly the most productive merger plan.
Although the proposed methodology could be applied in any sector where energy use optimization is of interest, the investigations were carried out in the greenhouse (GH) production through a sample of 30 GH farms from Al-Batinah region, Oman. The standard DEA model declared 40% of the GH farms efficient, with an average technical efficiency of 0.872, yet, the inverse DEA results revealed that nearly 45% of the productive mergers involve at least one efficient GH farm, i.e., energy gains are still possible even if the merging farms are presumably efficient. The post-merger GH farms showed a substantial potential for energy gains, ranging between 17.56 and 74.47%, on average, with the most significant proportions observed for electricity. The highest notable proportions of energy gains reached 81.26%, 78.13%, 89.74%, 75.60%, 90.36%, and 77.41% for fertilizers, machinery, water chemicals, electricity, and labor, respectively. The most productive merger plan revealed that GH farm mergers farms can improve the energy savings by a factor of more than 4, where the share of electricity represents alone 94.92%, followed by 3.83% for fertilizers and only 0.60% for water. These findings unequivocally demonstrate that mergers can have a considerable impact on enhancing energy efficiency, which, along the way, provides strong support for the implementation of local policies that endorse mergers as a viable strategy to achieving optimal energy utilization.

Keywords Energy efficiency · Merger · Data envelopment analysis (DEA) · Inverse DEA · Greenhouse production

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Extended author information available on the last page of the article

1 Introduction

More than half of carbon emissions causing global warming are from burning fossil fuels (US-Environmental Protection Agency, 2015), to such an extent that a reduction of carbon dioxide (CO_2) emissions to 350 ppm in the atmosphere may prevent no less than 2 °C temperature rise (Mathiesen et al., 2011). Carbon emissions can also affect negatively people's health as a result of potential increase of smog and air pollution (WHO, 2019).

It was reported that the agricultural sector's emissions amount 670 million tons of CO_2, corresponding approximately to 14% of the global warming impact (Nguyen et al., 2010). Therefore, ensuring efficient energy use is a major priority to mitigating environmental impacts and greenhouse gas (GH) emissions, besides reducing production costs and, consequently, improving market competitiveness (Mohammadi et al., 2014; Unakıtan & Aydın, 2018).

Dulling the negative effects of CO_2 emissions requires more penetration of alternative clean energy sources, such as wind and solar energy, in the design of new electric energy production systems (Papaefthymiou & Dragoon, 2016), along with ingenious managerial tools for the optimization of energy usage. Thus, developing robust tools becomes necessary to identify the energy consumption patterns that may boost the energy use efficiency as well as the sustainability of production systems (Yildizhan & Taki, 2019).

Data envelopment analysis (DEA) stands out as an extensively applied technique in agricultural efficiency research (Oukil & Zekri, 2021). Due to its nonparametric nature, the DEA methodology utilizes linear programming as a modeling framework to assess decision-making units (DMUs) relative to benchmarks that are possibly identified within the related homogeneous groups (Amin & Oukil, 2019b). DEA offers a notable advantage in its aptitude to deal with DMUs that are characterized by numerous inputs and outputs (Oral et al., 2015). Notably, DEA serves as a valuable tool for distinguishing inefficient DMUs and pinpointing the factors, i.e., inputs or outputs, that require reduction or expansion to enhance the overall performance of the unit (Hassan & Oukil, 2021). Moreover, as opposed to stochastic frontier analysis (SFA), DEA is able to achieve such assessment without necessitating neither specific functional forms for the data nor reliance on probability distributions (Oukil & Govindaluri, 2017; Sow et al., 2016).

Owing to its robust methodological framework, DEA's application scope is well recognized in optimizing energy consumption along with reducing environmental impacts of open field agricultural systems, where a variety of crops are cultivated, such as sugarcane (Ullah et al., 2019), apple (Zalaghi et al., 2021) and cotton (Singh et al., 2022), some of the most recent applications.

In the GH production, the contribution of DEA to energy efficiency is restricted to a few crops, including tomato (Nourani & Bencheikh, 2020), and cucumber (Soheilifard et al., 2021), which have apparently been studied exclusively in Iran and Algeria, two countries categorized as arid regions. In these studies, there is a consensus among all researchers that energy overconsumption is an inveterate trait of the GH production, regardless of the cultivated crop. Hence, the GH production is one of the most intensive agricultural production systems in terms of energy consumption as well as investments and yield (Bolandnazar et al., 2014).

The traditional application of the DEA approach to optimizing energy consumption often starts with a categorization of the GH farms into efficient and inefficient. Once the inefficient GH farms have been duly identified, potential energy savings are estimated through the associated slack values (Tho & Umetsu, 2022). Even so, it is still worthwhile to inquire whether the efficiency improvement scheme produced through slack analysis tactically the best.

To answer this question, we propose a restructuring strategy built on sharing resources among the GH farms instead of addressing inefficiency on an individual GH farm basis. The business transaction entailing consolidation of assets and resources within a group of DMUs is a corporate decision that falls under the strategic frame, referred to as Mergers & Acquisitions (M&A). Its primary objective is fundamentally fostering the collective production capabilities of the group (Gerami et al., 2021).

In the framework of mergers' assessment, the majority of DEA applications tend to focus on the estimation of the post-merger improvements in cost and profit efficiency, considering the levels of the existing inputs and/or outputs (Zeinodin & Ghobadi, 2020). Regarded from a more practical perspective, a decision maker (DM) may preferably adopt a rather prudent attitude by anticipating, even before the merger occurs effectively, the required amounts of the inputs and/or outputs that would allow the intended merger to accomplish an efficiency target, set a priori but does not need to necessarily be 100%. Inverse DEA (InvDEA) emerged as the best method to address such a scenario (Pendharkar, 2002). Lin et al. (2020) is the only M&A related study where InvDEA is applied to the energy sector, besides agriculture (Oukil, 2023; Oukil et al., 2022b) and higher education (Amin & Oukil, 2019a). All the remaining applications are found in the banking sector, See Emrouznejad and Amin (2023) for a recent review.

In light of the literature reviewed to date, the present paper's contribution resides in (1) emphasizing the merits of M&A for energy optimization, regardless of the application context; (2) evaluating the impact of M&A decisions on reducing energy consumption and, as a result, GHG emissions; (3) applying inverse DEA as a modeling tool for quantifying the energy gains that can be generated through potential merger decisions and (4) developing a new index, identified as synergy merge index (SMI), to measure synergy of a post-merger unit.

The real-world relevance of the recommended methodology is evidenced through an in-depth investigation conducted on 30 GH farms situated within Oman's Al-Batinah region. This investigation is exclusively dedicated to the GH production of cucumber, a crop that holds a pivotal importance within the country's GH agricultural landscape. The cucumber production not only dominates the GH cultivation sector but also represents the singular GH product exported from Oman.

Finally, it is essential to emphasize that, although the entire investigation is centered on the GH agriculture production as an illustrative contextual setting, the scope of application of the new procedure is readily expandable to encompass a larger spectrum of other industries facing energy-related challenges.

The rest of the paper proceeds as follows: In Sect. 2, we delve into the description of the study area. Section 3 presents the foundational aspects of the proposed procedure, encompassing concepts tied to DEA, as well as an exploration of the inverse DEA model. Moving on to Sect. 4, we offer an extensive discussion of the findings based notably on our case study. Section 5 introduces of a novel methodology dedicated exclusively to the optimal selection of post-merger partners. Lastly, in Sect. 6, we encapsulate the managerial implications arising from the proposed procedure, concluding with our final remarks.

2 Study area

Oman, situated along the Tropic of Cancer, falls within the category of some of the hottest and driest regions in the world. However, it is worth noting that the southern part of the country experiences a tropical climate (Oukil & Al-Zidi, 2018). With temperatures exceeding 50 °C, scarce rainfall and persistent drought, Oman's agricultural sector is completely dependent on irrigation (Naifer et al., 2011; Zekri, 2008). Despite these harsh conditions, the Omani government continues its journey toward transforming its oil wealth into large-scale economic growth, which involves agriculture as one of the vital sectors. A series of incentive programs are underway to promote new irrigation systems and GH farming (Al-Mezeini et al., 2020). The implementation of the GH technology is favorable to the arid climate of Oman as it increases humidity inside the GH and contributes 60–80% reduction in crop evapotranspiration, which represents a significant water saving, compared to outdoor farming (Al-Ismaili & Jayasuriya, 2016; Fernandes et al., 2003). Nevertheless, the GH production is primarily dependent on the availability of water resources for both irrigation and fan-pad cooling systems. The water requirements for the cooling systems alone represent about 67% of the total water demand (Al-Mulla, 2006). Moreover, alike most farming systems, a diversity of energy types are used over the crop production, the irrigation mechanisms, the chemical fertilization, and the applications of synthetic pesticides and herbicides (Raheli et al., 2017). The large dependence on fossil energy sources being established for the GH cultivation, it is worth emphasizing its effect not only on human health but also on the atmosphere via the nexus GH emissions-climate change phenomenon (Bolandnazar et al., 2014).

The GH agriculture production is primarily concentrated in Al-Batinah South, which happens to be Oman's most agriculturally intensive region. Cucumber cultivation takes a prominent role in this area, representing a dominant force through 89% of the entire GH agriculture production capacity (MAF, 2014) (Fig. 1).

Al-Batinah South is situated in the northern part of Oman, roughly 300 km northwest of Muscat, along the western coastline of the Sea of Oman. Its geographical coordinates range from latitudes 23°42′28″ to 23°32′55″ N and longitudes 57°19′49″ to 58°03′28″ E.

Dry climatic conditions with a pronounced rate of evaporation are the key characteristics of the Al-Batinah region. It is predominantly renowned for mild winters with low humidity levels and very hot, but occasionally humid, summers, with possible occurrence of sporadic and unpredictable showers. In the coastal areas, the average long-term annual air temperature stands at 28.5 °C, whereas in the mountainous regions, it averages 17.8 °C. In stark contrast to the coastal zone, the southern highland region experiences heavy rainfall as a common occurrence. Over an extended period, the region records an average annual precipitation of 50 mm, marked by considerable rainfall variability over time and location. High-rainfall years are often followed by extended dry periods (Kwarteng et al., 2009).

In recent years, Al-Batinah region witnessed significant expansion in its agricultural activities (Choudri et al., 2015). This agricultural growth within Al-Batinah contributes to over 53% of Oman's total cultivated land and serves as the primary source for the production of vegetables destined to the markets of the capital Muscat and the coastal city.

Among the six cities in Al-Batinah South, Barka stands out with 53% of the GH farms, and Al-Musannah comes next with 23%, while the remaining portion is

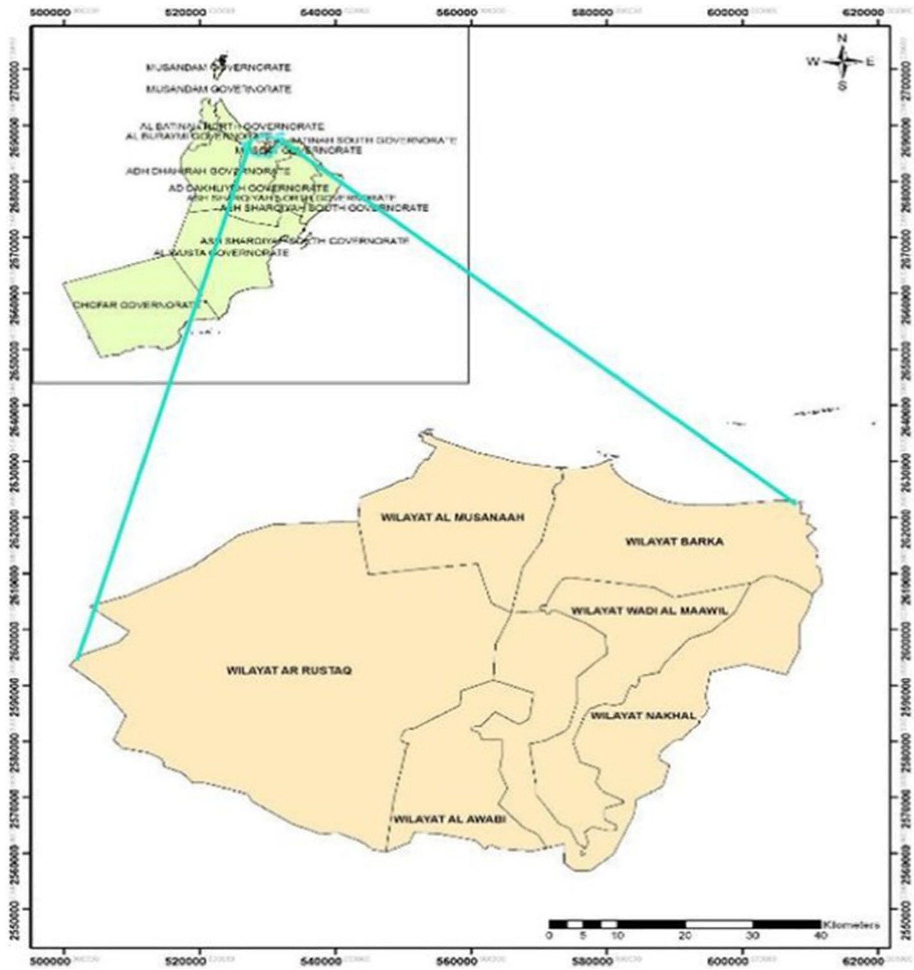

Fig. 1 Al-Batinah South on the map of Oman (Al-Maimani et al., 2019)

distributed among the others. Notably, the majority of GH farms fall under the category of "small scale," averaging 6.7 GHs per farm, with 55% of these farms operating with fewer than 5 GHs (Al-Maimani et al., 2019).

3 Methodology

The cucumber GH production accounts for the most significant proportion of Oman's GH facilities, nearing 89%. As such, cucumber GH farms are the exclusive focus of the present study as a viable sample to represent the GH agricultural production. Furthermore, concentrating on GH producers cultivating the same crop guarantees a consistent level of technological homogeneity, which is a prerequisite for employing conventional DEA models (Oukil et al., 2016).

The BCC and the CCR models, developed, respectively, by Banker et al. (1984) and Charnes et al. (1978), are the DEA models that are most frequently used for efficiency evaluation.

Irrespective of the specific model used, it is assumed that the resources of GH farms are fully controllable, and the central issue at hand is determining the most efficient management approach for these resources. In this regard, the study context aligns well with a DEA input-oriented model (Soltani et al., 2021).

3.1 Assessment of GH farm efficiency

Let's consider the problem of assessing G GH farms, where I and J represent the numbers of inputs x and outputs y for each GH farm $\mathrm{GH_g}$. Taking into account the production process, $\mathrm{GH_g}$ is demarcated by its inputs x_{ig} and outputs y_{jg}, for $i = 1, \ldots, I$ and $j = 1, \ldots, J$. Considering GH farm $\mathrm{GH}_o = (x_o\, y_o)$, its efficiency score e_o^* can be computed via the following DEA model:

$$
\text{(BCC)}\quad
\begin{aligned}
& e_o^* = \min\ \pi \\
& \text{s.t.}\quad \sum_{g=1}^{G} \alpha_g x_{ig} \le \pi x_{io} && i = 1, \ldots, I && (1) \\
& \sum_{g=1}^{G} \alpha_g y_{jg} \ge y_{jo} && j = 1, \ldots, J && (2) \\
& \textstyle\sum_{g=1}^{G} \alpha_g = 1 && && (3) \\
& \alpha_g \ge 0 && g = 1, \ldots, G &&
\end{aligned}
$$

Model BCC adopts an input orientation stance with variable returns to scale assumption. In other words, the DM is interested to know more about the inputs that must be reduced to improve the performance of an inefficient GH farm GH_o, assuming its outputs unchanged. As such, e_o^*, which is the optimal efficiency of GH_o represents the minimal input reduction level that is needed for GH_o to upgrade its status to full efficiency (Oukil & Govindaluri, 2020). Consequently, GH_o is considered efficient if $e_o^* = 1$; otherwise, it is deemed inefficient, implying that it is not utilizing its inputs in an optimal way. Constraints (1) and (2) describe the projection of GH_o on the efficiency frontier and establish formally that its inputs and outputs are linear combinations of the reference points. Constraint (3) serves as the convexity constraint. The intensity vector $\boldsymbol{\alpha} = (\alpha_1\, \alpha_2 \ldots \alpha_G)$ is the weighting scheme associated with the peers involved in evaluating GH_o (Oral et al., 2014).

Let's denote the optimal vector $\boldsymbol{\alpha}^* = (\alpha_1^*\, \alpha_2^* \ldots \alpha_G^*)$. A scenario where $\alpha_g^* > 0$ signifies that the strongly efficient farm $\mathrm{GH_g}$ could potentially serve as a benchmark for GH_o In this case, the reference set for GH_o encompasses all feasible benchmark farms. Hence, the value of α_g^* is practically interpreted as the level of endorsement provided by farm $\mathrm{GH_g}$ to GH_o with regard to achieving its efficiency goals (Oukil et al., 2021).

We utilize s_{io}^* to calculate the savings required from GH_o in terms of input i:

$$
s_{io}^* = e_o^* x_{io} - \sum_{g=1}^{G} \alpha_g^* x_{ig}\ i = 1, \ldots, I \tag{4}
$$

s_{io}^* is known as the slack value of input i and it is derived from the set of constraints (1).

$s_{io}^{*} = 0$ for $i = 1, ..., I$ and $\boldsymbol{\alpha}^{*} = \mathbf{1}$ denote the conditions for GH_o to be strongly efficient. On the other hand, if $e_o^{*} = 1$ but some or all of the values of s_{io}^{*} are strictly positive then, GH_o is weakly efficient (Moghaddas et al., 2022).

In the following section, we introduce the input-orientation form of the InvDEA linear program, which allows the evaluation of mergers involving pairs of GH farms.

3.2 Inverse DEA model for mergers

For the sake of modeling simplicity, we assume that there are two GH farms, GH_A and GH_B, planning to merge and form a new GH farm, which is hypothetically larger, denoted as F_m. However, it is worth noting that this assumption does not exclude the applicability of the proposed methodology to the mergers of more than two farms.

Let $\overline{\pi}$ represent the preset efficiency target for the post-merger GH farm F_m. When employing a DEA input-oriented approach, F_m preserves all the pre-merger outputs of GH farms GH_A and GH_B, while using the bare minimum of the corresponding input levels in order to achieve $\overline{\pi}$.

Let ∂_{iA} and ∂_{iB} be the minimum quantities of the ith input associated with GH_A and GH_B, respectively. As a result, the ith input level for F_m becomes $\partial_{iA} + \partial_{iB}$, whereas its jth output level remains $y_{jA} + y_{jB}$, with $i = 1, \ldots, I$ and $j = 1, \ldots, J$. Finding the optimal levels of inputs for F_m, under the aforementioned conditions, is an inverse optimization problem that can be modeled as follows (Amin & Ibn Boamah, 2020; Gattoufi et al., 2014).

$$
\text{(InvDEA)}\quad
\begin{array}{ll}
\min \ \sum_{i=1}^{I} (\partial_{iA} + \partial_{iB}) & \\
\text{s.t.} & \\
\sum_{k \in P} \alpha_k x_{ik} + \alpha_m (x_{iA} + x_{iB}) - (\partial_{iA} + \partial_{iB}) \times \overline{\pi} \le 0 & i = 1, \ldots, I \\
\sum_{k \in P} \alpha_k y_{jk} + \alpha_m (y_{jA} + y_{jB}) \ge (y_{jA} + y_{jB}) & j = 1, \ldots, J \\
\sum_{k \in P} \alpha_k + \alpha_m = 1 & \\
0 \le \partial_{iA} \le x_{iA}, \ 0 \le \partial_{iB} \le x_{iB} & i = 1, \ldots, I \\
\alpha_k \ge 0, \ k \in P, \ \alpha_m \ge 0 &
\end{array}
$$

The above InvDEA is referred to as an inverse DEA model due to the fact that the optimization problem is not any more concerned with finding the efficiency score for given amounts of inputs and outputs; Instead, the efficiency score $\overline{\pi}$ is now a known parameter, and the DM is rather interested in finding the minimum levels of inputs that are just needed for the merger F_m to reach $\overline{\pi}$, i.e., the optimal values ∂_{iA}^{*} and ∂_{iB}^{*} for $i = 1, \ldots, I$.

Let P represent the set of GH farms that are involved in evaluating F_m. The set P can be presented under two configurations. (1) P includes either GH_A or GH_B, which matches a *survival*. (2) Neither GH_A nor GH_B belong to P, which depicts a *consolidation* (Amin & Oukil, 2019a). In a survival, the acquiring GH farm will carry on operating with its previous name. However, in the case of a *consolidation*, the merging farms combine to form a new farm with a new name, such as F_m. Since the present study aims to enhance GH farm efficiency through consolidation, neither of the two merging GH farms is intended to be present in P.

Notwithstanding the type of merger, the intensity variables α_k will be restricted to $k \in P$, which necessarily comprises α_m corresponding to F_m. If the only optimal solution to the (InvDEA) model consists of $\alpha_m = 1$ and $\overline{\pi} = 1$, the merger becomes a *major* *consolidation* (Amin & Ibn Boamah, 2020). A major consolidation is a scenario where the optimal values satisfy the equations $\partial_{iA}^{*} = x_{iA}$ and $\partial_{iB}^{*} = x_{iB}$ for $i = 1, \ldots, I$.

4 Application

4.1 Data sampling

Data were systematically collected throughout the entire cropping season from a sample of 30 GH farms. To gain insights into cucumber GH production, the farmers were handed data sheets, enabling them to meticulously record information about both yield (output) and the array of resources (inputs) employed. The study encompassed a comprehensive examination of six inputs, which included *labor* (x_1), *machinery* (x_2), *fertilizers* (x_3), *chemicals* (x_4), *water* (x_5), and *electricity* (x_6), alongside the sole output variable, yield (y). For reference, Table 1 presents a concise summary of the values associated with these variables per hectare of land, as drawn from the sample of 30 GH farms.

The determination of energy-equivalent values has been accomplished through the utilization of a set of energy-equivalent coefficients, which are documented in Table 9. These coefficients were collated from an extensive array of literature sources, ensuring a comprehensive and reliable compilation. Figure 2, in turn, exhibits a graphical representation of the energy allocation proportions per individual input across the entire dataset of cucumber GH farms.

Electricity and fertilizers stand out as the primary consumers of energy, accounting for the highest proportions at 85.02% and 12.69%, respectively. This dominance of electricity as the foremost energy-consuming input is quite expected, given that all GH facilities rely on fan-pad cooling systems to maintain an optimal environment for crop growth. Additionally, the reliance on groundwater as, almost, the only source of irrigation necessitates the use of electric pumps for water extraction, which contributes significantly to the overall electricity consumption.

Table 1 Descriptive summary of the data sample

Data	Unit	Quantity per ha	Energy equivalent (MJ ha^{-1})	Proportion (%)
Inputs				
Labor	h	3878.16	7601.20	0.83
Machinery	h	105.66	1379.89	0.15
Fertilizers	kg	19,507.67	116,891.38	12.69
Chemicals	kg	52.88	6345.92	0.69
Water	m^3	5696.85	5810.79	0.63
Electricity	kWh	65,656.75	783,284.97	85.02
Total energy input			921,314.16	100.00
Output				
Cucumber	kg	123,454.80	98,763.84	
Total energy output			98,763.84	

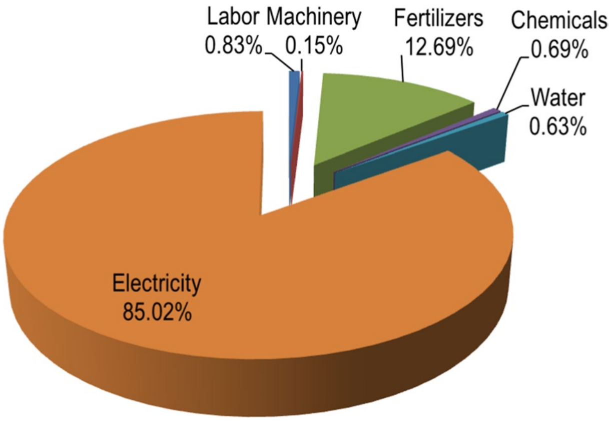

Fig. 2 Distribution of energy inputs of cucumber GH production

4.2 Energy input–output analysis

To reach a thorough understanding of the energy dynamics within the cucumber GH production, we computed the following energy indicators:

$$\text{Energy Use Efficiency} = \frac{\text{Energy Output (MJ ha}^{-1}\text{)}}{\text{Energy Input (MJ ha}^{-1}\text{)}} = 0.1072$$

A high Energy use efficiency ratio indicates a more efficient utilization of input energy. In our case, a ratio of 0.1072 implies that the production process of a single MJ of energy output necessitates at least 9.3285 MJ of energy inputs. In comparison to the findings of other studies, carried out within similar GH production conditions, Taki et al. (2012), Bolandnazar et al. (2014), Firoozi et al. (2014) and Pahlavan et al. (2012) have reported notably superior ratios of 0.56, 0.51, 0.26, and 0.29, respectively, indicating more efficient energy usage than what we have observed in our study. It is worth noting that Khoshnevisan et al. (2013) are the sole authors to report a ratio of 0.0912.

$$\text{Energy Productivity} = \frac{\text{Cucumber yield (kg ha}^{-1}\text{)}}{\text{EnergyInput (MJ ha}^{-1}\text{)}} = 0.134 \text{ kg/MJ}$$

Here, high values of Energy productivity indicate a more productive GH production system. In our study, we find that only 134 g of cucumber is produced for every 1 MJ of energy input. In practical terms, this means that a GH farmer must spend 7.4628 MJ of energy to produce 1 kg of cucumber, which is an extremely low productivity when compared to, for instance, the 0.64 kg/MJ reported by Bolandnazar et al. (2014).

$$\text{Specific Energy} = \frac{\text{Energy Input (MJ ha}^{-1}\text{)}}{\text{Cucumber yield (kg ha}^{-1}\text{)}} = 7.4628 \text{ MJ/kg}$$

The specific energy is the input energy to yield ratio of the farms in the cucumber GH production system. As the reciprocal of the energy productivity, the smaller its value, the better.Net Energy = Energy Output (MJ ha^{-1}) − EnergyInput (MJ ha^{-1})

Net energy represents the overall energy flow balance between the resources and the yield. It assumes a negative value when energy use efficiency is below 1, indicating energy loss, whereas it becomes positive when energy use efficiency exceeds 1 In our study, the calculated Net Energy stands at −822.55 GJ/ha, which can be interpreted as an energy deficit or loss of 822.55 GJ/ha within the context of the research.

4.3 Assessing the performance of GH farms

The optimal efficiency score e_g^* along with the corresponding optimal intensity vector $\boldsymbol{\alpha}_{\mathbf{g}}^*$ are computed for each GH farms GH_g, for $g = 1, \ldots, 30$, by solving the associated BCC model. The IBM-ILOG CPLEX software is duly used for this purpose. A concise presentation of the results is provided in Table 2.

Table 2 GH farms' DEA efficiency results with slack values

GH farm	e_g^*	Slack values (MJ ha^{-1})					
		Labor s_{1g}^*	Machinery s_{2g}^*	Fertilizers s_{3g}^*	Chemical s_{4g}^*	Water s_{5g}^*	Electricity s_{6g}^*
GH_{01}	0.8819	1005.55	95.34	6461.55	936.58	1182.13	155,882.33
GH_{02}	0.8614	995.70	270.69	10,885.87	251.08	1257.38	183,962.09
GH_{03}	1	0	0	0	0	0	0
GH_{04}	0.9057	886.17	81.01	5166.19	306.01	920.93	115,588.49
GH_{05}	0.6991	1425.13	436.60	18,907.66	3209.30	3059.72	190,142.03
GH_{06}	0.5612	6060.51	1172.94	113,394.29	3271.72	4542.01	496,557.71
GH_{07}	0.9986	3.18	1.11	161.99	15.13	12.09	1518.60
GH_{08}	1	0	0	0	0	0	0
GH_{09}	1	0	0	0	0	0	0
GH_{10}	0.7792	2198.47	366.22	36,553.88	466.89	1097.34	223,564.97
GH_{11}	0.5140	6562.30	705.26	57,355.45	3645.12	2211.43	438,804.00
GH_{12}	1	0	0	0	0	0	0
GH_{13}	0.5049	3154.05	692.84	59,543.87	1545.55	1740.11	264,523.54
GH_{14}	1	0	0	0	0	0	0
GH_{15}	0.5830	3632.41	620.61	56,021.49	4975.32	3099.76	321,005.89
GH_{16}	0.9999	2.01	0.11	4.59	0.74	0.48	128.20
GH_{17}	0.6637	2472.72	656.90	25,213.56	862.27	702.05	258,493.45
GH_{18}	1	0	0	0	0	0	0
GH_{19}	1	0	0	0	0	0	0
GH_{20}	1	0	0	0	0	0	0
GH_{21}	0.8094	2228.83	291.20	50,894.42	1421.45	637.58	50,665.78
GH_{22}	1	0	0	0	0	0	0
GH_{23}	0.7929	581.53	276.78	74,700.42	1307.91	2213.65	118,749.31
GH_{24}	1	0	0	0	0	0	0
GH_{25}	1	0	0	0	0	0	0
GH_{26}	0.7875	2707.71	308.41	33,690.71	2213.91	317.39	64,396.11
GH_{27}	0.9175	721.22	107.47	11,087.53	984.69	170.88	52,505.54
GH_{28}	1	0	0	0	0	0	0
GH_{29}	0.9197	285.40	122.69	7255.36	402.17	481.12	33,789.09
GH_{30}	0.9803	207.76	29.30	1284.96	52.83	72.14	12,533.53

The efficiency stands, on average, at 0.8720 together with a standard deviation of 0.1649. These statistics point to a notable degree of inefficiency within the sample of cucumber GH farms under study. It is also worth noting that 12 out of the 30 GH farms, that is 40%, are identified as strongly efficient. The latter proportion is comparable with a 36% level in Taki et al. (2012) while the average efficiency score is slightly below the score of 0.90 reported in Soheilifard et al. (2021).

Other cucumber GH production studies revealed average scores of 0.95 (Taki et al., 2012) and 0.99 (Bolandnazar et al., 2014; Firoozi et al., 2014; Khoshnevisan et al., 2013).

In order to reach efficiency, inefficient GH farms GH_o need to reduce energy consumption by the slack value s_{io}^{*} for each input i ($i = 1, ..., 6$). The latter values are the energy savings that are required from inefficient GH farms if they are aiming to achieve strong efficiency while keeping the energy outputs unchanged. Table 3 presents the energy saving pattern of the cucumber GH production per resource.

Through the results shown in Table 3, it appears that the overall input energy savings are 3997.49 GJ ha^{-1}, with electricity accounting for 74.62% of the total, followed by fertilizers at 14.22%. As a result, there is significant opportunity to increase energy usage efficiency by applying appropriate methods for optimal electricity and fertilizer utilization. The obtained energy saving index percentage is 13.06%. In more practical terms, assuming all inefficient GH farms succeed in improving their daily farming operations with regard to energy usage, the total energy savings achievable will not surpass 13.06%. This percentage is low contrasted to the highest value of 24.46% (Khoshnevisan et al., 2013) but slightly above the lowest value of 8.12% (Taki et al., 2012), reported by these authors for cucumber GH production systems.

The lower the input savings, the less work is required to increase efficiency when a GH farm's performance is assessed as a standalone unit. However, reviewing the strategy becomes necessary once the impact of a certain input is likely to be globally perceptible, as is the situation with energy and its environmental effects (Oukil et al., 2022a). In the sections that follow, we suggest GH farm merger as a method for strategically optimizing resources and look at how it affects energy savings.

4.4 Mergers of GH farms

Using the selected GH farms as a sample, we applied the InvDEA model to assess every potential pairwise GH farm merger, denoted as $F_m = (\mathrm{GH}_A, \mathrm{GH}_B)$, where $A \neq B$. In each case, we set the efficiency target at $\overline{\pi} = 1$. Given that we have a total of $G = 30$ GH farms,

Table 3 Energy savings per resource

Input	Present use (MJ ha^{-1})	Target use (MJ ha^{-1})	Energy saving (MJ ha^{-1})	Contribution to savings (%)
Labor	228,036.02	192,905.36	35,130.66	0.88
Machinery	41,396.70	35,161.19	6235.51	0.16
Fertilizers	3,506,741.51	2,938,157.70	568,583.80	14.22
Chemicals	190,377.71	164,509.01	25,868.70	0.65
Water	174,323.73	150,605.53	23,718.20	0.59
Electricity	23,498,549.20	20,515,738.55	2,982,810.65	74.62
Total	30,602,339.98	26,604,848.82	3,997,491.16	100.00

there exist 435 potential mergers F_m. The solution of the successive 435 InvDEA models to optimality reveals that 205 out of the 435 evaluated mergers qualify as major consolidations, where the post-merger GH farm F_{m} preserves the entire amounts of inputs from the merging GH farms, GH_A and GH_B, i.e., $\partial^*_{iA} = x_{iA}$, $\partial^*_{iB} = x_{iB}$, for all $i = 1, ..., 6$, and $\alpha^*_m = 1$. In the other hand, there are 230 post-merger GH farms that exhibit potential for enhanced productivity.

In the interest of space, Table 4 displays only the mergers involving GH_{01}.

The most striking feature of these results is certainly the fact that almost 45% of the mergers involve at least one efficient GH farm, with 13 mergers comprising exclusively strongly efficient GH farms. Though no further input gains are possible from an efficient GH farm that operates individually, the latter results suggest that the situation can be different under a merger scenario. Specifically, input gains are possible through mergers, even if the merging GH farms are both efficient.

Let's look, for example, at the post-merger GH farm F_4 that involves GH_{01} and GH_{05}. Table 4 shows clearly that the creation of requires GH_{01} and GH_{05} to contribute, respectively, with minimum energy levels of $\partial^*_{11} = 7760$ and $\partial^*_{15} = 0$ for labor, $\partial^*_{21} = 807$ and $\partial^*_{25} = 758$ for machinery, $\partial^*_{31} = 54721$ and $\partial^*_{35} = 62843$ for fertilizers, $\partial^*_{41} = 7932$ and $\partial^*_{45} = 3122$ for chemicals, $\partial^*_{51} = 4017$ and $\partial^*_{55} = 0$ for water, and $\partial^*_{61} = 293906$ and $\partial^*_{65} = 0$

Table 4 GH farm mergers with potential energy usages

	Farms		Labor		Machinery		Fertilizers		Chemicals		Water		Electricity	
F_m	GH_A	GH_B	∂^*_{1A}	∂^*_{1B}	∂^*_{2A}	∂^*_{2B}	∂^*_{3A}	∂^*_{3B}	∂^*_{4A}	∂^*_{4B}	∂^*_{5A}	∂^*_{5B}	∂^*_{6A}	∂^*_{6B}
F_1	GH_{01}	GH_{02}	7647	0	807	539	54,721	78,558	7932	1812	4552	0	606,046	0
F_2	GH_{01}	GH_{03}	5246	0	807	246	54,721	34,805	7932	1734	4622	0	662,587	0
F_3	GH_{01}	G_{04}	5816	0	807	291	54,721	54,793	7932	1874	4710	0	690,363	0
F_4	GH_{01}	G_{05}	7760	0	807	758	54,721	62,843	7932	3122	4017	0	293,906	0
F_5	GH_{01}	G_{06}	8516	4451	0	2124	13,641	258,422	5235	7456	4358	0	319,214	0
F_6	GH_{01}	G_{07}	8516	482	807	816	54,721	118,643	0	9347	3236	0	234,460	0
F_7	GH_{01}	G_{08}	8516	135	0	1726	45,036	86,439	0	11,495	3868	0	195,614	0
F_8	GH_{01}	G_{10}	8516	2028	124	1658	54,441	165,531	7932	2114	3491	0	274,481	0
F_9	GH_{01}	G_{11}	8516	738	218	1451	54,721	118,011	3884	7500	4294	0	389,760	0
F_{10}	GH_{01}	G_{13}	8516	717	345	1399	38,361	120,257	7932	3121	3753	0	219,802	0
F_{11}	GH_{01}	G_{15}	8516	722	91	1488	54,721	134,348	0	11,163	4571	0	527,426	0
F_{12}	GH_{01}	G_{16}	5714	0	807	369	54,721	34,622	7932	2062	4420	0	549,729	0
F_{13}	GH_{01}	G_{17}	8516	178	0	1637	54,721	74,977	7932	2564	4052	0	331,007	0
F_{14}	GH_{01}	G_{18}	5936	0	807	472	54,721	26,149	7932	2325	4186	0	427,502	0
F_{15}	GH_{01}	G_{20}	5083	0	807	207	54,721	34,109	7932	1630	4680	0	695,592	0
F_{16}	GH_{01}	G_{21}	8516	3746	531	1527	0	249,078	5039	7456	4278	0	299,007	0
F_{17}	GH_{01}	G_{22}	8516	1318	807	816	50,381	163,812	7271	2593	3849	0	424,647	0
F_{18}	GH_{01}	G_{23}	8516	629	435	1337	0	147,563	5316	6316	3924	0	209,759	0
F_{19}	GH_{01}	G_{26}	8516	1864	434	1451	29,268	158,518	1557	10,417	4064	0	245,121	0
F_{20}	GH_{01}	G_{27}	8516	722	277	1302	54,721	134,348	0	11,163	4571	0	527,426	0
F_{21}	GH_{01}	G_{28}	7635	0	807	622	54,721	52,090	7932	821	3784	0	394,519	0
F_{22}	GH_{01}	G_{29}	7502	0	807	547	54,721	90,328	7932	2590	4581	0	580,075	0

for electricity, all expressed in MJ/ha. Apparently, the values $\partial^*_{15} = 0$, $\partial^*_{55} = 0$ and $\partial^*_{65} = 0$ suggest that GH farm GH_{05} does not need to contribute to the post-merger F_4 with regard to human labor, water and electricity, expecting GH farm GH_{01} to be the exclusive provider of these energy inputs.

Observing that the energy inputs of GH_{01} and GH_{05} before the merger are $x_{11} = 8516$, $x_{15} = 4737$, $x_{21} = 807$, $x_{25} = 1451$, $x_{31} = 54721$, $x_{35} = 62843$, $x_{41} = 7932$, $x_{45} = 10667$, $x_{51} = 10011$, $x_{55} = 10170$, $x_{61} = 1320117$ and $x_{65} = 631970$, the calculation of the potential energy gains resulting from the merger F_4 amount to $\gamma_{11} = x_{11} - \partial^*_{11} = 8516 - 7760 = 756$ MJ/ha for labor. This represents a portion of the current energy usage of GH_{01}, with the labor energy of GH_{05} being fully saved, i.e., $\gamma_{15} = x_{15} - \partial^*_{15} = 4737 - 0 = 4737$ MJ/ha. Consequently, the merger F_4 generates cumulative energy gains that resulting from amount to $g_{13} = \gamma_{11} + \gamma_{15} = 5493$ MJ/ha for labor, constituting no less than 41.45% in labor energy savings jointly allocated to GH farms GH_{01} and GH_{05}. In a similar vein, the cumulative energy gains amount proportions of 30.69% for machinery, 0% for fertilizers, 40.57% for chemicals, 80.09% for water, and 84.94% for electricity. A comprehensive breakdown of these proportions alongside the associated cumulative energy gains g_{im} is presented in Table 5 for the mergers involving GH_{01} and all inputs $i = 1, ..., 6$. Meanwhile, the averages provided in Table 5 correspond to the entire set of 230 potentially productive post-merger GH farms.

The highest proportions of energy gains that are computed on the averages are 74.47% for electricity and 60.58% for water. The mergers' energy gains for labor, machinery, fertilizers, chemicals, water and electricity reach proportions as high as 77.41% (F_{184}), 78.13% (F_{129}), 81.26% (F_{129-}), 75.60% (F_{68}), 89.74% (F_{68}) and 90.36% (F_6), respectively. Recall, for instance, that F_6 is the merger of GH_{01} and GH_{07} whose efficiency scores are, respectively, $e^*_{01} = 0.8819$ and $e^*_{07} = 0.9986$. Under the individualist scheme, this means that GH_{01} and GH_{07} must shrink their current energy consumptions by, respectively, 11.81% and 0.14% to be able to aspire for full efficiency. Upon merging, these two GH farms have the potential to reach an efficiency target of $\pi = 1$ by preserving only portions of their combined energy inputs, as low as 9.64% for electricity and 17.15% for water. These proportions of energy gains are distributed among the post-merger GH farms as visualized in Fig. 3.

A notable trend emerges with electricity, where 200 post-merger GH farms out of a total of 230 record proportions of 60% and above of energy gains. Remarkably, the same proportion falls below 20% only two post-merger GH farms. This means that a substantial 86.95% of the mergers utilize less than 40% of the combined energy of the mergers while still achieving full efficiency. The pattern shifts slightly when it comes to energy gains from water. In this scenario, 130 post-merger GH farms record gain proportions that vary within the range [60%, 80%] and only 21 mergers exceed gain proportions of more than 80%. Though most of the energy gain proportions for fertilizers and chemicals fall on the bottom side of the picture, it is noticeable that there are picks of 81.26% (F_{129}) and 75.60% (F_{68}) for these inputs, respectively, which reflect substantial energy reductions. The distribution of gain proportions for the labor energy is apparently more uniform.

In a broader perspective, the energy inputs of fertilizers and chemicals stand as the resources that are the least impacted by the merger process, recording average proportion gains of 17.56% and 20.15%, respectively. While the mergers may not appear to significantly contribute to gains for certain inputs, itis important to recognize their potential within the GH production sector, which cannot be underestimated, especially considering the substantial proportions of potential gains across all resources, notably water and electricity. It is worth noting that these inputs are not only considered as scarce resources in

Table 5 Cumulated energy gains for GH mergers

F_m	Labor		Machinery		Fertilizers		Chemicals		Water		Electricity	
	g_{1m}	%	g_{2m}	%	g_{3m}	%	g_{4m}	%	g_{5m}	%	g_{6m}	%
F_1	8054	51.30	1415	51.24	0	0.00	0	0.00	14,533	76.15	2,041,642	77.11
F_2	8501	61.84	469	30.80	0	0.00	2027	17.33	11,491	71.31	1,770,548	72.77
F_3	12,098	67.53	568	34.09	0	0.00	1371	12.27	15,068	76.19	1,855,700	72.89
F_4	5493	41.45	693	30.69	0	0.00	7545	40.57	16,164	80.09	1,658,181	84.94
F_5	9360	41.92	1357	38.98	41,079	13.12	2697	17.53	16,004	78.60	2,132,541	86.98
F_6	1845	17.02	0	0.00	0	0.00	9668	50.84	15,628	82.85	2,197,922	90.36
F_7	1355	13.54	1754	50.40	9685	6.86	9595	45.49	16,331	80.85	1,806,906	90.23
F_8	7927	42.92	683	27.70	280	0.13	0	0.00	11,490	76.70	2,058,029	88.23
F_9	12,764	57.97	589	26.09	0	0.00	4047	26.23	10,267	70.51	1,833,216	82.47
F_{10}	5653	37.98	463	20.97	16,360	9.35	0	0.00	9772	72.25	1,634,555	88.15
F_{11}	7989	46.38	716	31.19	0	0.00	8700	43.80	12,873	73.79	1,562,515	74.76
F_{12}	17,991	75.90	438	27.13	0	0.00	3511	26.00	9209	67.57	1,737,457	75.96
F_{13}	7175	45.21	1124	40.71	0	0.00	0	0.00	8046	66.51	1,757,786	84.15
F_{14}	7414	55.54	429	25.11	0	0.00	1812	15.01	8281	66.43	1,769,974	80.55
F_{15}	9095	64.15	1244	55.10	0	0.00	9037	48.59	8860	65.44	734,539	51.36
F_{16}	7946	39.32	276	11.83	72,607	22.57	2893	18.80	9077	67.97	1,286,876	81.15
F_{17}	1254	11.31	0	0.00	4340	1.99	660	6.27	11,222	74.46	1,589,202	78.91
F_{18}	2179	19.24	372	17.36	267,880	64.48	2616	18.36	16,777	81.04	1,683,790	88.92
F_{19}	10,876	51.17	373	16.52	25,452	11.94	6374	34.74	7440	64.67	1,377,985	84.90
F_{20}	8017	46.46	530	25.13	0	0.00	8700	43.80	7510	62.16	1,428,905	73.04
F_{21}	3354	30.52	0	0.00	0	0.00	0	0.00	6703	63.92	1,056,250	72.81
F_{22}	4567	37.84	980	41.98	0	0.00	2417	18.68	11,420	71.37	1,160,713	66.68
Averages	5661	31.42	1101	36.42	59,101	17.56	3611	20.15	7947	60.58	1,176,395	74.47

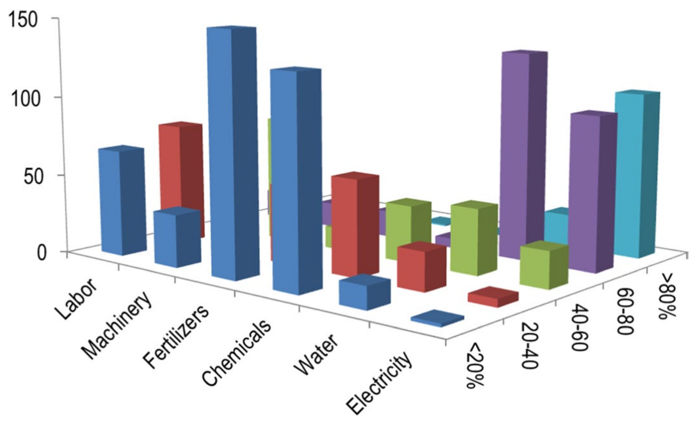

Fig. 3 Distribution of energy gains' proportions of GH mergers

arid regions but also happen to be the most extensively consumed resources in the cucumber GH production, as highlighted in prior studies (Al-Mezeini et al., 2020; Bolandnazar et al., 2014). Practically, such findings are strategically significant and could certainly prompt substantial support to framing state policies that would encourage mergers among GH farms. Viewed as long range decisions, mergers can confirm optimal consumption of scarce resources, like water and also electricity, rather than handling such important issues individually for separate GH farms. Besides their economic contribution, needless to emphasize the environmental influence of these decisions as a ground for GHG emissions mitigation.

It is worth noting that the majority of productive post-merger GH farms F_m, are pairs with shared partners. As an example, all mergers from F_1 to F_{22} involve GH_{01} alongside other GH farms. Clearly, a single GH farm cannot engage in a merger more than once with the same partner. Therefore, the DM becomes responsible for choosing carefully the most suitable partner for each individual GH farm from the list pairs $(\mathrm{GH}_A, \mathrm{GH}_B)$. In practice, such a process requires ranking alternative pairs $F_m = (\mathrm{GH}_A, \mathrm{GH}_B)$, and choosing the optimal set of mergers that do not overlap. In other words, pairs that consist of dissimilar GH farms GH_A and GH_B should be prioritized. In the following section, we will develop a novel approach designed to identify the best possible partnerships.

5 Identifying optimal partners for post-mergers

The synergistic impact of a post-merger GH farm $F_m = (\mathrm{GH}_A, \mathrm{GH}_B)$ starts to be perceptible once the merger of the individual GH farms GH_A and GH_B yields outcomes that considerably surpass the combined results of operating these GH farms independently (Oukil, 2023).

To foster the creation of an optimal synergy through mergers, it is crucial to develop a selection methodology that capitalizes on the potential post-merger results of the whole set of alternative pairs F_m. Accordingly, we introduce the Efficiency Merge Index (EMI) for assessing these alternatives.

Under the post-merger rationale, there is no doubt that the higher the cumulative energy gains g_{im} $(i = 1, ..., 6)$ the more striking the related post-merger GH farm F_m. Thus, g_{im} can be considered as the most convenient measure of a synergy merge. On this basis, the synergy merge index (SMI) of F_m can be defined as:

$\mathrm{SMI}_m = \frac{\text{Energy gains of } F_m}{\text{Energy usage of} F_m} = 100 \times \frac{\sum_{i=1}^{6} g_{im}}{\sum_{i=1}^{6} x_{im}}$ where $x_{im} = x_{iA} + x_{iB}$ for $i = 1, ..., 6$.

As a ratio of the total energy gains of the post-merger GH farm F_m over its current energy consumption, SMI_m measures the impact of the merger on reducing energy usage. The SMIs have been computed for all post-merger GH farms. Table 6 shows the results for the mergers F_1 to F_{22}.

First, the post-merger GH farms F_m are ranked in decreasing order of associated SMI_m, $m = 1, ..., 230$. The best mergers are selected according to the rank orders while discarding subsequent pairs that overlap with previously selected pairs.

As such, only eleven pairs of GH farms, presented in Table 7, are selected as best potential mergers.

$F_{203} = (\mathrm{GH}_{18}, \mathrm{GH}_{23})$, ranked 1st due to its highest SMI, is the first selected pair in the list. The next selected pair is $F_7 = (\mathrm{GH}_{01}, \mathrm{GH}_{08})$, which ranks 4th. Here, $F_{76} = (\mathrm{GH}_{05}, \mathrm{GH}_{18})$ and $F_{108} = (\mathrm{GH}_{07}, \mathrm{GH}_{18})$ are discarded, in spite of being ranked 2nd and 3rd, because of the overlaps on GH_{18} with F_{203} that has already been selected. Therefore, out of 30 GH farms, the mergers are apparently most productive with only 22 farms, excluding GH_{09}, GH_{12}, GH_{14}, GH_{19}, $\mathrm{GH}_{24}, \mathrm{GH}_{25}, \mathrm{GH}_{29}$ and GH_{30}. All pairwise mergers of GH farms from the latter list are unproductive. Interestingly, both GH farms in F_{211} are strongly efficient. Meanwhile, F_7, F_{37}, F_{179} and F_{203} are mergers of efficient and inefficient GH farms, whereas the rest of the mergers involve only inefficient ones.

Table 6 Computation of synergy merge indices for post-merger GH farms

F_m	GH_A	GH_B	Gains (MJ ha^{-1})	Usage (MJ ha^{-1})	SMI_m(%)
F_1	GH_{01}	GH_{02}	2,065,643.85	2,828,258.38	73.04
F_2	GH_{01}	GH_{03}	1,793,035.40	2,565,735.11	69.88
F_3	GH_{01}	G_{04}	1,884,806.06	2,706,113.76	69.65
F_4	GH_{01}	G_{05}	1,688,075.01	2,123,940.72	79.48
F_5	GH_{01}	G_{06}	2,203,038.15	2,826,455.24	77.94
F_6	GH_{01}	G_{07}	2,225,064.29	2,656,093.53	83.77
F_7	GH_{01}	G_{08}	1,845,625.84	2,198,454.31	83.95
F_8	GH_{01}	G_{10}	2,078,408.68	2,598,724.69	79.98
F_9	GH_{01}	G_{11}	1,860,883.19	2,449,977.22	75.96
F_{10}	GH_{01}	G_{13}	1,666,803.00	2,071,004.92	80.48
F_{11}	GH_{01}	G_{15}	1,592,793.99	2,335,840.81	68.19
F_{12}	GH_{01}	G_{16}	1,768,605.61	2,428,981.67	72.81
F_{13}	GH_{01}	G_{17}	1,774,131.13	2,259,714.19	78.51
F_{14}	GH_{01}	G_{18}	1,787,909.50	2,317,938.88	77.13
F_{15}	GH_{01}	G_{20}	762,774.63	1,567,534.80	48.66
F_{16}	GH_{01}	G_{21}	1,379,674.62	1,958,853.78	70.43
F_{17}	GH_{01}	G_{22}	1,606,677.90	2,270,689.04	70.76
F_{18}	GH_{01}	G_{23}	1,973,613.31	2,357,408.33	83.72
F_{19}	GH_{01}	G_{26}	1,428,501.12	1,889,712.50	75.59
F_{20}	GH_{01}	G_{27}	1,453,663.23	2,196,710.04	66.17
F_{21}	GH_{01}	G_{28}	1,066,306.83	1,589,237.96	67.10
F_{22}	GH_{01}	G_{29}	1,180,096.66	1,929,180.26	61.17

Table 7 Selected post-merger GH farms with potential energy usage & gains

	Farms		Gains (MJ ha^{-1})	Usage (MJ ha^{-1})	SMI_m(%)	**Rank**
F_m	GH_A	GH_B				
F_{203}	G_{18}	G_{23}	1,582,753.83	1,871,139.20	84.59	1
F_7	G_{01}	G_{08}	1,845,625.84	2,198,454.31	83.95	4
F_{106}	G_{07}	G_{16}	1,914,175.55	2,280,867.20	83.92	5
F_{75}	G_{05}	G_{17}	1,271,432.94	1,579,446.90	80.50	25
F_{37}	G_{03}	G_{06}	1,975,562.62	2,587,982.34	76.34	62
F_{135}	G_{10}	G_{11}	1,676,032.64	2,244,493.89	74.67	74
F_{34}	G_{02}	G_{26}	1,419,720.90	1,913,762.86	74.18	79
F_{58}	G_{04}	G_{13}	1,440,015.79	1,972,910.68	72.99	92
F_{179}	G_{15}	G_{28}	658,348.85	1,120,870.76	58.74	187
F_{217}	G_{21}	G_{27}	664,633.13	1,351,355.81	49.18	208
F_{211}	G_{20}	G_{22}	258,821.95	1,034,015.82	25.03	227
Total energy level	14,707,124.04	20,155,299.76				

With eleven post-merger GH farms entering the market, the total savings on energy inputs amount to 14,707.12 GJ ha^{-1}. Considering the current total energy consumption, which amounts to 27,639.42GJ ha^{-1}, adding the energy inputs of unmerged GH farms, the percentage of energy savings for the post-merger GH production system becomes 53.21%. Here, it is noteworthy that the latter figure unveils a significant enhancement of the energy savings, with more than fourfold its pre-merger value, which was 13.06% as determined through slack analysis. Figure 4 shows the distribution of these savings among the energy inputs.

Interestingly, the share of electricity consumption represents alone 94.92% of the post-merger energy gains, followed by 3.83% for fertilizers and only 0.60% and 0.39% for water and labor, respectively, besides relatively neglectable shares for chemicals and machinery energy inputs. The proposed pattern's shape aligns to a large extent with the energy inputs'

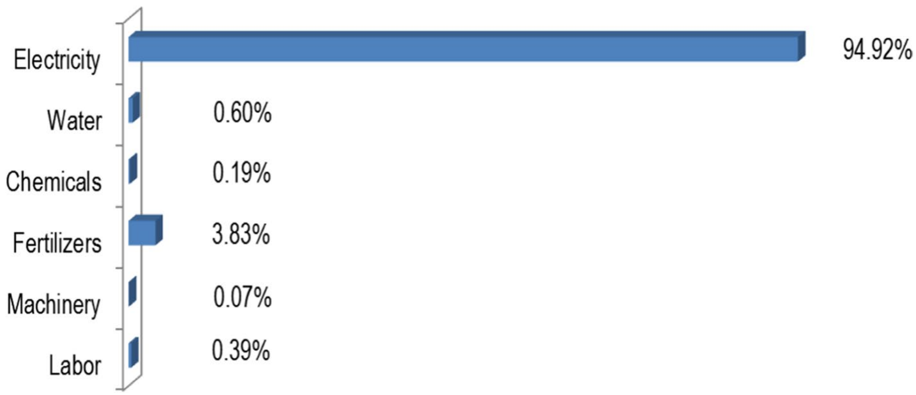

Fig. 4 Distribution in the post-merger energy gains per input'

distribution that has been duly discussed in Sect. 3.2. It also enables the farmers to address effectively the primary sources of energy overconsumption, notably electricity and fertilizers, which have been clearly identified.

6 Practical scope

The energy input contributions of each partner to pertaining post-merger GH farm are shown in Table 8.

For most post-merger GH farms, it is understood that the supply of water and electricity is the full responsibility of only one partner. Meanwhile, there is a better task sharing with the rest of energy inputs. Such a collaborative pattern enables not only relieving a part of the managerial burden from GH farmers but also consolidating the partnership through delegating responsibilities and sharing experience among the mergers' partners.

Given the region's consistently high solar irradiation levels year-round, there exists an opportunity to reduce electricity consumption by adopting solar energy (Saadi et al. 2016) as an alternative source for greenhouse sustainable production (Çakır & Şahin, 2015; Esen & Yuksel, 2013; Hassanien et al., 2016; Vourdoubas, 2015).

Energy savings for fertilizers can be incorporated through more appropriate fertilizers application besides seasonal soil analyses for a more accurate estimation of the needs. However, an exclusive usage of organic or microbial fertilizers is the preferred alternative.

The extensive use of machinery for on-farm operations, such as planting, harvesting, residue chopping fertilizer, and pesticide applications, is significantly reduced if conservation tillage procedures can be implemented. Furthermore, these approaches reinforce soil structure with a better potential for carbon storage as a result of more retention of vegetative matter. The application of chemical pesticides can be abridged or even discarded via an Integrated Pest Management (IPM) plan that ensures long-standing pest avoidance. Meanwhile, the human factor should not be overlooked over the entire process; planning training programs is an essential step toward developing the GH farmers' skills with respect to the application of the new practices and operating techniques besides raising their awareness about the eminence of energy mitigation as a global critical issue.

7 Concluding remarks

In this paper, we investigated possible contribution of M&As, as a strategic decision tool, toward an optimal energy usage and, a result, GH emissions mitigation in the GH production. To measure the scale of this contribution, we applied the inverse DEA methodology for the mergers of cucumber GH farms. Our study revolved around a case study featuring 30 cucumber GH farms in Oman's Al-Batinah region. Each GH farm was presented with six energy inputs: labor, machinery, fertilizers, chemicals, water, and electricity. Cucumber yield was the sole energy output considered over the study. Our results highlighted the predominance of electricity and fertilizers, with shares of energy consumption accounting for 85.02% and 12.69%, respectively. The fact that electricity is the main energy input was expected due to its extensive usage for cooling systems as well as groundwater abstraction for irrigation.

With an energy use efficiency of 0.1072, an energy productivity of 134 g/MJ and a specific energy of 7.4628 MJ/kg, the results revealed a high inefficiency level into the energy

Table 8 Selected post-merger GH farms with potential energy usages

	Farms		Labor		Machinery		Fertilizers		Chemicals		Water		Electricity	
F_m	GH_A	GH_B	∂_{1A}^*	∂_{1B}^*	∂_{2A}^*	∂_{2B}^*	∂_{3A}^*	∂_{3B}^*	∂_{4A}^*	∂_{4B}^*	∂_{5A}^*	∂_{5B}^*	∂_{6A}^*	∂_{6B}^*
F_{203}	G_{18}	G_{23}	4835	2519	230	1337	0	98,503	4137	6316	0	3516	166,995	0
F_7	G_{01}	G_{08}	8516	135	0	1726	45,036	86,439	0	11,495	3868	0	195,614	0
F_{106}	G_{07}	G_{16}	2328	6040	816	807	105,013	34,622	10,136	0	3451	0	203,479	0
F_{75}	G_{05}	G_{17}	4737	3200	0	1661	33,213	74,977	8733	2564	3787	0	175,143	0
F_{37}	G_{03}	G_{06}	5231	7054	0	1984	8889	258,422	3761	7456	3895	0	315,728	0
F_{135}	G_{10}	G_{11}	9956	1127	346	1451	127,410	118,011	2114	7500	3377	0	297,168	0
F_{34}	G_{02}	G_{26}	7186	3718	1934	0	46,326	158,518	1812	10,307	4124	0	260,118	0
F_{58}	G_{04}	G_{13}	9359	0	859	653	51,577	120,257	3246	3121	2860	0	340,963	0
F_{179}	G_{15}	G_{28}	8711	1611	1255	622	134,348	52,090	11,129	821	4067	0	247,866	0
F_{217}	G_{21}	G_{27}	11,691	2285	1527	689	266,965	37,990	7456	5514	3344	1129	265,766	82,366
F_{211}	G_{20}	G_{22}	5662	2573	1412	0	8151	163,812	10,291	0	3528	936	110,014	468,816

usage. In spite of the pessimistic traits of these results, the standard DEA model produced an average relative efficiency of 0.872 with 40% of the GH farms declared efficient. Accordingly, the percentage of energy saving index was 13.06%, which is lower when compared with similar indices of previously reported studies.

Subsequently, we employed the inverse DEA approach to explore potential consolidations between pairs of GH farms besides estimating the energy input levels needed for a merger to reach complete efficiency and pertaining potential energy gains. With 230 productive post-merger GH farms identified, our results indicate that more input gains can be achieved through mergers, irrespective of whether the merging GH farms are efficient or inefficient. More specifically, almost 45% of the productive mergers involve at least one efficient GH farm, with 13 mergers consisting of pairs of GH farms that are both strongly efficient. Thus, though no further input gains are possible from an efficient GH farm that operates individually, the situation is different under a merger scenario. In addition, the results relating to the energy gains that could potentially be achieved by each post-merger GH farm exhibited proportions that range from 17.56 to 74.47%, with electricity yielding the highest gains. Energy improvements post-merger were remarkable, with labor, machinery, fertilizers, chemicals, water, and electricity achieving substantial proportions as substantial as 77.41%, 78.13%, 81.26%, 75.60%, 89.74%, and 90.36%, respectively.

The consolidation process may produce pairs of post-merger GH farms that have one pre-merger GH farms in common. As such, the next step of the proposed methodology aimed at identifying the best selection of GH farms that can be paired without any overlap of. For this purpose, we introduced the SMI which enables determining the best matching among GH farms based on the expected post-merger savings. The implementation of the new approach enabled the selection of eleven most productive pairs of GH farms among the 230 candidate post-mergers. The inclusion of these GH post-merger farms into the GH farms' sample increased the percentage of energy saving from 13.06% to 53.21%, that is, more than 4 times improvement. In the meantime, it was noted that the share of electricity consumption represents alone 94.92% of the post-merger energy gains, followed by 3.83% for fertilizers and only 0.60% and 0.39% for water and labor, respectively, besides relatively insignificant shares for chemicals and machinery energy inputs.

Practically, such findings are strategically significant and could certainly prompt substantial support to framing policies that would eventually encourage mergers amongst GH farms. As longstanding options, mergers can optimize the consumption of scarce resources, like water and electricity, rather than handling such important issues individually for separate GH farms. Besides their economic contribution, needless to emphasize the environmental influence of these decisions as a ground for GHG emissions mitigation. Nonetheless, before developing merger related policies, additional inquiries may be essential to pinpoint the market incentives capable of motivating farmers to engage in mergers. Furthermore, expanding the data sample to encompass a larger number of GH farms becomes imperative for a more comprehensive assessment of the practical applicability of the present study.

In the future, research endeavors can delve into devising more rigorous approaches to address the selection problem. One alternative may consist in developing more advanced ranking techniques, which could potentially be based on the DEA cross-efficiency concepts (Oukil & Amin, 2015; Oukil & El-Bouri, 2021; Oukil et al., 2022c) where all the energy inputs could be used explicitly instead of resorting to aggregates. Meanwhile, it might be important to highlight the fact that the best partners' selection problem can be modeled as a network where the GH farms would stand as nodes connected with an edge for each productive merger. Hence, a very interesting route toward selecting the optimal set of partners could exploit the graphical properties of such a network, like sparsity (Letchford & Oukil, 2009; Oukil, 2008) and solve the corresponding combinatorial problem.

With regard to the inverse DEA model adopted for the present study, another possible research avenue may consider its extension into a formulation that may assign weights to the energy inputs to account for the individual importance of each input as perceived by the decision maker. Here, the implementation of an ordered weighted averaging operator (see, e.g., Saeidi et al., 2015) could be one option, which can also fit within the DEA cross-efficiency framework (2020b, 2022; Oukil, 2018, 2019, 2020a). Under the latter scheme, another venue may research the integration of the merger and the selection stage into a unified framework.

Finally, it is noteworthy that the results of the present study are restricted to pairwise mergers of GH farms under the operating conditions of the data sample employed for the case study. Other results may emerge if more than two GH farms are merging together. This particular aspect could be an interesting topic for future investigations.

Appendix

See Table 9.

Table 9 Energy equivalent coefficients in cucumber GH production

Data (Unit)	Energy equivalent (MJ Unit^{-1})	References
Inputs		
Human labor (h)	1.96	(Esengun et al., 2007; Hamedani et al., 2011; Zangeneh et al., 2010))
Machinery (h)	13.06	(Heidari et al., 2012; Mohammadi and Omid, 2010)
Fertilizers (kg):		
Nitrogen	66.14	(Mohammadi et al., 2010; Omid et al., 2011), Mandal et al. (2002)
Phosphate,P_2O_5	12.44	(Mohammadi et al., 2010; Omid et al., 2011), Rafiee et al. (2010)
Potassium, K_2O	11.15	(Mohammadi et al., 2010; Omid et al., 2011)
Micronutrients	120.00	(Banaeian et al., 2011; Zahedi et al., 2014)
Manure (kg)	0.30	(Khoshroo et al., 2013; Mohammadi et al., 2010)
Chemicals (kg)	120.00	(Heidari et al., 2012)
Water (m3)	1.02	(Mohammadi and Omid, 2010; Zangeneh et al., 2010)
Electricity (kWh)	11.93	(Banaeian et al., 2011; Mohammadi and Omid, 2010)
Seed (kg)	1.00	(Heidari et al., 2012; Mohammadi and Omid, 2010)
Output		
Cucumber (kg)	0.80	(Heidari et al., 2012; Mohammadi and Omid, 2010)

Declarations

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

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