energies

Article

Economic and Production-Related Implications for Industrial Energy Efficiency: A Logistic Regression Analysis on Cross-Cutting Technologies

Fábio de Oliveira Neves [1,*], Henrique Ewbank [2], José Arnaldo Frutuoso Roveda [1], Andrea Trianni [3,*], Fernando Pinhabel Marafão [1] and Sandra Regina Monteiro Masalskiene Roveda [1]

[1] Institute of Science and Technology, São Paulo State University (UNESP), Sorocaba 18087-180, Brazil; jose.roveda@unesp.br (J.A.F.R.); fernando.marafao@unesp.br (F.P.M.); sandra.regina@unesp.br (S.R.M.M.R.)
[2] Department of Production Engineering, Facens University, Sorocaba 18085-784, Brazil; henrique.vieira@facens.br
[3] Faculty of Engineering and Information Technology, University of Technology Sydney, Sydney 2007, Australia
* Correspondence: fabio.neves@unesp.br (F.d.O.N.); andrea.trianni@uts.edu.au (A.T.)

Abstract: Increased industrial energy efficiency (EE) has become one of the main environmental actions to mitigate carbon dioxide (CO_2) emissions, contributing also to industrial competitiveness, with several implications on the production system and cost management. Unfortunately, literature is currently lacking empirical evidence on the impact of energy efficiency solutions on production. Thus, this work primarily aims at investigating the economic and production-related influence on the reduction in industrial energy consumption, considering the cross-cutting technologies HVAC, motors, lighting systems and air compressor systems. The analysis is performed using data from previous studies that characterized the main EE measures for the cross-cutting technologies. Four logistic models were built to understand how costs and production influence energy efficiency across such cross-cutting technologies. In this way, motivating industries to implement measures to reduce electrical consumption, offering an economic cost–benefit analysis and optimizing industry processes so that the reduction in electricity consumption adds to industrial energy efficiency were the aims of this study. The results of this work show through the adjusted indicators that senior management is mainly responsible for energy savings. The operational measures of each piece of equipment can be oriented in the industry towards a specific maintenance process for each technology, becoming an active procedure in industrial productions to obtain EE. Additionally, maintenance planning and control is essential to the reliability of the reduced energy consumption of cross-cutting technologies. This article concludes with managerial implications and suggestions for future research in this field.

Keywords: energy efficiency; implications in the industrial sector; technological gap; economic and production-related indicators; logistic regression

Citation: Neves, F.d.O.; Ewbank, H.; Roveda, J.A.F.; Trianni, A.; Marafão, F.P.; Roveda, S.R.M.M. Economic and Production-Related Implications for Industrial Energy Efficiency: A Logistic Regression Analysis on Cross-Cutting Technologies. *Energies* **2022**, *15*, 1382. https://doi.org/10.3390/en15041382

Academic Editor: David Borge-Diez

Received: 20 December 2021
Accepted: 11 February 2022
Published: 14 February 2022

1. Introduction

The increase in greenhouse gas emissions related to the increased energy demand is one of the main global socio-environmental concerns and is calling for increased energy efficiency capable of reducing costs and protecting the environment [1,2]. The challenge is to make constant economic growth follow technological development, which supplies the ever-increasing demand for energy. The industrial sector represents one of the largest energy consumers [3]. In 2020, it was responsible for 38% (156EJ) of the total global final energy use, representing an average increase of 1% in energy consumption in the period 2010 to 2019, although in some regions, as a result of COVID-19, there was a 1.6% reduction [4]. Efficient energy consumption is necessary for improving environmental and financial indicators [5,6], leading to an energy improvement in operations and maintenance of the work environment [7,8]. Therefore, improving energy consumption becomes an important factor for industrial competitiveness [8,9]. Energy efficiency is also related to other important resources for the production system [10], thus becoming a paradigm in management priorities for decision-makers, due to a wide range of technical improvements: maintenance, renovation and readjustment of equipment, process control, and process productivity [5].

Several academic works have been analyzing specific interferences of cross-cutting technologies in the reduction in energy consumption, since the intervention of senior management directs projects in this area [11]. Interventions through cross-cutting technologies' technical actions are widely considered feasible since they are capable of bringing significant energy savings [6,12,13]. Among those, four cross-cutting technologies are particularly interesting, given their lion's share in industrial electricity consumption, namely, motor systems, compressed air systems, HVAC (heating, ventilation and air conditioning), and lighting systems. However, although several efforts have been made in terms of policies to leverage on energy management systems for industrial competitiveness, the implementation rate of energy efficiency measures for those cross-cutting technologies is still very low [12].

In addition, research efforts to understand the context of energy efficiency in the industrial sector must incorporate operating and capital costs, increased yield, and more efficient use of other resources as well. Worrell et al. [14] report from a macro perspective how the production-related or non-energy system can determine the feasibility of an energy efficiency project by evaluating the benefits of its potential. Therefore, it seems crucial to understand how the influence of factors related to economic issues and the production-related system affect industrial energy efficiency, which in turn may deeply affect the decision-making process [15].

Previous literature has investigated the relationships between productivity and costs in conjunction with cross-cutting technologies. Alhourani and Saxena [16] used a logistic model to verify the possibility of estimating the implementation of policy recommendations in the USA. Fleiter et al. [17] concluded that energy efficiency is essential to obtain substantial savings in industrial costs. In addition, other studies have stated that overcoming barriers is necessary to achieve the best energy consumption performance [13,14]. These studies enlighten how the understanding of the production system and the economic improvement contribute to efficient actions in production-related operation.

In addition to such works, the current academic literature so far has focused mainly on improving energy efficiency following two main lines of research. The first characterizes EEMs through a list of known attributes, such as the pioneering studies by Pye and McKane [18] that recognize that quantifying the full benefits of energy efficiency projects helps companies fully understand the financial opportunities for investments in EEMs. Additionally, Skumatz [19], who lists about 20 non-energy benefits across several dozens of projects completed in the decades prior to 2005, is developing methods to measure non-energy impacts—positive and negative—of commercial and industrial energy efficiency programs. Additionally, the second current takes a further step on the presentation of a list of attribute characterization of EEMs, providing a framework capable of incorporating a more general set of attributes, as shown by the precursor study by Mills and Rosenfeld [7] that provides a framework to understand the many benefits of investments in energy efficiency that outweigh the savings for the energy bill. Notably, most previous studies have addressed energy efficiency through these two strands, and as an academic contribution this work demonstrates a further step. It is important to check which are the influencers' aspects of the listed and structured attributes and how they act on the behavior of industrial energy consumption for cross-cutting technologies.

In this context, this study contributes to the discussion of gaps in industrial energy consumption that the set of values and actions of production (production) and cost management (economic) impose on the implementation of EE measures. Thus, knowing the role and influence of economic and productivity-related indicators in improving energy consumption becomes an important contribution tool for decision-makers, which also broadens the scope of this debate on how to characterize the factors for energy consumption. To a certain extent, this study aims to offer additional information to reduce the so-called "energy efficiency gap" [12] and show possible solutions, mainly related to economic and productivity-related influences. Confirmed by the recommendations of the Industrial Assessment Center (IAC), which shows that the implementation rate of the suggested measures related to energy efficiency was 52.7% in 2018, 50.2% in 2019 and 49.9% in 2020, showing that implementation rates close to 50% are relatively low [20], which empirically demonstrates the existence of an energy efficiency gap in the industrial sector. Therefore, main question of this work aims to discuss, through logistic regressions, which economic and production factors affect the electric energy-saving management of transversal technologies. Such factors include the following: air conditioning, motors, lighting and air compressors. Other works reinforce the need for analysis and verification of these gaps, as highlighted by the authors who developed a more general analysis to relate the economic or production-related influence on the amount of energy saved, as Xia and Zhang [21] developed a unified classification of energy system efficiency, such as performance efficiency, operation efficiency and equipment efficiency. Sola and Mota [22] studied the main economic scenarios, in addition to technological and behavioral changes, using energy in Brazilian industries, Neves et al. [6] verified the main economic and production-related indicators on the industrial production system, and finally Alhourani and Saxena [16] used the same methodology (logistic regression) to estimate the possibility of a recommendation to improve energy consumption as the estimation of periods of financial return and recommendation for improvement and number of hours worked per year in the US.

However, as far as we know, this is the first study performing a direct analysis of the relationship between economic and production indicators and how it influences each cross-cutting technology individually, thus enabling industrial managers better decision-making regarding the amount of electricity-energy savings. In addition, little is discussed about how the main causes of managerial implications of some indicators of a production-related and economic nature affect the relationships (cultural, production-related, and hierarchical) of industries regarding energy efficiency with cross-cutting technologies. This is performed to highlight support opportunities for small and medium-sized enterprises and to formulate policies to serve them more efficiently, in addition to critical industrial energy management. In this way, this work tries to supply this demand for the management of industrial energy consumption and contributes to the construction of this theme in the literature.

It is important to highlight that the transversal technologies HVAC and compressed air system for its operation have specific types of engines. However, what was diagnosed and studied in this work are industrial engines that are not associated with these technologies. This paper is divided into six sections. Section 2 presents the cross-cutting technologies for energy efficiency; Section 3 presents the methodological framework; Section 4 presents the results; Section 5 analyzes the results; and Section 6 concludes the study and provides some directions for decision-making.

2. Cross-Cutting Technologies for Energy Efficiency

Cagno et al. [10] and Trianni et al. [12] emphasize that improving energy efficiency depends on the best cross-cutting technologies to develop a robust program, seeking to determine a better horizon for improving energy consumption [23].

The Industrial Assessment Center [24], a program of the US Department of Energy, administered by the Advanced Manufacturing Office, reinforces how the improvements highlighted by Cagno et al. [25] and Trianni et al. [26] may be suitable for the development of EE projects in the industrial sector, in the USA and other countries. Over the years, the IAC program has conducted over 19,300 evaluations of more than 145,000 recommendations combined. According to the IAC, energy efficiency measures are identified with an Assessment Recommendation Code (ARC) for each cross-section technology (engine, lighting, compressed air, HVAC and others). There are several energy efficiency measures specific to the particular problems of each technology for each unique industrial sector. Still, the recommendations of the IAC are suitable as references for the development of works.

Although there are several types of cross-cutting technologies, only four were analyzed in this study due to their wide diffusion in industries in some sectors, which accounted for the highest energy consumption, in addition to being the foundation of the recommendations suggested by the Industrial Assessment Center. Table 1, through a systematic literature review, shows some individual implementation measures and how they tend to fit into the recommendations of the industrial assessment center. These recommendations focus on industry infrastructure, which includes different innovative methods for cross-cutting technologies. The measures in Table 1 become individual due to two explanations (1) because they are geographically distant from the great global industrial economic centers and (2) because they do not have an administrative and financial structure capable of meeting the implementation of the EEM.

Table 1. Industrial energy efficiency measurement systems.

	EEM	Description	Managerial Impact	ARC	Source
Motor	Minimum Efficiency Performance Standards	Brazilian motor regulation program and other equipment that defines its mandatory efficiency level.	EE for Variable-Speed Drives (VSDs).	2.4111; 2.4112; 2.4141	[27,28]
	Motor Rebate Program	Efficiency programs that benefit taxpayers with indirect and cascade-induced economic impacts.	EE for new premium efficiency engines, variable frequency drives (VFD).	2.4113; 2.4141; 2.4142; 2.4143	[29]
	Methodology for Evaluation of EE in Induction Motors	Unified training methodology and laboratory equipment in energy efficiency research for induction motors.	EE in electrical charge loss and reports CO_2 emissions.	2.4131;2.4132; 2.413; 2.4134	[30]
	National Project on Energy Saving through Upgrading Electric Motors	Chinese national economy project with the purpose of facilitating the application and dissemination of high efficiency EMs.	EE measures, Energy-saving Companies and measures environmental.	2.4151; 2.4152; 2.4153; 2.4154; 2.4155; 2.4156; 2,4157	[30,31]
	Motor drive controller	Control methodology of three-phase induction motor unit due to its rejection and disturbances.	EE for three-phase induction motor.	2.4144; 2.4145	[32]
Compressed Air	Optimization model of the industrial compressed air system	Compressed air system in the hot region on the effect of the inlet temperature on the isentropic efficiency of compressors and on the efficiency of intercoolers.	EE for ambient temperature, variation in isentropic efficiencies, and intercooler effectiveness.	2.4221; 2.4232; 2.4234; 2.4237; 2.4238	[33]
	Performance control methodology for compressed air systems	General computational approach applied to energy performance control for compressed air systems.	EE for operations, maintenance, and energy accounting in compressed air systems.	2.4233; 2.4235; 2.4236	[33]
	Energy management in compressed air systems	Energy management procedure to monitor and control electricity consumption and maintain the energy performance of compressed air systems.	Identification of Energy Inefficiency of Compressed Air.	2.4222; 2.4224; 2.4225; 2.4226; 2.4227	[34]
	Metric to characterize the performance of compressed air systems	Simplified method that uses unique metrics to determine the performance of compressed air systems regarding energy consumption.	EE for charge compressor.	2.4223; 2.4231;	[35]
Lighting systems	Optimization of indoor lighting tension	Variation of active and reactive power as a function of voltage for lighting devices.	EE for interior lighting.	2.7121; 2.7124; 2.7133	[36]
	Energy management system	Lighting system to improve the quality of ambient lighting.	EE for luminance with luxmeter.	2.7111; 2.7112; 2.7122; 2.7134; 2.7141; 2.7142; 2.7143	[37]
	Short and long term monitoring	Identify lighting efficiency measures in industrial manufacturing.	EE for lighting retrofit.	2.7123; 2.7131; 2.7132; 2.7135; 2.7144; 2.7145	[38]
HVAC	Energy efficiency management in HVAC systems	Energy efficiency in serial-production systems.	EE for machine recovery time.	2.7226; 2.7232; 2.7233; 2.7235; 2.7241; 2.7244; 2.7271; 2.7291; 2.7293	[39]
	Optimal scheduling strategy based on activity type and weather	Daily schedule of activities allowing energy savings.	EE for internal environmental.	2.7221; 2.7222; 2.7223; 2.7224; 2.7234; 2.7292; 2.7311; 2.7312; 2.7314	[40]
	On-demand ventilation and energy conservation of HVAC systems	Ventilation demand model and the system's projected and optimized exhaust rate determination.	EE for industrial exhaust systems.	2.7225; 2.7227; 2.7243; 2.7245; 2.7252; 2.7261; 2.7262; 2.7273; 2.7313; 2.7316	[41]
	Framework for dimensioning the HVAC	Sizing method that ensures a certain minimum level of performance of the HVAC system.	EE for safety factor.	2.7212; 2.7228; 2.7242; 2.7251; 2.7263; 2.7264; 2.7272; 2.7315	[42]

Table 1 shows studies that propose a positive performance in implementing measures that reduce energy consumption. Most of these works consider isolated EE analysis for each cross-cutting technology.

The studies covered in Table 1 address a wide range of energy management programs that have been adopted for efficient energy consumption in the industrial sector. The literature and industry analysis show that the implications of production when installing energy efficiency measures tend to generate revenue and, depending on the company's contribution, there will be an increase in the added value for shareholders. Linked to these aspects, the implementation of EEMs tends to motivate decision-makers in the company's production capacity. Neves et al. [6] and Worrell et al. [14] show that the search for energy efficiency tends to improve productivity. Agyekum et al. [43] show that the improvement of the various components of their study will contribute to the reduction in costs associated with production from their facilities. Menghi et al. [44] demonstrate the need to extend energy management steps to structure the boundaries of energy management process assessment methods. Hasan and Trianni [45] describe that in productive technological support it is important since energy management includes the control of devices that consume energy and can optimize energy consumption, becoming a customary rudiment of energy management. Moreover, as shown in the works highlighted in Table 1, the adoption of EE measures leads to lower maintenance and replacement costs of transversal technology components. This is because some of the industry finances are recorded when cross-technological functioning is in use after the adoption of EEMs. Adding to these aspects are the energy savings according to the four types of activities raised by Worrell and Biermans [46]: (i) a simple renewal or restoration of existing functions; (ii) an optimization in the use of an existing technology; (iii) an adaptation of the equipment; (iv) a new installation of low-energy-consumption equipment is important to differentiate the decision-making behavior according to the specific energy savings of each transversal technology [13]. In short, taking the proposals for academic research and government projects, as highlighted in Table 1 and in the Industrial Assessment Center database, it is noteworthy that both academia and industry lack approaches to analyze the behavior of heterogeneous production and economic aspects that intervene in transversal technologies: engines, lighting systems, compressed air systems and HVAC.

Still, considering aspects of electricity consumption savings for each transversal technology, Makane and Hasanbeigi [47] show in their studies of motor systems that some EE measures provide productivity benefits in addition to energy savings. Developing countries such as Thailand, Brazil, and Vietnam have a higher percentage of the total energy use of motorized systems. For the same authors, considering aspects of electricity consumption savings for each technology, they show in their study of motor systems that some EE measures provide productivity benefits in addition to energy savings. Zuberi et al. [48] complement through their work in Switzerland that the energy savings by electricity by EMDS are approximately 17% of projected savings in the Swiss program Prognos AG for the period 2010–2035. The authors point out that the motors are operating beyond their expected useful life, making it difficult to implement measures to reduce electricity consumption. Furthermore, for Makane and Hasanbeigi [47], the potential for technical savings in electricity from compressed air systems compared to total energy use varies between 29 and 56%. Heidari et al. [49] portray that the transversal technology of the lighting system and the annual energy savings will gradually decrease with the replacement of energy-advanced technologies, such as the replacement of fluorescent LEDs. Continuing cost-effectiveness will continue to improve in the future as it will have a direct rebound effect, as the price of the lamps will decrease and the efficiency will increase. Additionally, Lu et al. [50] show that the electricity savings in Taiwan for the cross-sectional HVAC technology have a high potential for energy savings, as they correspond to twice the energy consumption and are able to achieve 14.4% energy savings in the industrial sector.

In addition to all the work carried out in this area, as shown in Table 1 together with the recommendations of the Industrial Assessment Center, they lack an empirical analysis aimed at analyzing the potential of energy savings with some characteristics of energy efficiency measures, considering some financial and production-related factors. Such an analysis would shed light on the following:

(a) link energy efficiency to operations and production activities;
(b) propose new concepts and guidelines to the academic environment on economic and productive factors that help in industrial energy efficiency;
(c) provide constructive contributions to policy-makers on the importance of implementing energy efficiency measures, given the implications for production.

3. Methodology

To address gaps in the relationship between production-related and economic indicators that affect energy consumption of the technologies of the production system, in this section we describe the data set and present the dependent and independent variables that were used to fit the model by statistical logistic regression related to cross-cutting HVAC technologies, engines, lighting, and air compressors.

Data were extracted from previous literature [12]. In which 192 energy efficiency measures initially identified through a broad systematic review of the literature were retrieved. From this point of identification, they were structured and standardized using the same level of detail shown in the Industrial Assessment Center, thus resulting in 88 energy-efficiency measures. A total of 19 specific measures were for the engine system, 15 were for the air compressor system, 16 were for the lighting system and 38 were for the HVAC system.

3.1. Variables for Analysis

Table 2 shows the indicators used for fitting. They are dummy variables with some intervention (1) or no energy improvement intervention (0). The sample spaces for the HVAC, motor, air compressor, and lighting system are 46, 23, 23 and 23, respectively.

Table 2. Indicators fitted to the logistic regression model.

Name	Source
Amount of electricity saved (*AES*)	[12]
Costs (*C*)	[12,51]
Working environment (*WE*)	[12]
Corporate involvement (*CI*)	[12,52]
Productivity (*P*)	[12,53,54]
Operation and maintenance (*OM*)	[12,54,55]
Check-up frequency (*CF*)	[12,56]

The dependent and independent variable data sets show how the structure of the work develops to find the main factors that influence the four transversal technologies. The summary of each indicator can be found below:

Dependent Variable

Amount of electricity saved: greater responsibility of industries for electricity conservation than for energy tariffs.

Independent variables

Costs: costs related to the routine operation of cross-cutting technologies: adaptation, fees, modernization of equipment.

Work environment: related to organizational culture; employees satisfied with their work environment can be more production related.

Corporate involvement: awareness at all hierarchical levels of energy efficiency goals for the entire production unit and the entire corporation.

Productivity: relationship between energy intensity and productivity of industries aiming to improve energy efficiency.

Operation and maintenance: constant maintenance of cross-cutting technologies so that the operation is not compromised, including the adoption of energy efficiency measures.

Check-up frequency: continuous management and periodic verification of cross-cutting technologies so that their operation does not affect energy consumption.

The variables listed above were used to generate four logistic regression models and to verify their economic and production-related influence on the amount of energy saved in the cross-cutting technologies HVAC, engines, lighting systems, and air compressor.

Both the dependent variable and the independent variables are justified by the fact that, in addition to energy, economic, and production system issues, industrial decision-makers need adequate details on the impact that investment has on the existing production system, on the effective implementation issues to be addressed, as well as the interaction an EEM may have with other parts of the production system. Additionally, the attributes result from a selection process that is consolidated in the literature, in which they do not overlap each other; thus, they are not redundant and conflicting.

3.2. Model

The logistic regression was used to measure the economic and production-related influence of variables on the amount of energy saved in small and medium-sized companies. This type of analysis is appropriate when the dependent variable (ASE) is dichotomous rather than continuous. In a logistic regression model, the linear regression between the natural logarithm of the odds ratio for the probability of response should be less than the limit and the independent variables [35].

$$O = \frac{P_i}{1 - P_i} \tag{1}$$

The variables of probability of the desired and written event in Equation (1), where O is a dummy variable that acquires values of 1 (there was energy saved by cross-cutting technology) and 0 (there was no energy saved), and $1 - Pi$ is a vector of explanatory variables. The $\frac{Pi}{1-Pi}$ probability ratio expresses the success of the desired event for the occurrence of the unwanted failure.

In the fitting of the logistic regression, the dependent variable is transformed into a continuous value by calculating the odds ratio within the interval $(-\infty;\infty)$; the odds and probability ratios express the same information differently.

Equation (2) is the most traditional representation of a logistic regression model.

$$\frac{P_i}{1 - P_i} = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni} \tag{2}$$

where β is the vector of the estimated parameters indicating the importance of the weight of the individual inputs X_i.

To assess the significance of logistic regression, the F test was used in addition to the statistics of coefficients estimated by the standard error, being equal to or different from zero. In the selection of logistic regression models, the independent variables with a significance level $\leq$5% were selected. Thus, to consider the developed model valid, the necessary premises had to be met [35–37].

3.3. Validation of Logistic Regression Models

At onset, five criteria were used to validate the logistic regression models [48–50]. The results of the acceptance test were evaluated by univariate statistical analysis (analysis of variance, ANOVA), $p < 0.05$

1. The quality measurement of the four logistic regression models was performed using the lowest Akaike information criterion (AIC);
2. The significance level of the four models was determined by the Mcfadden's pseudo-R^2.

According to Mcfadden [57], the ρ^2 (pseudo-R^2) tends to have low values. Therefore, values in the range between 0.2 and 0.4 are considered excellent. ρ^2 can be interpreted as R^2, but it does not indicate large values.

All statistical analyses were performed in the computer environment R, version 3.5.3 [58].

Accuracy and receiver operating characteristic (ROC) curves were drawn for each logistic model of cross-cutting technologies.

The Wald test was used to assess whether the parameters are statistically significant. The validation tests are the most commonly found in the literature. Petrucci [59], Grondys et al. [60], Tait et al. [61], Cantore [62], Kovacova [63], Yamaguchi et al. [64], and Jencová et al. [65] proposed logistic regression models with validation by *p*-value, Akaike, Macffaden's determination coefficient, and accuracy.

3.4. Bootstrap

As the data for some technologies are few, the bootstrap range for BCa, Percentile and Normal, and Basic-Theory for each cross-cutting technology was determined. As a result, β coefficients correspond to the original equations [66].

The distinguished classes of bootstrapping methods are used to validate different types of analysis. Recently, they have been used mainly in projects involving multiple regression models such as logistics [67].

The onset of an arrangement of a particular sample or of indirect total effects depends on a data set of extension n for the exchange of an original sample to occur. In the words, a random observation can be chosen ∞ times. In a sample size equal to n, the values of i, a_i, and b_i measure a_ib_i, where $\sum_i (a_ib_i)^*$ with an "*" characterizes an estimation from a resampled data set. This procedure is resumed k times (we repeated it 1000 times), producing k times the indirect and specific effects of the independent variables on the dependent variables. The distribution of these k estimates is an empirical, non-parametric estimated calculation of the distribution of indirect interest effects.

Let the distribution of a statistic be $\theta b = T\ (Fb)$ for the normal bootstrap of n samples, with mean $\theta = T(F)$ and standard deviation $se\ (F)$. Let $\hat{se} = se\ (\hat{F})$ be an estimate of $se\ (F)$. Demonstrated in Equation (3).

$$P\left[\mu_{\alpha/2} \leq \frac{\hat{\theta}-\theta}{\hat{se}} \leq \mu_{1-\alpha/2\alpha}\right] \approx 1-\alpha, \tag{3}$$

where φ is the normal cdf from which the Cl is $\theta \pm \mu_{1-\alpha/2}\ \hat{se}$ [67].

The simplest method for inferring about a univariate sample of parameter θ using a bootstrap simulation is the confidence interval using the percentile method. This is equivalent to reading a percentile histogram $\hat{\theta}_b^*$ $b = 1, \ldots, B$ produced by bootstrap, where $\hat{\theta}_B^{*(\alpha)}$ denotes the α percentile of bootstrap estimates. The IC at the level $1-\alpha$ is determined by Equation (4).

$$\lceil \hat{\theta}_B^{*(\frac{\alpha}{2})}, \hat{\theta}_B^{*1-(\frac{\alpha}{2})} \rceil \tag{4}$$

The accelerated bias-corrected percentile (BCa) method offers a substantial improvement over the simple percentile approach. For the basic percentile method to work, it is necessary for the transformed estimator *(θ)* to be impartial, with a variance that does not depend on θ. BCa increases φ in two parameters in order to meet the best conditions, ensuring an approximate pivot, where there is a monotonically increasing function φ and the constants a and b, such as the principle shown in Equation (5).

$$\cup^* = \frac{\varphi\ (\hat{\theta}^*) - \varphi(\hat{\theta})}{1 + a\varphi(\hat{\theta})}. \tag{5}$$

4. Results

The data fed to fit the best logistic regression model were used with data from previous studies [13]. Thus, it is possible to have an overview of the unique characteristics of EEMs that industrial decision-makers consider a clear opportunity to face the implementation of measures that reduce energy consumption.

The best adjusted logistic regression models, after selecting the indicators, went through the steps detailed in Section 3.2 (F Test, error estimate, and p value), Section 3.3 (Anova, AIC, McFadden's Pseudo-R^2, and Accuracy) and Section 3.4 (bootstraps), as Table 3 shows. It was possible to identify which variables influenced the amount of energy saved in HVAC, motor, lighting systems, and compressed air.

Table 3. Adjusted logistic regression model.

BAT	Variables	β	SE (β)	*p*-Value
Motor	Interceptor	−5.32	2.17	0.0145
	CF	1.91	0.76	0.0118
Compressor	Interceptor	−2.079	1.061	0.0499
	P	2.996	1.214	0.0136
HVAC	Interceptor	−1.5404	0.6362	0.01547
	OM	2.1823	0.7466	0.00347
Lighting	Interceptor	−2.639	1.035	0.01079
	OM	4.585	1.488	0.00206

Table 4 shows the results of the validation tests according to the selection of variables by AIC, accuracy, significance of the model by means of Wald, and McFadden's pseudo-R^2.

Table 4. Validation of tests for logistic regression.

BAT	AIC	Pseudo-R^2	Wald	Accuracy
Motor	24.54	0.36	0.02	0.83
Compressor	27.03	0.28	0.02	0.78
HVAC	57.21	0.17	0.005	0.71
Lighting	17.37	0.55	0.005	0.92

As described in Section 3.3, McFadden's pseudo-R^2 can be considered strong because of its characteristics of presenting fitted data. Table 1 shows the factors that were not fitted. The rejection occurred in the p-value test. Finally, the ROC curve was plotted to show the performance of the ASE of the binary classifier.

The ROC curve (Figure 1) corresponding to the motor shows that the model had a predictive capacity of 85%. The predicted capacity for the air compressor was 79%, for HVAC it was 72%, and for the lighting system it was 90%.

Table 5 shows the value of bootstrap intervals that fitted due to the n value of data (Section 3.1).

A discussion of the indicators fitted for each specific model of logistic regression follows. It intends to facilitate the identification of specific characteristics of each technology.

The adjustment of logistic regression models, through the steps shown in Section 3 above and its subsections, can be useful for industries to understand which economic and production-related indicators influence electric power consumption. Such an understanding would, in turn, allow for the identification of specific energy occurrences of each cross-cutting technology that can be repaired and consequently reduce electric power consumption.

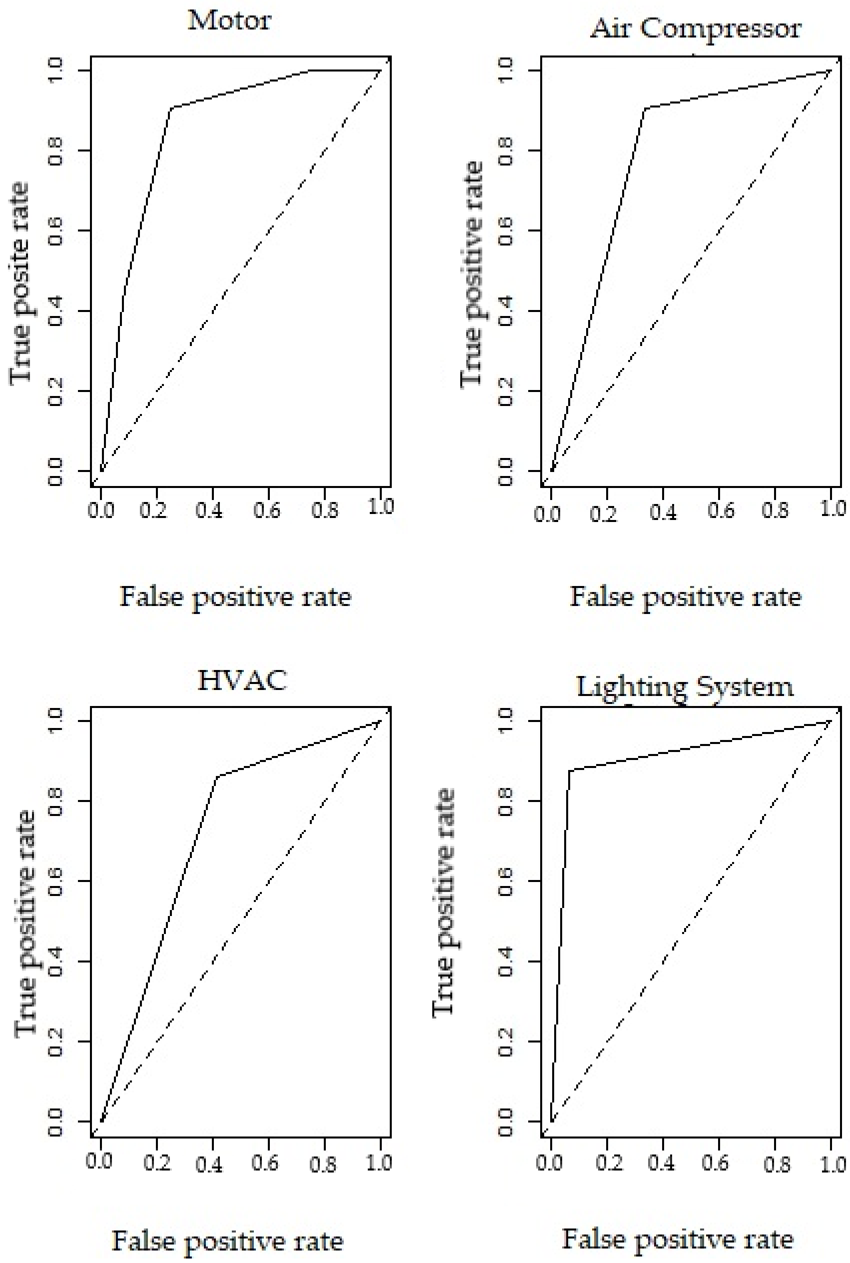

Figure 1. Predictive performance of transversal technologies.

Table 5. Bootstrap interval.

BAT	Variables	Normal	Percentile	Bca
Motor	Interceptor	−39.22; 47.78	−65.16; −2.44	−59.79; −1.27
	CF	−17.36; 14.26	0.88; 22.27	0.44; 20.85
Compressor	Interceptor	−12.95; 20.53	−20.57; −0.51	−19.56; 0.33
	P	−20.79; 14.17	1.1; 20.17	−16.72; 20.86
HVAC	Interceptor	−7.94; 6.59	−19.57; −0.45	−2.95; −0.32
	OM	−6.03; 8.58	0.81; 20	0.45; 3.58
Lighting	Interceptor	−14.86; 23.62	−25.57; −1.3	−25.57; −0.58
	OM	−38.98; 20.16	2.42; 51.13	1.18; 23.13

5. Discussion

In this section, reserved for discussion, an analysis of logistic regression models for cross-cutting technologies is performed. In addition, it discusses the influence of attributes, used as indicators, adjusted on industrial electric power consumption.

5.1. Motor Systems

The most suitable logistic regression model for the motor was:

$$ln\left(\frac{AES}{1-AES}\right) = -5.32 + 1.91CF \tag{6}$$

According to the adjusted logistic model of Equation (6), the check-up frequency indicator (*CF*) acts on the variable *AES* (Tables 3 and 4 and Section 3.2). This means that when there is a one-unit increase in the *CF* dummy variable, the amount of electricity saved should increase your chances of logging by 1.91.

The identification of the check-up frequency on the amount of electricity saved through Equation (6) shows that it is the attribute that tends to be faced by industries to improve the electric efficiency of the motor.

The *CF* will reduce repair maintenance and damage to the motor, allowing for a lower electric energy consumption.

The preventive check-up on electric motors helps to save electricity by constantly maintaining the motors in a good condition. Preventive check-up, such as cleaning and increasing moisture, helps to avoid excessive heat exchanges with the environment, resulting in greater savings in electricity consumption. Specifically, moisture prevents the corrosion of motor shafts, bearings, and industrial rotors. Cleaning impedes the rise in temperature of the cooling fan conjunct, thus modifying the means of heat transfer and increasing the amount of energy necessary for motor operation [68]. In preventive maintenance, electrical devices impede short circuits, which could affect motor energy efficiency. For Soria et al. [69], electrical devices, under different operating conditions, become more active than their total capacity. This event may happen suddenly and may affect the motor, causing turns and coils in shorting them. Therefore, the induction systems supplied by alternating current energy have great potential for electricity savings mainly with the change in energy consumption by centrifugal charge for touch [70].

In a way, as Hajian et al. [32] already highlighted and confirmed Equation (6), the check-up of motors as a means of prevention (cleaning, moisture, and electrical devices) is one of the main tools for obtaining electricity savings. Since a clean and moisture-free machine performs its main activity more efficiently, as it would be less susceptible to interruption due to failures in adjustment and abrupt cessation, it would facilitate the observation of any effects and abnormalities of the engine, consequently keeping the driving force of industrial engines stable. Accordini et al. [71] show with the writing in their work that developing a method of frequent check-ups can identify important impacts on the every dimension of electrical economy in every engine system and, in this way, have a more comprehensive view of measures for adopting the electrical consumption of the engine. Still, adding to Accordini et al. [71], Trianni et al. [72] state that the adoption of electrical saving measures represents a great challenge for the industrial manager, and to develop parameters by means of frequent check-ups, mainly in specific points of the motors, such as in the methods, use of filter, in the inverter isolation, in AC and DC reactors, among others, will provide certainty as to how this decision-making will take place.

Such strategies demonstrated in the previous paragraphs (Equation (6)) allow industrial managers to give industrial engines a longer service life, in which maintenance will provide greater efficiency to industrial engines and, therefore, maintain energy efficiency.

As highlighted in the industrial assessment center recommendations, one should develop a repair/replace policy (ARC 2.4151), standardize engine inventory (ARC 2.4155), establish a preventive maintenance program (ARC 2.4156), and establish a predictive maintenance program (ARC 2.4157).

5.2. Compressed Air Systems

The most suitable logistic regression model for air compressor was:

$$ln\left(\frac{AES}{1-AES}\right) = -2.079 + 2.996P \quad (7)$$

According to the logistic model of Equation (7), the indicator production (P) affects the AES variable. It means that when there is a one-unit increase in the dummy variable P, the amount of electricity saved increases its log odds by 2.996. The production attribute shows that the influence of the compressed air system is an important explanatory phenomenon for the implementation of a diagnosis that led to a reduction in energy consumption through the industrial production system. The efficient and synchronized operation of industrial pneumatic machines can identify an adversity earlier. Hence, failures in compressed air as a result of the production system can be continuously corrected, thus leading to energy efficiency.

Production systems affect the energy management of air compressors, mainly the suitability for the use of electric cargo [73]. The energy that runs through pipes, elbows, valves, and others interferes with the demand and the electrical consumption of the compression system, causing a loss of pressure and consequently changing the thermodynamic state of the fluid through the compression ratio and the pressure of constant work. This phenomenon causes an increase in the effective work per unit of mass.

Furthermore, the amount of energy consumed has an effective relationship with the excessive production system, leading to greater work pressure. Adjusting the compressor pressure induces the compressor to run for a longer time, which leads to a substantial increase in electricity consumption. Thus, the system for regulating the working pressure of air compressors makes production demand more flexible, thus contributing to the improvement in energy efficiency [73,74].

In addition, the location of air compressors in the plant of the industry, mainly in those that have a minimum number of production systems, may reduce energy costs when the ACs are closer to the specific equipment [75,76].

Saidur et al. [77] demonstrated that the administration and operation of the VSD motor of air compressors leads to savings in energy. Bunse et al. [75] showed the existence of solutions available at a manufacturing process level for energy savings at the company, plant, and process levels. Doyle and Cosgrove [76] demonstrate that further expansions for monitoring leaks in air compressors can be related to a non-production system. Nehler [73] noted that energy efficiency measures and non-energy benefits should be studied individually to recognize the main effects of energy use on production, in line with Cabello Era et al. [34], which shows that having a real dimension of energy consumption is so important to the efficient evaluation of electricity that it becomes significant in monitoring the efficiency of industrial air compressors. Equation (7) also confirms that if compression works properly in the production system and the management is coherent, the amount of electricity consumed in ACs tends to be controllable; in this way, it may reasonably decrease electric consumption since the industry can reach 10% of electric consumption savings in compressors.

The strategies presented above reinforce the idea that industrial production, when cohesive with compressed air systems, minimizes expenditure on energy consumption. Cabello Eras et al. [34], as is also portrayed by Equation (7), highlight that when the industrial production system monitors and controls electricity consumption, it can highlight the inefficiencies that are often hidden in the total electricity consumption of the industry, which can reach savings of 10% [12]. Moreover, there is a highlight in the recommendation, from the industrial assessment center, 2.4223, 2.4235, 2.4236 and 2.4239, that talks about the recommendations that affect productivity and are a good parameter to reduce electricity savings and consequently energy, install a direct action unit in place of compressed air pressure, remove or close unnecessary compressed air lines, eliminate leaks in inert gas and compressed air lines/valves, and eliminate or reduce the use of compressed air.

5.3. HVAC

The best logistic regression model for HVAC was:

$$ln\left(\frac{AES}{1-AES}\right) = -1.54 + 2.18OM \quad (8)$$

According to Equation (8), the operation and maintenance (*OM*) indicator affects the variable *AES*. Thus, by increasing the dummy variable *OM* by one unit, the opportunity to grow the amount of electricity in the industrial sector expands to log 2.18. The identification of the influence of the operation and maintenance attribute on the amount of electricity saved shows that any anomaly related to voltage, current or frequency deviation leads to problems in the functioning of the HVAC system equipment. Conversely, it can also present itself as a facilitator in the creation of roadmaps that allow the establishment of a set of measures leading to the reduction in industrial electricity consumption [78].

The independent variable operation and maintenance affect the *AES* of the HVAC system due to the allocation of this type of system in the industrial space and the sensitivity of the HVAC exposure time to the heating and cooling energy needs of the building [79]. Preventive maintenance is the most appropriate measure to minimize downtimes, so that the entire production system environment is not affected when a failure occurs [80].

For Khan et al. [81], operation and maintenance are related to the amount of electricity saved. This decrease in energy consumption is related to top management guidelines for the proper functioning of the HVAC system. Top management is responsible for training technicians to ensure a good industrial operation and consequently for allocating financial resources to operating HVAC systems, meeting the proper standards of the activities in buildings. According to the authors, the operation of preventive maintenance involves the organizational culture of top management. In addition to what was shown by Khan et al. [81], Equation (8) also suggests that cost reduction, with electricity savings, in building acclimatization is associated with the replacement of components of the HVAC system component, added by Mawson and Hughes [82], who demonstrates that the operation and maintenance is a hegemonic factor in the functioning of the HVAC system, since the conditions between the inadequate energy flow inside the buildings cannot deal directly with its monitoring. Most of the amount of electricity saved is registered when the technology manages to be active so as not to interfere with thermal comfort or to interrupt work.

The adjustment of the operation and maintenance attribute helps to recognize how the use of the industrial HVAC system is a fundamental issue for the occupational environment, as this attribute, as shown in the previous paragraphs, and the installed location of the HVAC system change the entire acclimatization, improvement arrangement and quality of the workplace.

In addition to the points highlighted above specifically for the HVAC system, the two main recommendations from the industrial assessment center are the following: use computer programs to optimize HVAC performance (ARC 2.7226) and avoid introducing hot, humid or dirty air into the HVAC system (ARC 2.7228). In this way, the attribute EE measures will help OM during preventive maintenance and adapting to building standards.

5.4. Lighting Systems

Finally, the best logistic regression model for the lighting system was:

$$ln\left(\frac{AES}{1-AES}\right) = -2.64 + 4.58\,OM \quad (9)$$

According to the logistic model of Equation (9), the operation and maintenance (*OM*) indicator affects the *AES* variable. It means that when there is a one-unit increase in the *OM* dummy variable, the amount of electricity saved increases its log odds by 4.58. The operation and maintenance attribute acts on the *AES* so that the deviation related to light projection can reduce the quality of the indoor working environment. From another perspective, the influence of *OM* on the amount of electricity saved helps to establish a program of measures that promotes the reduction in electric consumption of the lighting system [83–85].

The independent variable operation and maintenance affect the *AES* of the lighting system due to the luminosity helping the thermal and structural comfort of the environment, facilitating the work of the employees.

Thus, as Equation (9) shows, the operation of lighting systems not exceeding the performance limits of lamps and lamp maintenance, such as ballast cleaning, improve the lighting of the industrial space. Schratz et al. [86] show, as does Equation (8), that lighting systems require a routine replacement and inspection of lamps and ballasts to ensure their performance. The guidelines indicate that lamps should be replaced upon reaching 70% of the initial light output. Often, facility managers demand a complete replacement of both lamps and ballast routinely in order to improve ambient lighting comfort, in addition to the regulation of the entry of moisture in the environment and of the deterioration of gaskets and other hardware. In addition, the disposal operation of conventional accessories usually requires specialized handling and recycling due to the hazardous nature of materials (phosphorus and mercury) [86].

Thus, as in Equations (8) and (9) show that the adjustment of the operation and maintenance attribute allows one to recognize how the use of the industrial lighting system is a matter of local structure, as this attribute boosts the quality of the occupational circle.

That said, as shown in Equations (6)–(9), the maintenance planning of cross-cutting technologies becomes a driver to facilitate the technical and intellectual development of the teams that monitor industrial electricity consumption. In addition to contributing to industrial managers, it shows new academic paths beyond attributes and subsequent frameworks developed by other authors. The verification of the influence of attributes on the amount of electricity saved are alternative paths for the research carried out so far. Opening a new quantitative possibility to verify the attributes that interfere with energy electricity.

As also highlighted in Equations (8) and (9) show that the recommendations associated with the operation and maintenance attribute are essential to adapt the electrical saving measures, and consequently energy. Among them, the following stand out in the industrial Assessment Center: keeping lamps and reflectors clean (ARC 2.7123), practice of turning off the light when not necessary (2.7124), disconnecting ballasts (2.7122) and replacing lamps with more advanced technologies such as halogens and fluorescent for LED ones (2.7142).

6. Managerial Implications

The managerial implications of implementing and planning EEMs for cross-cutting technologies allow for measuring the consequent improvement in energy consumption in the organization. The indicators of Equations (6)–(9) may help to establish an electricity policy for a continuous improvement of energy management systems [87].

Nevertheless, a major barrier to policy formulation for reducing electricity savings to generate energy efficiency is the absence of relevant indicators for potential and successful implementation. Equations (6)–(9) can establish energy policies through a system of continuous improvement based on the adjusted attributes and their respective measures that shape these attributes. Such policies include energy policies for replacing old light bulbs with LED lights, a biannual cleaning policy for the HVAC system, checking for leaks in the lines of the compressed air system, and establishing predictive maintenance of the engine system to increase its life cycle. With the establishment of these consumption-reduction measures through continuous improvement, the company will better direct where to act in the reduction in electricity consumption of the four transversal technologies studied.

The potential of energy savings is associated with the operational aspects of the equipment. The purpose is to establish adequate operational parameters from the point of view of energy performance, so that there are real energy consumption savings. The electricity management of transversal technologies must be directed towards recognizing and finding the economic and production aspects that support the best operational performance of the equipment, as highlighted by means of Equations (6)–(9) [88].

The fitted indicators' operation and maintenance, check-up frequency, and productivity, according to Equations (6)–(9), are influencers of cross-cutting technologies, motors, HVAC, lighting systems, and compressed air. They need to receive special attention from managers through constant preventive maintenance, according to suggestions of the manufacturers of cross-cutting technologies, in addition to specific actions implemented at stages guided by previously defined goals and metrics [88].

The structuring of energy management systems allows for redefining responsibility in decision-making processes and helps to control electricity expenditure considering the P, OM, and FCP indicators. Therefore, the influence of the electric performance of production processes and of cross-cutting equipment undergoes a management innovation initiative within organizations [25,89], so that they do not affect the company's primary actions and thus do not impede energy efficiency, in addition to leading to productivity improvements [90] and the creation of sets of projects for a possible reduction in energy consumption costs. As Mills and Rosenfelds [7] pointed out, cross-cutting technologies are not autonomous energy systems. A certain characteristic may improve the quality of the energy service and its functionality. Reinforced by Madan [91], the managerial impacts of several types of programs, such as safety of equipment maintenance, scheduled maintenance and increased reliability of useful life, result in the reduction in energy consumption costs, in addition to promoting competitive advantages. However, for that, there is a need for joint actions, such as an innovative management system.

7. Conclusions and Policy Recommendation

This study contributes to the field of industrial energy efficiency in three ways. First, it provides the main characteristics that a company must have to reduce energy consumption considering both economic and production-related aspects. Addressing the main applications from a specific management perspective in the cross-cutting technologies HVAC, lighting systems, motors and compressed air systems, mainly related to the decision-making of industrial managers, demonstrates that top management is mainly responsible for the structural changes in the organization of a culture of energy consumption, with a strategic resource positioning with the objective of seeking energy efficiency, according to the adjusted indicators. Second, specific operational measures for each piece of equipment allow for structuring responsibilities so that the organization's specific standards are met, equipment is not overloaded, the performance of cross-cutting technologies is enhanced and their results are gradually reduced in energy consumption. Thirdly, the study shows that maintenance control planning is essential for the reliability of cross-cutting technologies activity for energy consumption. The preservation of cross-cutting equipment is an innovative method in the ease and technical and intellectual development of employees.

The present article brings new content and guidance for industrial energy efficiency research. In addition, the verification of the action of attributes on energy consumption takes a step beyond the aspects of surveying attributes and their respective characterization, towards the behavior of the performance between the relation of attributes.

Based on our results, top management support in maintenance and measures to be implemented and in helping to save energy show the importance of some activities for transversal technologies, such as improving engine health; efficient synchronization of pneumatic air compressor machines; the efficient allocation of HVAC systems to improve the thermal environment; and the adequate allocation of low-energy-consumption lamps in a suitable place for lighting the entire environment. In addition to expressing, through the characteristics of EEMs, connections with the production resources of transversal technologies, their adaptability, the replacement of parts and equipment, production control and distortions of financial support due to high and low energy consumption are also shown.

For the technical committees, this work is relevant to improve the guidance strategies of corporate energy consultants, showing the need for engine check-up guidelines for proper functioning to avoid damage, as well as the compressed air system in establishing its synchronization with the activities that require its use. Additionally, the HVAC system and lighting used to develop projects such as thermal comfort and lighting are adequate for the proper functioning of the employees' work.

The limitation of this work presents alternatives for the creation of future work, such as the expansion and creation of a database of energy efficiency measures, for several countries; the lack of compelling information linking EEMS with barriers; the need for an explicit link between EEMS and production resources; the lack of metrics to assess the impact of EEMs on resources to increase productivity, better use of technologies, environmental compliance and worker comfort.

With the results presented, it is possible to discuss policies to be developed within the industry and even for government managers, as established by the IPCC, taking as parameters the factors adjusted in the four logistic regression models. The indicators analyzed in this work present as the following fundamental behavior: the maintenance system expands specific technical potentials for the engines, compressed air systems, lighting systems and HVAC and presents congruence in policies to reduce electricity consumption. This facilitates the implementation of electricity savings and tends to lead the industry to an adequate potential for energy efficiency. Consequently, this work opens a door for government sectors to present policies in their reports that guide how the behavior adopted for each of the four technologies studied in the industrial sector should be.

In terms of limitations of this study, the results may differ in other regional contexts, especially when it comes to the institutional (regulatory) scenario. Furthermore, this study is based on data found on the industrial assessment center in addition to previous literature. Although, self-reported survey data are commonly used in the literature to measure economic and productive-system performance (thus making this study consistent with previous literature). Therefore, this perception may exceed or underestimate the actual performance achieved depending on the specificity of each country.

Author Contributions: Conceptualization, F.d.O.N. and H.E.; methodology, H.E. and F.d.O.N.; software, F.d.O.N.; validation, F.d.O.N., H.E. and A.T.; formal analysis, A.T.; investigation, F.d.O.N.; resources, S.R.M.M.R.; data curation, F.d.O.N.; writing—original draft preparation, F.d.O.N.; writing—review and editing, F.d.O.N.; visualization, A.T., J.A.F.R., F.P.M. and S.R.M.M.R.; supervision, A.T., J.A.F.R., F.P.M. and S.R.M.M.R.; project administration, F.d.O.N., A.T., S.R.M.M.R.; funding acquisition, S.R.M.M.R. All authors have read and agreed to the published version of the manuscript.

Funding: This study was financed in part by the Coordination for the Improvement of Higher Education Personnel-Brazil (CAPES)-Finance Code 001.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Zhang, X.P.; Cheng, X.M.; Yuan, J.H.; Gao, X.J. Total-factor energy efficiency in developing countries. *Energy Policy* **2011**, *39*, 644–650. [CrossRef]
2. Iorgulescu, M. Study of energy efficiency in industry. In Proceedings of the 2017 10th International Symposium on Advanced Topics in Electrical Engineering, ATEE 2017, Bucharest, Romania, 23–25 March 2017; pp. 573–578. [CrossRef]
3. IEA/International Energy Agency Data. Available online: https://www.iea.org/data-and-statistics?country=WORLD&fuel=Energysupply&indicator=TPESbySource (accessed on 20 November 2020).
4. IEA/International Energy Agency. *Tracking Industry 2021*; IEA/International Energy Agency: Paris, France, 2021.
5. Tanaka, K. Review of policies and measures for energy efficiency in industry sector. *Energy Policy* **2011**, *39*, 6532–6550. [CrossRef]
6. Neves, F.D.O.; Ewbank, H.; Roveda, J.A.F.; Trianni, A.; Marafão, F.P.; Roveda, S.R.M.M. Economic, Environmental and Productive Practices Influence on the Industrial Energetic Efficiency. *Rev. Gestão Sustentabilidade Ambient.* **2020**, *9*, 513. [CrossRef]

7. Mills, E.; Rosenfeld, A. Consumer Non-Energy Benefits Making Energy-Efficiency Improvements. *Energy* **1996**, *21*, 707–720. [CrossRef]
8. Thollander, P.; Paramonova, S.; Cornelis, E.; Kimura, O.; Trianni, A.; Karlsson, M.; Cagno, E.; Morales, I.; Jiménez Navarro, J.P. International study on energy end-use data among industrial SMEs (small and medium-sized enterprises) and energy end-use efficiency improvement opportunities. *J. Clean. Prod.* **2015**, *104*, 282–296. [CrossRef]
9. Cooremans, C. Investment in energy efficiency: Do the characteristics of investments matter? *Energy Effic.* **2012**, *5*, 497–518. [CrossRef]
10. Cagno, E.; Trucco, P.; Trianni, A.; Sala, G. Quick-E-scan: A methodology for the energy scan of SMEs. *Energy* **2010**, *35*, 1916–1926. [CrossRef]
11. He, K.; Wang, L. A review of energy use and energy-efficient technologies for the iron and steel industry. *Renew. Sustain. Energy Rev.* **2017**, *70*, 1022–1039. [CrossRef]
12. Trianni, A.; Cagno, E.; De Donatis, A. A framework to characterize energy efficiency measures. *Appl. Energy* **2014**, *118*, 207–220. [CrossRef]
13. Cagno, E.; Trianni, A. Evaluating the barriers to specific industrial energy efficiency measures: An exploratory study in small and medium-sized enterprises. *J. Clean. Prod.* **2014**, *82*, 70–83. [CrossRef]
14. Worrell, E.; Laitner, J.A.; Ruth, M.; Finman, H. Productivity benefits of industrial energy efficiency measures. *Energy* **2003**, *28*, 1081–1098. [CrossRef]
15. Trianni, A.; Cagno, E.; Marchesani, F.; Spallina, G. Classification of drivers for industrial energy efficiency and their effect on the barriers affecting the investment decision-making process. *Energy Effic.* **2017**, *10*, 199–215. [CrossRef]
16. Alhourani, F.; Saxena, U. Factors affecting the implementation rates of energy and productivity recommendations in small and medium sized companies. *J. Manuf. Syst.* **2009**, *28*, 41–45. [CrossRef]
17. Fleiter, T.; Hirzel, S.; Worrell, E. The characteristics of energy-efficiency measures–a neglected dimension. *Energy Policy* **2012**, *51*, 502–513. [CrossRef]
18. Pye, M.; McKane, A. Making a stronger case for industrial energy efficiency by quantifying non-energy benefits. *Resour. Conserv. Recycl.* **2000**, *28*, 171–183. [CrossRef]
19. Skumatz, L.A.; Dickerson, C.A. Extra! Extra! Non-Energy Benefits Swamp Load Impacts For PG&E Program! In Proceedings of the ACEEE Summer Study on Energy Efficiency in Buildings Proceedings, Washington, DC, USA, 23–28 August 1998; pp. 301–312.
20. Industrial Assessmenter Center Search IAC Recommendations. Available online: https://iac.university/searchRecommendations (accessed on 2 January 2021).
21. Xia, X.; Zhang, L. Industrial energy systems in view of energy efficiency and operation control. *Annu. Rev. Control* **2016**, *42*, 299–308. [CrossRef]
22. Sola, A.V.H.; Mota, C.M.M.; Kovaleski, J.L. A model for improving energy efficiency in industrial motor system using multicriteria analysis. *Energy Policy* **2011**, *39*, 3645–3654. [CrossRef]
23. Letschert, V.; Desroches, L.B.; Ke, J.; McNeil, M. Energy efficiency–How far can we raise the bar? Revealing the potential of best available technologies. *Energy* **2013**, *59*, 72–82. [CrossRef]
24. IAC Database Industrial Assessmenter Center. Available online: https://iac.university/#database (accessed on 1 March 2020).
25. Cagno, E.; Trianni, A. Exploring drivers for energy efficiency within small- and medium-sized enterprises: First evidences from Italian manufacturing enterprises. *Appl. Energy* **2013**, *104*, 276–285. [CrossRef]
26. Trianni, A.; Cagno, E.; Farné, S. Barriers, drivers and decision-making process for industrial energy efficiency: A broad study among manufacturing small and medium-sized enterprises. *Appl. Energy* **2016**, *162*, 1537–1551. [CrossRef]
27. Agyekum, E.B.; Adebayo, T.S.; Bekun, F.V.; Kumar, N.M.; Panjwani, M.K. Effect of two different heat transfer fluids on the performance of solar tower csp by comparing recompression supercritical co2 and rankine power cycles, China. *Energies* **2021**, *14*, 3426. [CrossRef]
28. Menghi, R.; Papetti, A.; Germani, M.; Marconi, M. Energy efficiency of manufacturing systems: A review of energy assessment methods and tools. *J. Clean. Prod.* **2019**, *240*, 118276. [CrossRef]
29. Hasan, A.S.M.M.; Trianni, A. A review of energy management assessment models for industrial energy efficiency. *Energies* **2020**, *13*, 5713. [CrossRef]
30. Worrell, E.; Biermans, G. Move over! Stock turnover, retrofit and industrial energy efficiency. *Energy Policy* **2005**, *33*, 949–962. [CrossRef]
31. McKane, A.; Hasanbeigi, A. Motor systems energy efficiency supply curves: A methodology for assessing the energy efficiency potential of industrial motor systems. *Energy Policy* **2011**, *39*, 6595–6607. [CrossRef]
32. Zuberi, M.J.S.; Tijdink, A.; Patel, M.K. Techno-economic analysis of energy efficiency improvement in electric motor driven systems in Swiss industry. *Appl. Energy* **2017**, *205*, 85–104. [CrossRef]
33. Heidari, M.; Majcen, D.; van der Lans, N.; Floret, I.; Patel, M.K. Analysis of the energy efficiency potential of household lighting in Switzerland using a stock model. *Energy Build.* **2018**, *158*, 536–548. [CrossRef]
34. Lu, S.M.; Lu, C.; Tseng, K.T.; Chen, F.; Chen, C.L. Energy-saving potential of the industrial sector of Taiwan. *Renew. Sustain. Energy Rev.* **2013**, *21*, 674–683. [CrossRef]
35. Andrade, C.T.C.; Pontes, R.S.T. Economic analysis of Brazilian policies for energy efficient electric motors. *Energy Policy* **2017**, *106*, 315–325. [CrossRef]

36. Garcia, A.G.P.; Szklo, A.S.; Schaeffer, R.; McNeil, M.A. Energy-efficiency standards for electric motors in Brazilian industry. *Energy Policy* **2007**, *35*, 3424–3439. [CrossRef]
37. Choi, J.K.; Eom, J.; McClory, E. Economic and environmental impacts of local utility-delivered industrial energy-efficiency rebate programs. *Energy Policy* **2018**, *123*, 289–298. [CrossRef]
38. Zhou, Y.; Xu, G.; Minshall, T.; Liu, P. How do Public Demonstration Projects Promote Green-Manufacturing Technologies? A Case Study from China. *Sustain. Dev.* **2015**, *23*, 217–231. [CrossRef]
39. Liu, P.; Zhou, Y.; Zhou, D.K.; Xue, L. Energy Performance Contract models for the diffusion of green-manufacturing technologies in China: A stakeholder analysis from SMEs' perspective. *Energy Policy* **2017**, *106*, 59–67. [CrossRef]
40. Hajian, M.; Soltani, J.; Markadeh, G.A.; Hosseinnia, S. Adaptive nonlinear direct torque control of sensorless im drives with efficiency optimization. *IEEE Trans. Ind. Electron.* **2010**, *57*, 975–985. [CrossRef]
41. Benedetti, M.; Bonfà, F.; Introna, V.; Santolamazza, A.; Ubertini, S. Real time energy performance control for industrial compressed air systems: Methodology and applications. *Energies* **2019**, *12*, 3935. [CrossRef]
42. Cabello Eras, J.J.; Sagastume Gutiérrez, A.; Sousa Santos, V.; Cabello Ulloa, M.J. Energy management of compressed air systems. Assessing the production and use of compressed air in industry. *Energy* **2020**, *213*, 118662. [CrossRef]
43. Shaw, W.; Mathews, M.; Marais, J. Using specific energy as a metric to characterise compressor system performance. *Sustain. Energy Technol. Assess.* **2019**, *31*, 329–338. [CrossRef]
44. Boharb, A.; Allouhi, A.; Saidur, R.; Kousksou, T.; Jamil, A.; Mourad, Y.; Benbassou, A. Auditing and analysis of energy consumption of an industrial site in Morocco. *Energy* **2016**, *101*, 332–342. [CrossRef]
45. Gordić, D.; Babić, M.; Jovičić, N.; Šušteršič, V.; Končalović, D.; Jelić, D. Development of energy management system–Case study of Serbian car manufacturer. *Energy Convers. Manag.* **2010**, *51*, 2783–2790. [CrossRef]
46. Lee, A.H.W. Verification of electrical energy savings for lighting retrofits using short- and long-term monitoring. *Energy Convers. Manag.* **2000**, *41*, 1999–2008. [CrossRef]
47. Brundage, M.P.; Chang, Q.; Li, Y.; Xiao, G.; Arinez, J. Energy efficiency management of an integrated serial production line and HVAC system. *IEEE Trans. Autom. Sci. Eng.* **2014**, *11*, 789–797. [CrossRef]
48. Khan, K.H.; Ryan, C.; Abebe, E. Day Ahead Scheduling to Optimize Industrial HVAC Energy Cost Based on Peak/OFF-Peak Tariff and Weather Forecasting. *IEEE Access* **2017**, *5*, 21684–21693. [CrossRef]
49. Liu, G.; Gao, J.; Zeng, L.; Hou, Y.; Cao, C.; Tong, L.; Wang, Y. On-demand ventilation and energy conservation of industrial exhaust systems based on stochastic modeling. *Energy Build.* **2020**, *223*, 1101–1158. [CrossRef]
50. Sun, Y.; Gu, L.; Wu, C.F.J.; Augenbroe, G. Exploring HVAC system sizing under uncertainty. *Energy Build.* **2014**, *81*, 243–252. [CrossRef]
51. Woodruff, M.G.; Jones, T.W.; Dowd, J.; Roop, J.M.; Seely, H.E.; Muller, M.R. Evidence from the industrial assessment program on energy investment decisions by small and medium-sized manufacturers. In Proceedings of the Intersociety Energy Conversion Engineering Conference, Honolulu, HI, USA, 27 July–1 August 1997; pp. 2138–2142. [CrossRef]
52. Worrell, E. *Managing Your Energy An ENERGY STAR ® Guide for Identifying Energy Savings in Manufacturing Plants*; University of California, Berkeley: Berkeley, CA, USA, 2010.
53. Sandberg, P.; Söderström, M. Industrial energy efficiency: The need for investment decision support from a manager perspective. *Energy Policy* **2003**, *31*, 1623–1634. [CrossRef]
54. Lilly, P.; Pearson, D. Determining the full value of industrial efficiency programs. In *Proceedings ACEEE Summer Study on Energy Efficiency in Industry*; ACEEE: Washington, DC, USA, 1999; pp. 349–362.
55. Lung, R.B.; McKane, A.; Leach, R.; Marsh, D. *Ancillary Savings and Production Benefits in the Evaluation of Industrial Energy Efficiency Measures*; Report for ACEEE Summer Study on Energy Efficiency in Industry; University of California, Berkeley: Berkeley, CA, USA, 2005.
56. Wulfinghoff, D.R. *Energy Efficiency Manual*; Energy Institute Press: Wheaton, MD, USA, 1999.
57. McFadden, D. Quantitative methods for analysing travel behaviour ofindividuals: Some recent developments. In *Behavioural Travel Modelling*; Routledge: London, UK, 2021; pp. 279–318.
58. *R: A Language and Environment for Statistical Computing R Foundation for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2020.
59. Petrucci, C.J. A primer for social worker researchers on how to conduct a multinomial logistic regression. *J. Soc. Serv. Res.* **2009**, *35*, 193–205. [CrossRef]
60. Grondys, K.; Androniceanu, A.; Dacko-Pikiewicz, Z. Energy management in the operation of enterprises in the light of the applicable provisions of the energy efficiency directive (2012/27/EU). *Energies* **2020**, *13*, 4338. [CrossRef]
61. Tait, P.; Saunders, C.; Guenther, M.; Rutherford, P. Emerging versus developed economy consumer willingness to pay for environmentally sustainable food production: A choice experiment approach comparing Indian, Chinese and United Kingdom lamb consumers. *J. Clean. Prod.* **2016**, *124*, 65–72. [CrossRef]
62. Cantore, N. Factors affecting the adoption of energy efficiency in the manufacturing sector of developing countries. *Energy Effic.* **2017**, *10*, 743–752. [CrossRef]
63. Kovacova, M.; Kliestik, T. Logit and Probit application for the prediction of bankruptcy in Slovak companies. *Equilibrium* **2017**, *12*, 775–791. [CrossRef]

64. Yamaguchi, Y.; Miyachi, Y.; Shimoda, Y. Stock modelling of HVAC systems in Japanese commercial building sector using logistic regression. *Energy Build.* **2017**, *152*, 458–471. [CrossRef]
65. Jenčová, S.; Štefko, R.; Vašaničová, P. Scoring model of the financial health of the electrical engineering industry's non-financial corporations. *Energies* **2020**, *13*, 4364. [CrossRef]
66. Marchetti, D.; Wanke, P. Brazil's rail freight transport: Efficiency analysis using two-stage DEA and cluster-driven public policies. *Socio-Econ. Plan. Sci.* **2017**, *59*, 26–42. [CrossRef]
67. Shrout, P.E.; Bolger, N. Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychol. Methods* **2002**, *7*, 422–445. [CrossRef] [PubMed]
68. Brückner, S.; Liu, S.; Miró, L.; Radspieler, M.; Cabeza, L.F.; Lävemann, E. Industrial waste heat recovery technologies: An economic analysis of heat transformation technologies. *Appl. Energy* **2015**, *151*, 157–167. [CrossRef]
69. Arreola Soria, O.; Conde Enríquez, A.; Trujillo Guajardo, L.A. Overcurrent relay with unconventional curves and its application in industrial power systems. *Electr. Power Syst. Res.* **2014**, *110*, 113–121. [CrossRef]
70. Alsofyani, I.M.; Idris, N.R.N. A review on sensorless techniques for sustainable reliablity and efficient variable frequency drives of induction motors. *Renew. Sustain. Energy Rev.* **2013**, *24*, 111–121. [CrossRef]
71. Accordini, D.; Cagno, E.; Trianni, A. Identification and characterization of decision-making factors over industrial energy efficiency measures in electric motor systems. *Renew. Sustain. Energy Rev.* **2021**, *149*, 111354. [CrossRef]
72. Trianni, A.; Cagno, E.; Accordini, D. Energy efficiency measures in electric motors systems: A novel classification highlighting specific implications in their adoption. *Appl. Energy* **2019**, *252*, 113481. [CrossRef]
73. Nehler, T. Linking energy efficiency measures in industrial compressed air systems with non-energy benefits—A review. *Renew. Sustain. Energy Rev.* **2018**, *89*, 72–87. [CrossRef]
74. Saidur, R.; Rahim, N.A.; Hasanuzzaman, M. A review on compressed-air energy use and energy savings. *Renew. Sustain. Energy Rev.* **2010**, *14*, 1135–1153. [CrossRef]
75. Bunse, K.; Vodicka, M.; Schönsleben, P.; Brülhart, M.; Ernst, F.O. Integrating energy efficiency performance in production management–Gap analysis between industrial needs and scientific literature. *J. Clean. Prod.* **2011**, *19*, 667–679. [CrossRef]
76. Doyle, F.; Cosgrove, J. An approach to optimising compressed air systems in production operations. *Int. J. Ambient. Energy* **2018**, *39*, 194–201. [CrossRef]
77. Saidur, R.; Hasanuzzaman, M.; Rahim, N.A. Energy, economic, and environmental analysis of the Malaysian industrial compressed-air systems. *Clean Technol. Environ. Policy* **2012**, *14*, 195–210. [CrossRef]
78. Singh, B.; Chandra, A.; Al-Haddad, K. *Power Quality. Problems and Mitigation Techniques*, 1st ed.; Wiley: Hoboken, NJ, USA, 2015; ISBN 9781118922057.
79. Gul, M.S.; Patidar, S. Understanding the energy consumption and occupancy of a multi-purpose academic building. *Energy Build.* **2015**, *87*, 155–165. [CrossRef]
80. Au-Yong, C.P.; Ali, A.S.; Ahmad, F. Improving occupants' satisfaction with effective maintenance management of HVAC system in office buildings. *Autom. Constr.* **2014**, *43*, 31–37. [CrossRef]
81. Khan, K.H.; Ryan, C.; Abebe, E. Optimizing HVAC Energy Usage in Industrial Processes by Scheduling Based on Weather Data. *IEEE Access* **2017**, *5*, 11228–11235. [CrossRef]
82. Mawson, V.J.; Hughes, B.R. Optimisation of HVAC control and manufacturing schedules for the reduction of peak energy demand in the manufacturing sector. *Energy* **2021**, *227*, 120436. [CrossRef]
83. Anumba, C.J.; Ren, Z.; Thorpe, A.; Ugwu, O.O.; Newnham, L. Negotiation within a multi-agent system for the collaborative design of light industrial buildings. *Adv. Eng. Softw.* **2003**, *34*, 389–401. [CrossRef]
84. Katunský, D.; Dolníková, E.; Doroudiani, S. Integrated lighting efficiency analysis in large industrial buildings to enhance indoor environmental quality. *Buildings* **2017**, *7*, 47. [CrossRef]
85. Al-Ghaili, A.M.; Kasim, H.; Hassan, Z.; Jorgensen, B.N. Lighting Systems Designed for Energy Savings in Buildings (LSD-ESB): A Review. In Proceedings of the 2020 8th International Conference on Information Technology and Multimedia, ICIMU 2020, Selangor, Malaysia, 24–25 August 2020; pp. 14–19. [CrossRef]
86. Schratz, M.; Gupta, C.; Struhs, T.; Gray, K. Reducing energy and maintenance costs while improving light quality and reliability with led lighting technology. In Proceedings of the IEEE Conference Record of Annual Pulp and Paper Industry Technical Conference, Charlotte, NC, USA, 23–27 June 2013; pp. 43–49. [CrossRef]
87. Rudberg, M.; Waldemarsson, M.; Lidestam, H. Strategic perspectives on energy management: A case study in the process industry. *Appl. Energy* **2013**, *104*, 487–496. [CrossRef]
88. Reinders, G. *Optimizing Energy Management Helps Companies Achieve Strategic Business Objectives*; Corporate Real Estate Leader: Atlanta, GA, USA, 2004.
89. May, G.; Stahl, B.; Taisch, M. Energy management in manufacturing: Toward eco-factories of the future–A focus group study. *Appl. Energy* **2016**, *164*, 628–638. [CrossRef]
90. Porter, M.E.; Van der Linde, C. Green and Competitive: Ending the Stalemate. *Harv. Bus. Rev.* **1995**, *73*, 120–134.
91. Madan, R. The human side of energy efficiency: The value of training. *Steam Dig.* **2002**, *73*, 43–44.