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An Integrated DEMATEL-MMDE-ISM Approach for Analyzing Environmental Sustainability Indicators in MSMEs

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Abstract: The Micro, Small and Medium Enterprises engaged in manufacturing activities are facing various environmental challenges encompassing material and energy consumption; waste generation and disposal; water and air pollution; etc. Hence, it becomes important to adopt policies, strategies, and technologies, which may help to bring down the adverse impacts of manufacturing on the environment. In this context, the current study identified the 15 critical environmental sustainability indicators to gauge the impact of their manufacturing activities on the environment taking a case of lock manufacturing industries. To understand the interdependence among the selected indicators, the study further utilizes an integrated DEMATEL-MMDE-ISM approach to analyse the inputs of industry professionals. The results of the study highlighted that design of products, which can be disassembled, reused, or recycled and are free from hazardous materials play a significant role in enhancing the environmental sustainability of the concerned industry. The study is expected to aid decision-makers (industry practitioners and academic researchers) to identify strategic areas in order to achieve higher environmental sustainability in manufacturing organizations.

Keywords: Small and Medium Enterprises; Lock Manufacturing; Environmental Indicators; DEMATEL; MMDE; ISM; MICMAC.

1. Introduction

The manufacturing sector is an indispensable part of the global economy wherein the sustainability concepts are gaining widespread attention across the world. Sustainability, as a concept originated with Brundtland (1987) report that conceptualized sustainability as satisfying the demands of the current generation without adversely affecting the ability of succeeding generations to fulfil its own needs (Gupta et al. 2018). Governments are enacting stricter legislation to bring down the adverse environmental effects of production and related operations that have pushed manufacturers to adopt the principles of sustainability in production (Huang and Badurdeen 2017). In this context, sustainable manufacturing practices aim to create products through non-polluting processes, consuming less natural resources and energy but at the same time they must be economically viable and safe (Sengupta et al. 2018).

Nowadays, an increasing emphasis on sustainability has contributed to the growth and advances of its assessment tools that may provide a quantifiable data for decision making for an organization seeking to incorporate sustainable manufacturing practices/technologies (Moldavska and Welo 2015). Sustainability assessment relies on a set of indicators which provide a simple, quantifiable/measurable, affordable, and communicable method to assess a manufacturing unit (Linke et al. 2013). Such indicators provide valuable information leading to better policymaking and enable assessment of the level of sustainability achieved as compared to the desired goal(s).

Manufacturing has become a crucial area for the growth in developing countries, like India, and is playing a significant impact on the economic growth and employment generation. By 2022, the Government of India intends to increase the GDP share of manufacturing to 25% (IBEF 2019). India's MSME sector alone contributes about 40% manufacturing share of GDP and is 2nd largest employer of the country (MSME 2013). Despite immense contribution to the Indian economy, MSMEs contribute 70% of the total industrial pollution resulting in serious health hazards and damage to the environment and thereby the ecosystem. Even though plenty of studies are available on environmental impact of MSMEs manufacturing, the assessment of the same using indicators still remains an under-researched topic in this sector (Nulkar 2014).

Thus, the focus of this study is on Indian MSME's in general considering a case of locks manufacturing industry in particular. Typical activities in a lock manufacturing unit include casting, machining, finishing, sheet metal operations, electroplating, painting, and assembling the components in an assembly line; having a significant impact on the environment. However, to address the environmental issues, many researchers have identified critical indicators that may enable manufacturers to improve their environmental impact but it is not enough for manufacturers to merely know the critical-indicators, but also to understand the interdependence amongst each other.

This study is further extended in order to explore the interdependence of the critical environmental indicators taking into account the views of industry professionals based on an integrated DEMATEL-MMDE-ISM approach (Singh & Bhanot, 2020). DEMATEL is a commonly utilized multi-criteria decision-making technique to analyze and solve complex problems that involve interlinked factors. It checks the interdependence among factors by developing a map reflecting cause and effect relationship via matrices and identifies the critical factors. Further, MMDE is a scientific approach, which furnishes an appropriate threshold value for decision-making. However, ISM provides a hierarchical structure among interdependent factors wherein MICMAC analysis is conducted to assess the strengths of the relationship amongst the interlinked factors. The study intends to help manufacturing organizations to prioritize the most critical indicators to enhance their environmental performance.

This paper is organised as follows: Section 1 presents the background and context of the study. Section 2 highlights related literature to describe the state of the art research in manufacturing sustainability assessment and discusses the gaps that exist in the published literature featured in the present study. Section 3 covers problem statements and critical environmental indicators relevant to manufacturing activities in the MSME sector. Section 4 contains the detailed description of the methodology adopted for the study. The findings of the present study are explained and further discussed in section 5. Section 6 presents the concluding remarks along with limitations and future scope in Section 7.

2. Literature Review

This section presents the numerous studies on manufacturing sustainability assessment frameworks utilizing environmental indicators and hence, attempts to identify the existing research gaps.

Veleva & Ellenbecker, (2001) proposed one of the earliest frameworks for sustainability assessment using the definition of sustainable production (LCSP, 1998). This framework proposed Twenty-two core indicators, comprising both quantitative and quantitative, along with guidelines of their implementation. However, GRI grouped Indicators into three major categories viz. economic, environmental, and social as highlighted in Figure 1 (GRI 2002, 2016). Similarly, World Summit on Social Development (2005) described the Environmental protection, Economic and Social development, as the three main pillars of sustainability (Roy and Pramanick 2019) being interdependent and mutually reinforcing. Using GRI guidelines, Samuel et al., (2013) recommended 30 indicators for the environmental performance assessment in Malaysian petrochemical industry.

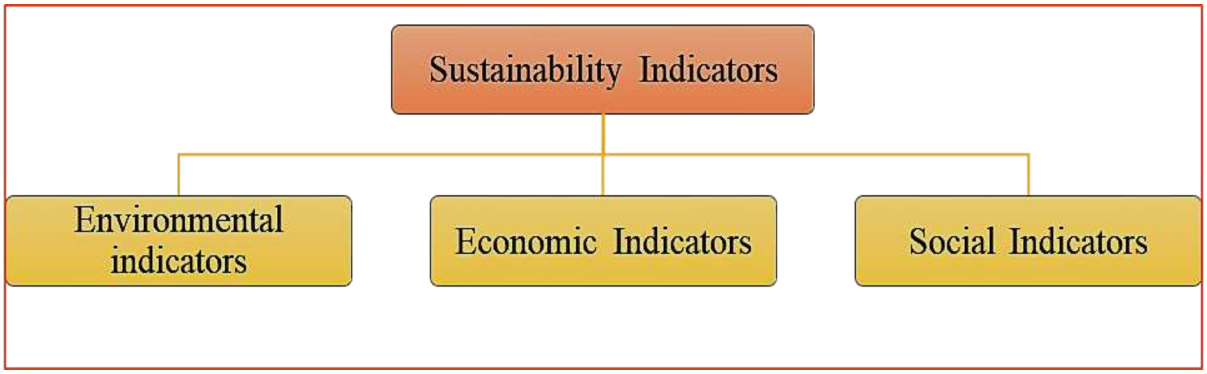

Figure 1: Classification of Sustainability Indicators (GRI 2002, 2016; Feil et al. 2015; Moldavska and Welo 2015).

Kinderyte, (2010) emphasized the need for the SMEs based indicator systems for sustainability assessment and identified 24 quantitative and 20 qualitative indicators by systematically analyzing existing systems like Dow Jones & GRI indexes and further used the expert's opinions to determine their significance. Winroth et al., (2016) opined that, a suitable set of indicators are necessary to enhance the sustainability at shop floor level as well. This study identified a set of 27 indicators that could be useful for a production manager.

Singh et al., (2014) recognized the need for developing indicators for assessment of manufacturing SMEs and proposed a broader list of indicators for SMEs. Similarly, Feil et al., (2015) proposed 26 indicators consisting of 12 environmental indicators, 7 each of social and economic indicators for manufacturing enterprises. Ahmad and Wong, (2019) also reviewed the indicators of sustainability for manufacturing sectors by taking into account of triple bottom line (environment, economy, and society) perspective.

Ocampo et al., (2016) proposed a fizzy hierarchy process based index for sustainable manufacturing using indicators. The developed model may be useful in identification of focus areas of the sustainability in manufacturing but required further confirmation using multivariate analysis. Bui et al., (2017) suggested a framework for sustainability assessment of the mining industry using a fuzzy AHP approach. It used 20 indicators comprising 9 economic, 8 environmental and 3 social indicators, however, it did not take into account the interrelations between these indicators. Beekaroo et al., (2019) developed an index using a multiple regression model to enumerate the environmental effect of manufacturing activities. The authors concluded that four economic, nine environmental, and two social indicators had a significant weightage in the quantified sustainability index. However, the index did not take into account the interdependence of indicators and had limited applications on small-medium enterprises. Kluczek, (2016) used the analytical hierarchy process to integrate activity areas requiring sustainability improvement with proposed technological changes and technology adopted to provide a rough infrastructure for sustainability assessment. The presented approach was found to be suitable for comparisons of different processes within the production system.

Tseng et al., (2009) employed a combination of fuzzy theory and ANP approach to understand the interdependence between sustainable production indicators (SPI). To overcome the challenge of modeling, measuring, and integrating performance metrics Garbie, (2015) introduced a framework to investigate the links between "socio-economic, environmental-economic and social-environmental Sustainability" using a hypothetical example. A DEMATEL-MMDE-ISM based approach adopted by Bhanot et al., (2017) analyzed the gaps in the fundamental understanding of industry and academia professionals towards enablers and barriers in implementing sustainable manufacturing. The authors explored the reasons for differences in opinions of academia and industry professionals by utilizing, ten enablers and ten barriers that play a critical role in improving aspects of sustainability in manufacturing organizations.

Gunasekaran & Spalanzani, (2012) emphasized the need to implement environmental friendly manufacturing and sustainable products to help organizations attain sustainability. Achieving sustainability in product manufacturing requires products to be assessed for sustainability which requires suitable methodologies and their integration with all dimensions of sustainability. A methodology for product sustainability assessment was developed by Ghadimi et al., (2012) utilizing the Fuzzy Analytical Hierarchy Process (FAHP) by assigning weights and concluded that Weighted Fuzzy Assessment Method (WFAM) helps in better decision making regarding the product's sustainability improvements. A Product Sustainability Performance Index (PSPI) was proposed by Feng & Mai, (2016) for comparing the relative sustainability performance of products by utilizing quantitative and qualitative information for the assessment.

When it comes to measuring sustainability implementation, Eslami et al., (2019) reported that environmental dimension is the one of the most targeted area by researchers among all three dimensions of sustainability. Material, water, energy and other resources utilized during the processes are some of the key areas of environmental performance. From the literature review, it is evident that indicators play a prominent role in understanding the adverse impact of manufacturing on the environment. In the recent past, researchers and agencies have extensively proposed new indicators and utilized them for environmental performance assessment. Thus, many studies have mainly focused on developing indicators based assessment frameworks for environmental performance in manufacturing industries. However, studies focused on the interdependent interactions among environmental indicators are very few. It is also evident that there is a scarcity of research to enhance the understanding of implementing environmental aspects towards the Indian MSME sector. Therefore, the agenda of this research work is to identify the critical indicators relevant to environmental performance aspect of manufacturing and further identifying the interdependent relations among indicators in the context of Indian MSME sector. In this perspective, such relationships will highlight the interaction between indicators and help in identifying the improvement areas of environmental performance.

3. Problem Description

Indian Micro Small and Medium Enterprises (MSMEs) are emerging as one of the largest, highly vibrant sectors of the Indian economy. It is one of the largest employers in the country, making up about 40% of employments from the organized sectors. There are around 19 million MSMEs and are helping in industrialization of rural and under-developed regions of the country. However, the manufacturing share of MSME in GDP is showing a declining trend over the last few years which is currently 6.11 percent approximately (CII 2018).

To overcome the challenges faced by Indian MSMEs, the Indian government has taken numerous initiatives to revive the sector. However, many important initiatives like green manufacturing promoting environmentally friendly practices needs to be adopted at large scale in this sector. As per the estimates, Indian MSMEs chiefly depend on locally procured raw materials and other resources and at the same time contribute about 70 percent of industrial pollution (Singh et al., 2018). Therefore, this necessitates the need of MSMEs to adopt environmentally focused manufacturing practices for inclusive economic development. Increased generation of waste, greenhouse gases, land, and water are some of the major environmental concerns considering which adopting green and environmentally friendly technologies is the need of the hour for Indian MSMEs in general.

The present paper is an effort to study the environmental performance assessment issues among MSMEs in a selected industrial cluster of lock manufacturing units of Aligarh, Uttar Pradesh in India. The lock manufacturing industry of Aligarh contributes about 80 percent turnover of the Indian lock industry. This Lock industry cluster has around 2000 medium and small-scale industries. Products range include padlock, door lock, security locks, smart locks, and automotive lock, etc. while it primarily uses ferrous and nonferrous raw materials in production. Activities in a fully functional lock manufacturing units involve procuring raw material, designing and developing components, manufacturing lock components including keys, finishing each component, electroplating them, assembly, and quality control at each stage of manufacturing, packaging, and shipping/storage. Manufacturing processes employed in a unit includes casting, machining, finishing, sheet metal operations, electroplating, painting, assembling the components in the assembly line, etc. The machinery employed in lock manufacturing ranges from automatics, semiautomatic, and manual. However, the processes are either semiautomatic or manual owing to the large variety of components involved in locks production.

With increasing emphasis on environmentally conscious manufacturing, there is an upsurge in the discussions linked to its benefits. However, there is a lack of awareness regarding the adoption of these practices and to measure environmental performance using indicators. While some organizations have started to use indicators for the assessment of environmental performance, implementation is slow due to a large number of indicators and a lack of comprehensive frameworks that could assist management in decision-making and strategy development. Thus, it is important to identify the critical indicators that can provide an effective framework for the assessment of environmental performance in the lock manufacturing sector. From our literature review in Section 2, one can observe that few researchers have provided a set of indicators that can be utilized for the environmental impact assessment of Indian small and medium-sized enterprises involved in manufacturing. Besides, there is a lack of research work that explores the interdependence among the environmental indicators for strategic implementation. This paper identifies the critical indicators of environmental performance by exploring the literature and utilizes the views of industry professionals to establish interrelation/interdependence among indicators based on the methodology highlighted in Figure 2 adopted for present study.

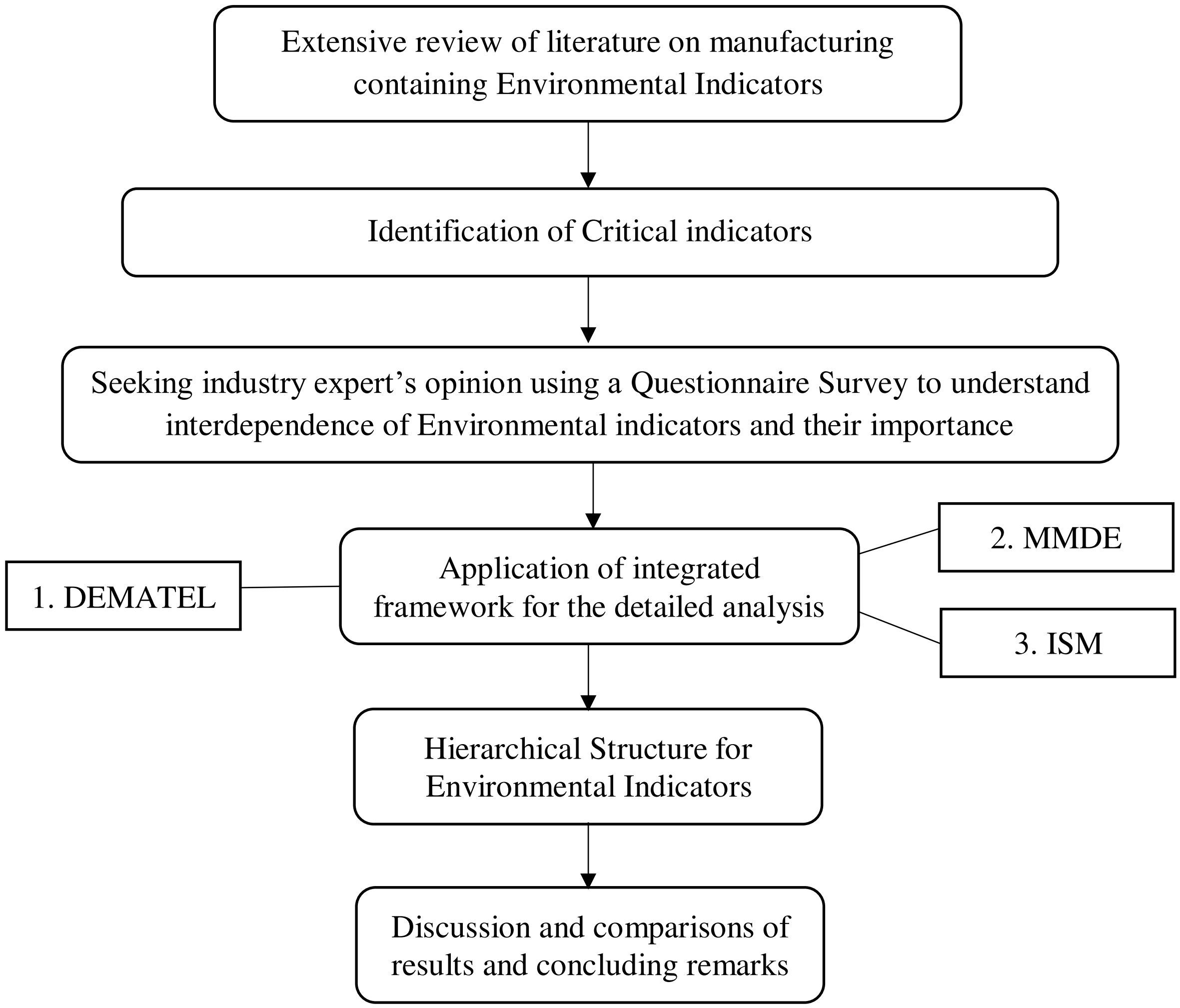

Figure. 2. Methodology for identifying cause and effect relationship between critical indicators

The methodology depicted in Figure 2 intends to propose a comprehensive framework to understand the interdependence among the environmental indicators in our study. This framework utilizes three methods namely, DEMATEL, MMDE and ISM. DEMATEL provides the flexibility to evaluate the relationships among factors on a 0-4 integer scale and prioritizes the factors (indicators) based on the interactions and the significance of the effects of factors on each other. It further tells about the "Cause and Effect" relationship among multiple factors. After DEMATEL approach, the MMDE (maximum mean de-entropy) algorithm provides a cut-off value for delineating the cause-effect relations among factors. Then, a hierarchal structure of environmental indicators is obtained by utilizing the ISM-MICMAC approach.

4. Indicators of Environmental Performance

Environmental impacts of manufacturing and allied activities on ecosystem, land, water and air is measured with the help of indicators. Since environmental protection has emerged as one of the major concerns for manufacturing organizations, a large no of indicators have been proposed to evaluate the progress, identify the deficiencies and make strategies towards improving environmental performance (Joung et al. 2013). Majority of environmental indicators are related to energy, materials, emission, waste, product design, water and land, etc. wherein the importance of these indicators have been well documented in many studies (Veleva and Ellenbecker 2001; Krajnc and Glavič 2003; Tseng et al. 2009; Amrina and Yusof 2011; Joung et al. 2013; Amrina and Vilsi 2015; Feil et al. 2015; Park and Kremer 2017; Sikdar 2019)

It is very difficult to focus on fixed set of indicators that can be used universally in the context of manufacturing (Singh et al., 2012). In our previous study, we identified a total of 49 indicators (Table A1, Appendix A1) frequently used in context to manufacturing. After applying Pareto analysis, this study narrowed down to a list of 15 critical indicators frequently used by researchers. The selected indicators are discussed herewith.

Energy Consumption (EN_1): Energy consumption indicators provide a quantitative measure in attaining energy sustainability by manufacturing organizations (GRI 2002, 2018). This indicator measures the capability of an organization to use energy efficiently. Bui et al., (2017) described total energy consumption as the most significant factor in achieving Environmental protection goals in manufacturing.

Renewable and Non-Renewable Energy Consumption (EN_2): These indicators provide an insight in the manufacturing organizations success to use renewable energy and reducing the dependence on non-renewable sources (GRI 2002). Increased energy consumption from renewable sources shows the organizations commitment for improving environmental aspects (Lin et al., 2010).

Energy Intensity (EN_3): This indicator determines input energy flows of the manufacturing unit. This is used to measure the ratios of energy usage that attribute energy efficiency on how manufacturing facility is using the energy (Kluczek 2016). The declining value of energy utilized per unit product means that the product is becoming more sustainable with respect to energy consumption.

Recycling and Reuse of Water (EN_4): Time and again, many researchers have recommended recycling and reuse of water due to limited availability of fresh supply of water (Veleva and Ellenbecker 2001; Krajnc and Glavič 2003; Anderson 2003). Further, this indicator helps in determining organizations efforts towards reducing their reliance on fresh water measures (GRI 2002, 2016; Walsh et al. 2016).

Amount of Water Consumption (EN_5): Total water used by a manufacturing unit as a core indicator was proposed by Global Reporting Initiative (GRI 2002, 2016) to assess how efficiently water has been utilized. Total water consumed by a production unit or water consumed per unit product were used as indicators of water consumed by the manufacturing unit (Skerlos et al. 2008; Samuel et al. 2013).

Fresh Water consumption (EN_6): Veleva & Ellenbecker, (2001a) proposed fresh water consumption as an indicator for environmental performance due to its significant importance. Manufacturing activities like electroplating consume significant amount of clean water which is often obtained by withdrawing fresh water from water bodies and then cleaning it through treatment. The higher consumption of fresh water hence leads to adverse impact on biodiversity and lowering of water table. Therefore, a reduced fresh water consumption reflects the organizations improved environmental performance (GRI, 2016; Lin et al., 2010; Tseng, 2013).

Solid Waste (EN_7): Debris, Scrap parts, filter material, chips, etc. produced during manufacturing constitute major source of solid wastes. Many studies have utilized Solid Waste as an indicator measured in terms of ratio of mass or volume of solid waste generated to the solid used in manufacturing (Tan et al. 2015; Singh and Sultan 2018; Beekaroo et al. 2019). Park & Kremer, (2017) described quantity of solid waste generated as an important environmental indicator for manufacturing. Shashi et al., (2018) concluded that significant reductions in solid waste leads to significant environmental performance improvement in SME enterprises.

Waste Reduction and Management (EN_8): This indicator refers to the total waste by weight and disposal method (Veleva and Ellenbecker 2001; GRI 2002, 2016, 2018). This is particularly an important indicator as waste minimization and resource preservation has a direct effect on environmental performance. Bour et al., (2019) concluded that a good waste management policy involving reuse, recycling and waste reduction among other practices not only improved environmental performance but results in increased profit margin as well. Waste minimization and promotion of recycling of material is found to have high correlation in context of implementing environment friendly practices in Indian manufacturing (Gupta et al. 2018).

Water Pollution (Discharge of effluent and pollutant) (EN_9): This indicator quantitatively provides information about water effluents discharged by the manufacturing unit. Some of the most toxic substances in the wastewater include heavy metals and volatile organic compounds (VOCs), originating from manufacturing activities such as cooling, lubricating coating and cleaning. Such pollutants and effluents present in discharged water create concerns like biochemical oxygen demand in water bodies, grease, fats, oils, and Water acidification. Feil et al., (2019) identified wastewater effluents a critical indicator to measure the environmental performance of manufacturing in SMEs.

Recycled Materials (EN_{10}): The efficient use of material is achieved by adapting technologies for recycling and reprocessing of material. Recycled material consumption and reused materials have been frequently used as indicators of environmental performance. Many studies have measured recycled material in terms of percentage of materials used that are recycled input materials (Azapagic et al., 2016; Fan et al., 2010; GRI, 2016). This indicator recognizes the organization's ability and its success to use recycled input materials for achieving environmental protection goals with respect to materials consumption.

Material Consumption (EN_{11}): Inefficient utilization of material in manufacturing leads to not just pollution in the form of waste but also puts an extra cost of handling the waste (Gupta et al. 2015). So material indicator relates to the conservation of materials measured in terms of weight and volume. Material consumption consist of the raw materials needed for production, associated materials, non-renewable materials, semi-finished parts used in manufacturing (GRI 2002, 2016). Quantitatively this indicator is measured as Material use per unit of production on mass basis like kg/PU (Krajnc and Glavič 2003) or m^3/PU (Veleva et al. 2001; Fan et al. 2010; Winroth et al. 2016).

Total Air Emissions (EN_{12}): This indicator takes into account all the gaseous emissions like taking CO_2, SOx, NOx and persistent organic pollutants (POP) (GRI 2002, 2016). The air pollution indicators are a reliable systematic way of measuring environmental impacts and air emissions are generally measured in conjunction with wastewater and solid waste (Ahmad et al. 2019). Air emission as an indicator for evaluating the environmental impact has been used in different contexts such as cement manufacturing (Amrina et al., 2016), die-casting process planning (Singh et al., 2012), Indian Electrical Panel Industries (Gupta et al. 2015), etc.

Greenhouse Gas Emissions (EN_{13}): Carbon Dioxide Emissions and Air Pollution are useful air quality related indicators (Park and Kremer 2017). Kai et al., (2016) proposed Global Warming Potential (GWP) in terms of CO_2 or equivalent and potential acidification indicators measured in terms of SO_2 or equivalent as useful air quality related indicators for sustainable additive manufacturing in medium and large enterprises.

Green Product Design (EN_{14}): It refers to design of products that can be disassembled, reused or recycled being free of hazardous materials (Veleva and Ellenbecker 2001; Güngör 2006) and has been found to be an important indicator for assessing environmental performance for manufacturing activities (Fan et al. 2010). A product developed with high ability of recycling, reuse, remanufacturing and reprocessing attributes contributes to the efficient utilization of resources.

Land Pollution/Soil Protection (EN_{15}): Manufacturing units generate large amount of different wastes which requires land area for disposal. It leads to the degradation of land quality and pollution of water bodies and eventually some of these wastes also cause air pollution (Zhu 2016). This indicator hence provides information about the amount of pollutant directly going to the nearby lands, landfills (Veleva & Ellenbecker, 2001a).

Thus, based on the identification of critical indicators, an integrated framework has been applied, the details of which have been presented in the next section.

4. Method

The present work integrates DEMATEL, MMDE, and ISM techniques to identify interdependent relations among critical environmental indicators (Singh & Bhanot, 2020). There is a specific reason behind the selection of each techniques and the entire integrated approach in particular for the present work. DEMATEL provides flexibility in evaluating the interactions on an appropriate scale of 0-4 among factors (indicators) under consideration. However, integrating results obtained from DEMATEL with ISM requires threshold value, for which many researchers rely on discussion with a group of experts. This method of setting threshold value is time-consuming and requires several rounds of discussion with experts until all of them agree on a common value. This problem is resolved by the MMDE method, which is a scientific algorithm to determine a suitable threshold value by utilizing entropy calculations. ISM is an established technique to construct the hierarchical structure, by identifying the interrelationships among the factors. Researchers often use ISM in combination with MICMAC analysis. The MICMAC analysis, based on the multiplication properties of matrices, is used to analyze the strengths of the relationships between the factors. Step-by-Step procedure for each method is explained in the following sections:

4.1. DEMATEL

Decision Making Trial and Evaluation Laboratory (DEMATEL) is a MCDM technique used to solve complicated decision-making problems involving intertwined factors. DEMATEL is a structural modeling approach based on graph theory. This technique solves problems visually by developing structural models and useful in analyzing cause and effect relations among factors having complicated causal relationships (Bacudio et al. 2016). DEMATEL helps in identifying the most influential factors among a set of interdependent factors (Wu and Lee 2007).

This technique is used extensively in solving a variety of problems e.g. supplier selection for green supply chain (Hsu et al., 2013); cost effective sustainable manufacturing system (Nujoom et al. 2019): enablers and barriers related to sustainable manufacturing (Bhanot et al. 2017); challenges in implementing environmental sustainability in automobile manufacturing (Mathiyazhagan et al. 2018); structured model for drivers of sustainable consumption and production (Luthra et al. 2017), etc. The DEMATEL analysis has been done using Python program wherein algorithm has been developed based on existing steps (Hsu et al. 2013). The DEMATEL steps followed for this study are explained as follows:

Step I: Collect opinions from industry professionals using individual direct-influence matrix based Questionnaire.

For this study, 23 industry professionals having adequate knowledge and expertise of lock manufacturing industry were contacted through phone, email and personal visits. Out of these 23 professionals, 16 were interested in this research. A standard individual direct-influence matrix based Questionnaire was prepared and sent to these 16 industry professionals. Each expert was informed about the scope of the study and relevant information was provided with the questionnaire. However, to avoid any bias in the responses, any meeting and data sharing among experts was avoided. Subsequently, ten complete responses were obtained for further analysis.

Step II: Compute the Average Matrix using individual direct-influence matrices collected from industry professionals.

The industry professionals indicated the degree to which an indicator in "i"th row influences the indicator in "j"th column. Using an integer scale of 0 to 4, the experts indicated the extent of influence of indicator in "i"th row on the indicators in "j"th column; indicating "No influence (0)", "Low influence (1)", "Medium Influence (2)", "High influence (3)" and "Very High Influence (4)".

Let x_{ij}^{k} represents the extent of influence of indicator in in "i"th row on the indicator in "j"th column estimated by expert "k". This will give a $n \times n$ non-negative matrix for each respondent represented by $X^{k} = \left[x_{ij}^{k}\right]_{n \times n}$ Where X^{k} is called individual direct-influence matrix and principle diagonal elements $(i = j)$ for all respondent's matrix is 0. So, an $n \times n$ average matrix (A) can be calculated by aggregating all individual direct-influence matrices obtained from industry professionals as per the equation (1):

$$A = [a_{ij}]_{n\times n} = \frac{1}{h}\sum_{k=1}^{h} x_{ij}^{k} \tag{1}$$

Step III: Calculate Normalized Initial Direct Relation Matrix (D).

It can be obtained from average matrix (A), as per the equation (2):

$$D = \frac{A}{S} \tag{2}$$

$$S = max\left(max_{\ 1\le i\le n}\sum_{j=1}^{n} a_{ij}\,,\ \ max_{1\le i\le n}\sum_{i=1}^{n} a_{ij}\right) \tag{3}$$

Where, $s > 0$

Step IV: Calculate Total Relation Matrix(T_{RM}).

T_{RM} is computed from normalized direct influence matrix (D) by utilizing the relation shown in equation (4):

$$T_{RM} = [t_{ij}]_{n\times n} = D(I-D)^{-1} \tag{4}$$

Where, ***I*** is an $n \times n$ Identity matrix.

Step V: Calculate R and C from T_{RM} .

R and C are $n \times 1$ and $1 \times n$ vectors respectively, where R represents the sum total of rows whereas C represents sum total of columns of the matrix T_{RM} and calculated as per equations 5 and 6:

$$R = [r_i]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} \tag{5}$$

$$C = [c_j]_{1\times n} = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n} \tag{6}$$

Here, r_i indicates the sum of total influence exerted by the i^{th} indicator on other indicators and obtained by adding the i^{th} row elements of matrix T_{RM}. Similarly, c_j represents the total influence received by j^{th} indicator from the other indicators and obtained by adding the j^{th} column elements of matrix T_{RM}. $R + C$ and $R - C$ are called "Prominence" and "Relation" respectively. $R + C$ denotes the degree of determining role played by the indicator (i.e. the influence or Prominence given or received of the indicator) while $R - C$ represents the net effect produced by a factor (i.e. the degree of one factor being influenced or casual influence by other factors) (Si et al. 2018).

Step VI: Preparing a Causal Diagram.

A cause-effect plot is prepared with $R + C$ (prominence) on horizontal axis and $R - C$ (relation) on vertical axis. Positive $R - C$ values indicates that factor belongs to cause group, whereas, negative $R - C$ values means factor belongs to effect group i.e. such factors are influenced by the other factors.

4.2. MMDE Algorithm

The main advantage of DEMATEL methodology is that it quantifies the degree of significance furthermore highlights the strength of various factors among themselves. The total relation matrix (T_{RM}) derived from DEMATEL can be further utilized to get a hierarchical structure (impact-relations map) by the application of ISM technique. However, before applying ISM, a suitable threshold value is chosen and mostly determined by taking the opinion of experts or decision-makers. In this context, MMDE (Maximum mean de-entropy) algorithm (Chung-Wei and Gwo-Hshiung 2009) is the only scientific technique that provides a reliable threshold value and eliminates the need for experts. MMDE algorithm, uses the entropy approach in combination with de-entropy and mean de-entropy. For this study, a Python code for MMDE algorithm has been prepared and steps for obtaining threshold value using MMDE algorithm are described as follows:

Step I: Transform total relation matrix $\boldsymbol{T_{RM}}$ of order $n \times n$ into an ordered set $\mathrm{T_{RM}}$ namely**,** $\{\boldsymbol{t_{11}}, \boldsymbol{t_{12}}, \dots, \boldsymbol{t_{21}}, \boldsymbol{t_{22}}, \dots, \boldsymbol{t_{nn}}\}$. Subsequently, the elements of set $\mathrm{T_{RM}}$ are rearranged in descending order, and then transformed to a ordered triplet $(\boldsymbol{t_{ij}}, \boldsymbol{x_i}, \boldsymbol{x_j})$ set denoted by T^*_{RM}.

Step II: Obtain the dispatch-node set $\boldsymbol{T^{Di}}$ by taking out the second element from $\boldsymbol{T^*_{RM}}$. The $\boldsymbol{T^{Di}}$ can be defined as follows::

$$\boldsymbol{T^{Di}} = \{x_i\} = \{x_1, x_2, x_3, \dots \dots \dots \dots \dots . x_{n \times n}\} \tag{7}$$

Step III: calculate the mean de-entropy of $\boldsymbol{T^{Di}}$**.** Make a new set $\boldsymbol{T^{Di}_t}$ from $\boldsymbol{T^{Di}}$ by taking its first **t** elements, where, $t = 1,2,3 \dots \dots \dots \dots \dots .. C(\boldsymbol{T^{Di}})$, and $C(\boldsymbol{T^{Di}})$ represents the no of variables. Similarly, $\boldsymbol{N}(\boldsymbol{T^{Di}})$ corresponds to the No of variables with distinct value and used to determine the probabilities of different elements.

Furthermore, determine $\boldsymbol{H^{Di}}$ of $\boldsymbol{T^{Di}_t}$, then find $\boldsymbol{H^{Di}_t}$ by using relation as per equation (8).

$$\boldsymbol{H^{Di}_t} = H\left[\frac{1}{\boldsymbol{N}(\boldsymbol{T^{Di}})}, \frac{1}{\boldsymbol{N}(\boldsymbol{T^{Di}})}, \dots \dots \dots \dots \dots \frac{1}{\boldsymbol{N}(\boldsymbol{T^{Di}})}\right] - K\left[\frac{k_1}{C(\boldsymbol{T^{Di}})}, \frac{k_2}{C(\boldsymbol{T^{Di}})}, \dots \dots \dots \dots \dots \frac{k_t}{C(\boldsymbol{T^{Di}})}\right] \tag{8}$$

Now determine mean de-entropy ($\boldsymbol{MDE^{Di}_t}$) values according to equation (9)

$$\boldsymbol{MDE^{Di}_t} = \frac{\boldsymbol{H^{Di}_t}}{\boldsymbol{N}(\boldsymbol{T^{Di}_t})} \tag{9}$$

Where k represents the frequency of variable x_i.

Step IV: From $\boldsymbol{C}(\boldsymbol{T^{Di}})$ mean de-entropy values select the maximum $\boldsymbol{MDE^{Di}_t}$ designate it as $\boldsymbol{T^{Di}_{max}}$.

$$\boldsymbol{T^{Di}_{max}} = \max\left(\boldsymbol{MDE^{Di}_t}\right) = \{\boldsymbol{x_1}, \boldsymbol{x_2} \dots \dots \dots \dots \dots \dots \boldsymbol{x^{max}_t}\} \tag{10}$$

Step V: Derive an ordered receive-node set $\boldsymbol{T^{Re}}$ and $\boldsymbol{T^{Re}_{max}}$(maximum mean de-entropy receive-node set) by following procedure similar to step 2 to 4.

Step VI: The maximum information set is constructed and threshold value is determined. This is done by creating a subset, $\boldsymbol{T^{Th}}$, from the first u elements of triple set $\boldsymbol{T^*_{RM}}$. $\boldsymbol{T^{Th}}$**,** consist of all elements of $\boldsymbol{T_{max}^{Di}}$ and $\boldsymbol{T_{max}^{Re}}$ in dispatch-node and receive-node respectively. The least influence value in $\boldsymbol{T^{Th}}$ is the threshold value, and the process is summarized in equation (11) as follows:

$$\boldsymbol{T^{Th}} = \{\boldsymbol{t_{ij}}, \boldsymbol{T_{max}^{Di}}(\boldsymbol{x_i}), \boldsymbol{T_{max}^{re}}(\boldsymbol{x_j})\} \tag{11}$$

4.3. ISM

Interpretive Structural Modelling (ISM) is used to ascertain the relationship amongst selected factors (indicators). Through ISM, a group of different but directly interrelated factors are structured into a well-defined systematic model (Hussain et al. 2016). ISM helps in constructing, a comprehensive multilevel model can be constructed by dividing a complex set of factors in to several smaller set of factors (Talib et al. 2011; Sarabi et al. 2020) thereby helping to turn loosely visualized models into well-defined, clearly articulated ones.

Steps followed for ISM method are as follows:

Step I: Initial Reachability matrix (I_{RM}) has been considered for ISM. I_{RM} is derived by transforming total relation matrix (T_{RM}) into a matrix having 0 and 1 after the application of threshold value obtained by MMDE algorithm..

Step II: Modify the initial reachability matrix (I_{RM}) by checking it for transitivity i.e. if factors $\boldsymbol{X}$ and $\boldsymbol{Y}$ are related and $\boldsymbol{X}$ is related to another factor $\boldsymbol{Z}$, then it means that $\boldsymbol{Y}$ is necessarily related to $\boldsymbol{Z}$. After checking for all the transition links, initial reachability matrix (I_{RM}) transforms to a final reachability matrix (F_{RM}) is obtained.

Step III: For each factor, antecedent sets and reachability sets are derived. The final reachability matrix (F_{RM}) partitioned in to different level through a series of iterations based on antecedent and reachability sets.

Step IV: Prepare a diagraph plot based on the level portioning (step III) of the factors by removing transitive links.

Step V: Transform the Digraph into an ISM model by adding statements in place of nodes.

Step VI: MICMAC analysis carried to obtain dependence and driver power of the factors (indicators) and obtain key factors that drive the system(Talib et al. 2011). In accordance to the factors, driver and dependence power, MICMAC analysis classifies factors into four clusters presented as follows:

Cluster I: Autonomous Factors – These factors are relatively cut off from the system and have weak or no dependence on other factors.

Cluster II: Dependent Factors – These are primarily dependent on other factors.

Cluster III: Linkage Factors – These are connecting factors that are unstable and mostly influence others.

Cluster IV: Independent Factors – These have weak influence from others factors and have to be paid maximum attention owing to the strong key factors.

5. Results and Discussion:

In this section, the results obtained from the application of the integrated framework on the lock manufacturing industries belonging to MSME sector of India is presented and discussed in detail as per the opinion of industry professionals.

Integrated approach of analyzing the Environmental Indicators

According to the description in the method section, the DEMATEL approach was applied after a pair-wise comparison of the indicators of lock manufacturing units belonging to Indian MSMEs. An Average Matrix (T_{av}) (Appendix A2) was prepared depending on the opinions of the industry professional, which were recorded through a questionnaire.

An Average Matrix plot was prepared as per the pair-wise comparison for better understanding (Figure 3) with dark shades presenting higher impact. Figure 3 clearly shows that $EN_1$and EN_2 have the highest impact on EN_{13}, which is evident from the high average values of 3.8 in each case. Similarly, EN_6 has the highest impact on EN_4, which is obvious from the high average value of 3.8.

Likewise, the high impact of EN_4 on EN_5 and EN_{10}; EN_{11} on EN_7; and EN_{13} on EN_3 is evident from the high average value of 3.6 in each pair. As the impact of row indicators on column indicators decreases, the shade of the corresponding cell becomes lighter. For better understanding, a scale is given alongside the average matrix plot. Based on the Average Matrix (T_{av}) (Figure 3 and Appendix A2), a Total Relation Matrix (T_{RM}) is prepared as shown here.

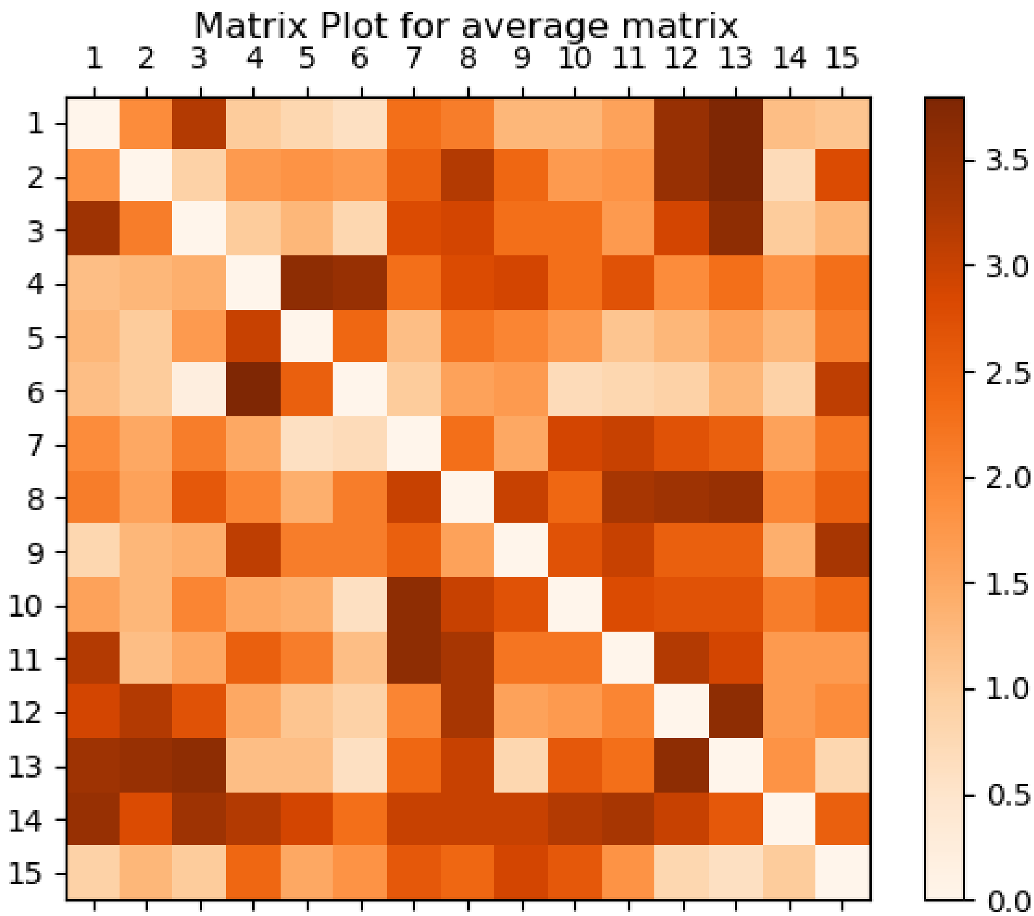

Figure 3: The Average Matrix plot for Environmental indicators

$$\boldsymbol{T_{RM}} = \begin{array}{cc} & \begin{array}{ccccccccccccccc} EN_1 & EN_2 & EN_3 & EN_4 & EN_5 & EN_6 & EN_7 & EN_8 & EN_9 & EN_{10} & EN_{11} & EN_{12} & EN_{13} & EN_{14} & EN_{15} \end{array} \\ \begin{array}{c} EN_1 \\ EN_2 \\ EN_3 \\ EN_4 \\ EN_5 \\ EN_6 \\ EN_7 \\ EN_8 \\ EN_9 \\ EN_{10} \\ EN_{11} \\ EN_{12} \\ EN_{13} \\ EN_{14} \\ EN_{15} \end{array} & \begin{pmatrix} 0.11 & 0.14 & 0.178 & 0.12 & 0.1 & 0.085 & 0.177 & 0.18 & 0.134 & 0.14 & 0.15 & 0.211 & 0.222 & 0.103 & 0.127 \\ 0.162 & 0.106 & 0.139 & 0.154 & 0.136 & 0.123 & 0.198 & 0.221 & 0.175 & 0.164 & 0.171 & 0.226 & 0.237 & 0.103 & 0.182 \\ 0.197 & 0.154 & 0.118 & 0.133 & 0.121 & 0.099 & 0.204 & 0.212 & 0.169 & 0.175 & 0.167 & 0.215 & 0.234 & 0.108 & 0.146 \\ 0.153 & 0.138 & 0.153 & 0.126 & 0.184 & 0.171 & 0.201 & 0.219 & 0.194 & 0.183 & 0.196 & 0.196 & 0.209 & 0.132 & 0.181 \\ 0.124 & 0.105 & 0.13 & 0.161 & 0.079 & 0.125 & 0.14 & 0.167 & 0.144 & 0.138 & 0.128 & 0.145 & 0.156 & 0.098 & 0.144 \\ 0.106 & 0.092 & 0.082 & 0.167 & 0.126 & 0.063 & 0.119 & 0.137 & 0.124 & 0.102 & 0.107 & 0.118 & 0.13 & 0.08 & 0.153 \\ 0.157 & 0.132 & 0.157 & 0.138 & 0.101 & 0.092 & 0.133 & 0.19 & 0.146 & 0.181 & 0.187 & 0.199 & 0.198 & 0.116 & 0.158 \\ 0.189 & 0.159 & 0.194 & 0.178 & 0.143 & 0.144 & 0.233 & 0.173 & 0.207 & 0.199 & 0.224 & 0.248 & 0.255 & 0.145 & 0.194 \\ 0.139 & 0.134 & 0.147 & 0.186 & 0.145 & 0.134 & 0.199 & 0.186 & 0.122 & 0.186 & 0.197 & 0.202 & 0.206 & 0.119 & 0.194 \\ 0.163 & 0.139 & 0.167 & 0.152 & 0.129 & 0.101 & 0.228 & 0.221 & 0.185 & 0.13 & 0.198 & 0.214 & 0.218 & 0.137 & 0.176 \\ 0.203 & 0.143 & 0.164 & 0.179 & 0.15 & 0.119 & 0.235 & 0.235 & 0.18 & 0.185 & 0.141 & 0.233 & 0.232 & 0.133 & 0.167 \\ 0.191 & 0.181 & 0.182 & 0.148 & 0.121 & 0.105 & 0.191 & 0.226 & 0.159 & 0.166 & 0.177 & 0.154 & 0.238 & 0.126 & 0.163 \\ 0.206 & 0.191 & 0.205 & 0.143 & 0.124 & 0.099 & 0.204 & 0.225 & 0.145 & 0.188 & 0.187 & 0.24 & 0.165 & 0.13 & 0.141 \\ 0.243 & 0.206 & 0.235 & 0.228 & 0.196 & 0.168 & 0.262 & 0.271 & 0.233 & 0.242 & 0.25 & 0.27 & 0.268 & 0.117 & 0.22 \\ 0.113 & 0.11 & 0.113 & 0.148 & 0.112 & 0.111 & 0.172 & 0.171 & 0.163 & 0.158 & 0.145 & 0.135 & 0.134 & 0.092 & 0.097 \end{pmatrix} \end{array}$$

This cause and effect analysis (Appendix A3) is further presented graphically in the form of a casual diagram of indicators (Figure 4). The X-axis represents the Degree of Prominence $(R + C)$, denoting the degree of determining role played by an indicator or in other words, it represents the influence (Prominence) given or received of the indicators. While Y-axis represents Casual Degree $(R - C)$, which represents the net effect produced by an indicator i.e. the degree of one indicator being influenced (casual influence) by other indicators. So environmental indicators having positive $R - C$ values belongs to cause group i.e. such indicators have net influence over others. Whereas, indicators having negative $R - C$ values belong to effect group i.e. such indicators are influenced by the other indicators.

From Appendix A3 and Figure 4, it is evident that based on prominence, (R+C) indicators can be arranged as $EN_8 > EN_{13} > EN_{12} > EN_{11} > EN_7 > EN_4 > EN_{10} > EN_4 > EN_9 > EN_3 > EN_1 > EN_2 > EN_{15} > EN_5 > EN_6$. However, it can be observed from the R-C values that EN_{14}, EN_2, EN_4, EN_3, EN_{11}, EN_{10}, EN_5 and EN_9 belong to the cause group, whereas EN_6, EN_8, EN_1, EN_{15}, EN_{12}, EN_{13} and EN_7 belong to the effect group.

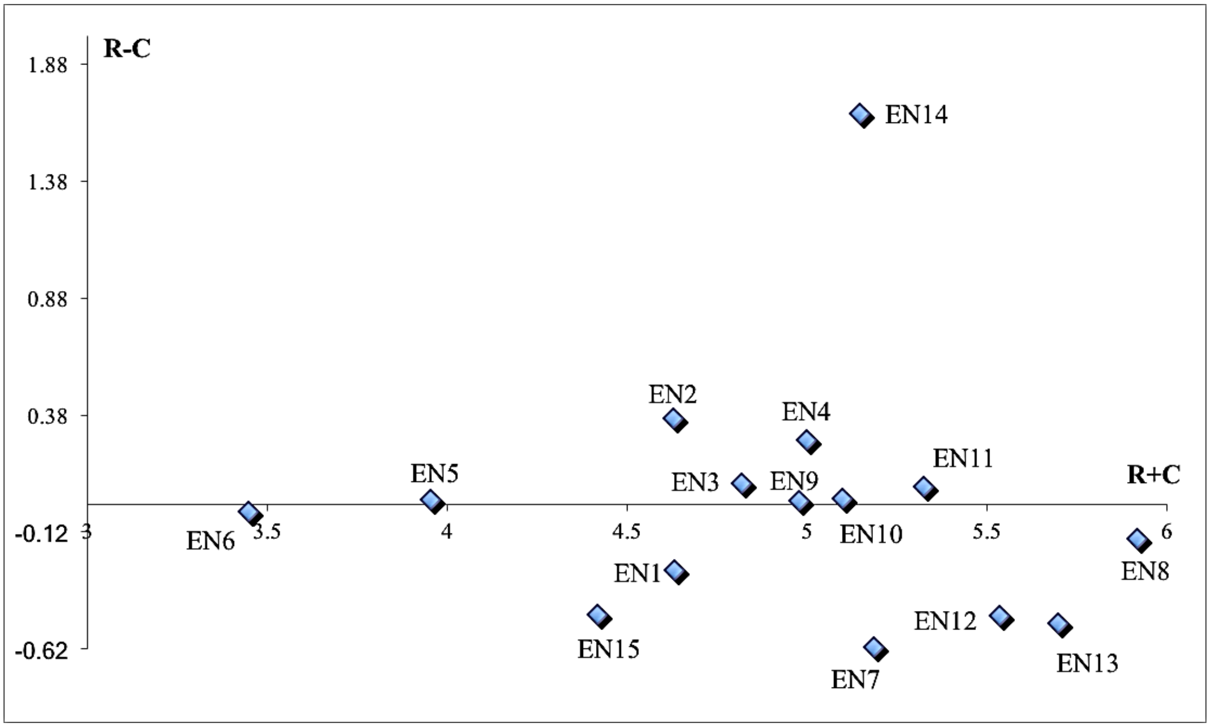

Figure 4: Casual Diagram for Environmental Indicators

After DEMATEL analysis, a final threshold value of 0.22 was obtained by applying MMDE algorithm on the Total Relation Matrix (T_{RM}). By utilizing this threshold value, the Total Relation Matrix (T_{RM}) was transformed into Initial Reachability Matrix (I_{RM}) so that the structural relationship between the indicators can be obtained. The cell values of T_{RM} above 0.22 (Threshold value) were replaced by 1 while the other cell values were replaced by 0; hence, the Initial Reachability Matrix I_{RM} consisted of cell values 0 and 1.

Based on the Initial Reachability Matrix (I_{RM}), the ISM technique was applied, and a digraph plot was prepared. The digraph plot shown in Figure 5 clearly indicated the significant impact of EN_{14} (shown by No 14) on the other indicators as well as the lack of participation of indicators EN_5 and EN_6. The Initial Reachability Matrix (I_{RM}) was subsequently transformed into a Final Reachability Matrix (F_{Rm}) after checking it for transitive relationships.

$$
\boldsymbol{I_{RM}} = \begin{array}{c c}
 & \begin{array}{ccccccccccccccc} EN_1 & EN_2 & EN_3 & EN_4 & EN_5 & EN_6 & EN_7 & EN_8 & EN_9 & EN_{10} & EN_{11} & EN_{12} & EN_{13} & EN_{14} & EN_{15} \end{array} \\
\begin{array}{c} EN_1 \\ EN_2 \\ EN_3 \\ EN_4 \\ EN_5 \\ EN_6 \\ EN_7 \\ EN_8 \\ EN_9 \\ EN_{10} \\ EN_{11} \\ EN_{12} \\ EN_{13} \\ EN_{14} \\ EN_{15} \end{array} &
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\
1 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix}
\end{array}
$$

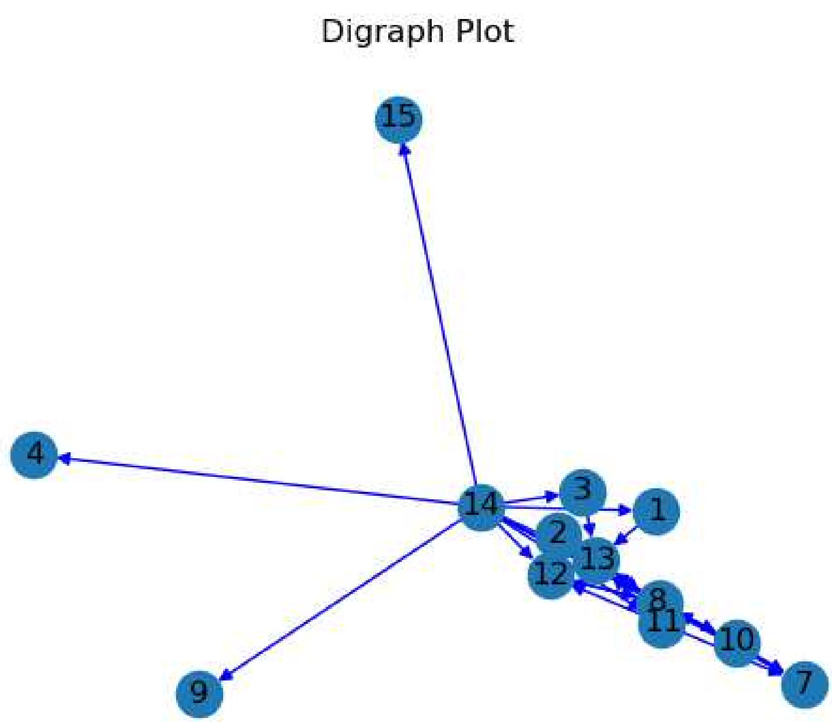

Figure 5: Digraph plot for Environmental Indicators

$$\boldsymbol{F_{RM}}= \begin{array}{cc} & \begin{array}{ccccccccccccccc} EN_1 & EN_2 & EN_3 & EN_4 & EN_5 & EN_6 & EN_7 & EN_8 & EN_9 & EN_{10} & EN_{11} & EN_{12} & EN_{13} & EN_{14} & EN_{15} \end{array} \\ \begin{array}{c} EN_1 \\ EN_2 \\ EN_3 \\ EN_4 \\ EN_5 \\ EN_6 \\ EN_7 \\ EN_8 \\ EN_9 \\ EN_{10} \\ EN_{11} \\ EN_{12} \\ EN_{13} \\ EN_{14} \\ EN_{15} \end{array} & \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \end{array}$$

The reachability and antecedent sets (Table 1) of Environmental indicators were derived from the Final Reachability Matrix (F_{RM}). For a given indicator, the “reachability set” includes the indicator itself and indicators, which it may affect, while the “antecedent set” consisted of the indicator itself and indicators affecting it. Subsequently, the intersection of both sets obtained for all indicators and level of each indicator is determined. The indicators having same reachability and the intersection sets occupy the first level. In order to assess the next level indicators, the first level indicators were then isolated from the other indicators for the next stage-iteration. The same procedure was repeated until the level was identified for each indicator.

Table 1 shows the level partitioning of environmental indicators to be placed in the ISM model. In the table, the number inside the sets table (i.e., Reachability Set, Antecedent Set, and Intersection Set) represented the respective indicator. For example, the set number [1, 3, 7, 8, 9, 11, 12, 13] in the reachability set against the factor EN_1 meant a set of [EN_1, EN_3, EN_7, EN_8, EN_9, EN_{11}, EN_{12}, EN_{13}] indicators and so on.. However, the numbers related to the Levels as given in the column indicated the Rank of the indicator.

On the basis of the levels assigned (Table 1) to various environmental indicators, statistically valid structural ISM model was prepared and presented in Figure 6. Arrows further link the indicators based on the relations derived from the Initial Reachability Matrix (I_{RM}). It can be seen from the ISM model (Figure 6) that EN_{14} is the most critical indicator of environmental performance in lock manufacturing. Thus, indicators measuring environmental concerns at the product design level were found to be significantly affecting other indicators.

Table 1: Level Partitioning of Environmental Indicators

Factors	Reachability Set	Antecedent Set	Intersection Set	Levels
EN_1	[1, 7, 8, 11, 12, 13]	[1, 14]	[1]	3
EN_2	[2, 7, 8, 11, 12, 13]	[2]	[2]	3
EN_3	[3, 7, 8, 11, 12, 13]	[3, 14]	[3]	3
EN_4	[4]	[4, 14]	[4]	1
EN_5	[5]	[5]	[5]	1
EN_6	[6]	[6]	[6]	1
EN_7	[7]	[1, 2, 3, 7, 8, 10, 11, 12, 13, 14]	[7]	1
EN_8	[7, 8, 11, 12, 13]	[1, 2, 3, 8, 10, 11, 12, 13, 14]	[11, 12, 13, 8]	2
EN_9	[9]	[9, 14]	[9]	1
EN_{10}	[7, 8, 10, 11, 12, 13]	[10, 14]	[10]	3
EN_{11}	[7, 8, 11, 12, 13]	[1, 2, 3, 8, 10, 11, 12, 13, 14]	[11, 12, 13, 8]	2
EN_{12}	[7, 8, 11, 12, 13]	[1, 2, 3, 8, 10, 11, 12, 13, 14]	[11, 12, 13, 8]	2
EN_{13}	[7, 8, 11, 12, 13]	[1, 2, 3, 8, 10, 11, 12, 13, 14]	[11, 12, 13, 8]	2
EN_{14}	[1, 3, 4, 7, 8, 9, 10, 11, 12, 13, 14, 15]	[14]	[14]	4
EN_{15}	[15]	[14, 15]	[15]	1

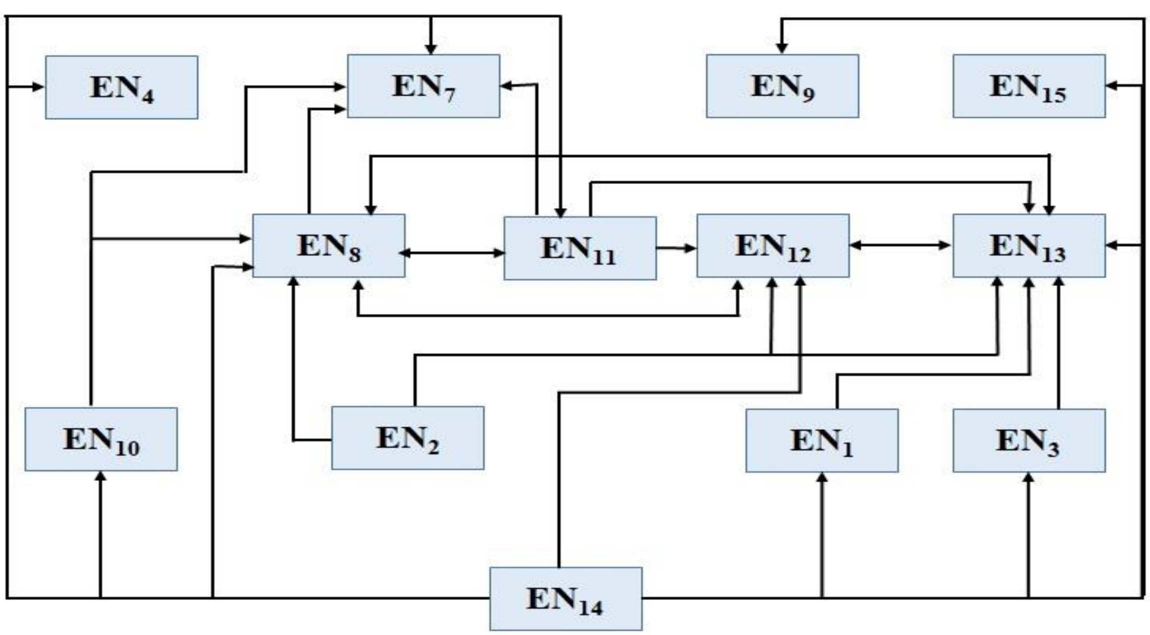

Figure 6: ISM model for Environmental Indicators

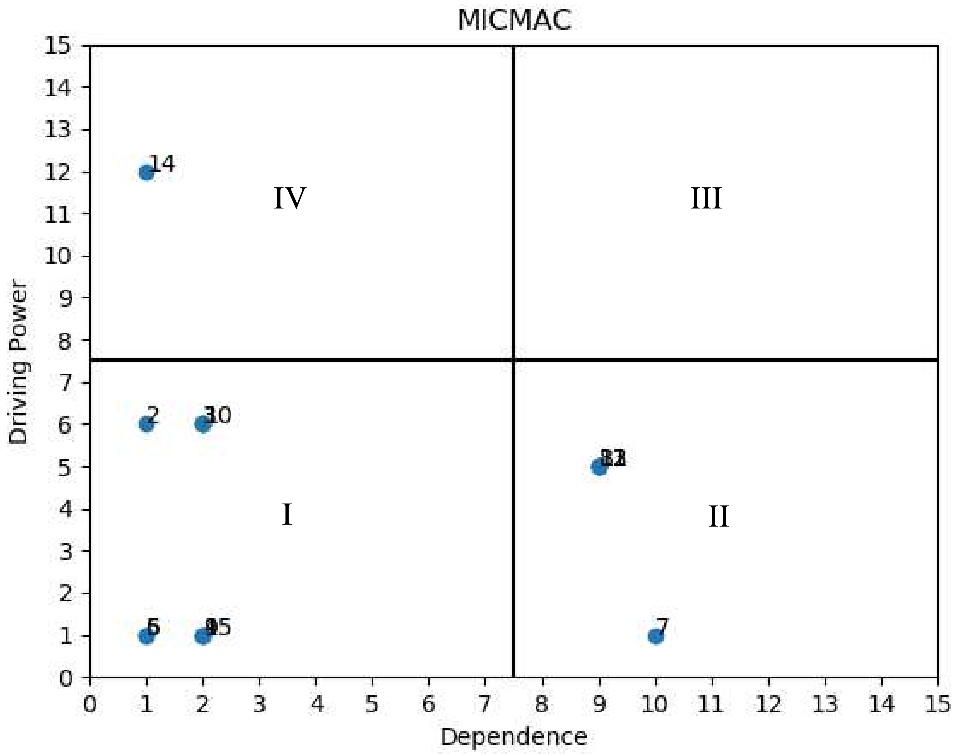

Figure 7: MICMAC Analysis of Environmental Indicators

MICMAC was used to test the intensity of the correlation between dependency and driving powers of indicators. Based on their dependency and driving powers the indicators had been classified into four clusters as evident from figure 7.

Cluster-I represented the autonomous indicators having weak driving and dependence power. This cluster constituted nine (EN_1, EN_2, EN_3, EN_4, EN_5, EN_6, EN_9, EN_{10}, EN_{15}) indicators (60%), i.e., Energy Consumption (EN_1), Renewable and Non-Renewable Energy Consumption (EN_2), Energy Intensity (EN_3), Recycling and reuse of water (EN_4), Amount of Water Consumption (EN_5), Use of fresh water (EN_6), Recycled Materials (EN_{10}), and Land pollution/Soil Protection (EN_{15}). Cluster-II presented the dependence indicators with weak driving power but having strong dependence power. 33.33.% indicators were identified under cluster-II , which were Solid waste (EN_7), Waste Reduction and Management (EN_8), Material consumption (EN_{11}), Total Air Emissions (EN_{12}), and Greenhouse Gas Emissions (EN_{13}). From the model, it is evident that EN_8, EN_{11}, EN_{12}, and EN_{13} only affected EN_7 and generally had mutual effect among themselves. However, all these indicators were greatly affected by level 3 and level 4 indicators. Cluster-III represented the linkage indicators; however, no indictor fell in this cluster. Cluster-IV consisted of indicators having strong driving power but weak dependence power. Only one indicator (6.67%), i.e., Green product design (EN_{14}) was found under this cluster and it played a governing role in environmental performance of lock manufacturing.

Discussion on significant relationships between the Environmental Indicators

Green product design (EN_{14}) has significant effect on eleven indicators that emphasizes on recycling like Recycling and reuse of water (EN_4), Recycled Materials (EN_{10}). Similarly, EN_{14} is found to significantly affect the waste reduction and pollution control indicators like Solid waste (EN_7), Waste Reduction and Management (EN_8), Water pollution (EN_9), Total Air Emissions (EN_{12}), Greenhouse Gas Emissions (EN_{13}), and Land pollution/Soil Protection (EN_{15}). Indicators involving resource consumption such as Energy Consumption (EN_1), Energy Intensity (EN_3), and Material consumption (EN_{11}) are also found to be significantly affected by EN_{14}. Developing a product with high ability to recycle and reuse contributes to the conservation of natural resources (Huysman et al. 2015). Therefore, managers must incorporate practices, which enable designing of products using free hazardous materials so that these materials can be disassembled, reused or recycled (Tseng 2013).

Renewable and Non-Renewable Energy Consumption (EN_2) not only has significant effect on Total Air Emissions (EN_{12}) and Greenhouse Gas Emissions, but it also significantly affects Waste Reduction and Management (EN_8). A major portion of environmental pollution from manufacturing industries is a direct outcome of energy used from non-renewable energy sources. Hence, using the renewable energy sources will automatically result in reduced air emission (Jovane et al. 2008; Tseng et al. 2013; Martinico-Perez et al. 2018) .

Material consumption (EN_{11}) has significant impact on indicators like solid waste (EN_7), waste reduction and management (EN_8), Total Air Emissions (EN_{12}), and Greenhouse Gas Emissions (EN_{13}), so it has a critical role in the enhancement of environmental performance in the manufacturing sector. Material consumption (EN_{11}) as an indicator measures the efficient utilization of material, and material efficiency is closely associated with three major objectives of any manufacturers, namely, reducing materials cost, reducing waste (generation of all kinds and its handling), and reducing environmental pollution from manufacturing activities (Ho et al. 2019).

Waste reduction and management (EN_8) indicator is affected by the indicator, recycling of materials (EN_{10}), apart from EN_2, EN_{11}, and EN_{14} as discussed above. The adoption of effective strategies and techniques for waste management conserves resources, reduces raw material consumption, encourages recycling and reuse of materials, minimizes environmental and land pollution and prevents health and social problems (Singh et al. 2018). Latif et al., (2017) observed that high material recycling percentage coupled with an effective waste management strategy results in higher waste management index, which increases the environmental performance score in manufacturing organization.

Greenhouse Gas Emissions (EN_{13}) is significantly affected by Energy Consumption (EN_1) and Energy Intensity (EN_3) apart from the indicators discussed earlier in this section. Therefore, reducing energy consumption and improving energy efficiency are considered as important parameter (Joung et al. 2013; Nulkar 2014; Bekun et al. 2019; Mavi and Mavi 2019; Akdag and Yıldırım 2020) for diminishing greenhouse gas emission and enhancing environmental performance in lock manufacturing.

It can be inferred from the above discussion that the incorporation of recycling and reuse in the products design will play a significant role in enhancing environmental performance of lock manufacturing industries belonging to the MSME sector; hence, the indicator EN_{14} will prominently affect other indicators. The environmental impacts specific to a product are largely determined during the design stage; therefore, it is amply beneficial to take product design decisions that facilitates environmentally conscious manufacturing (Ilgin and Gupta 2010; Haapala et al. 2013). Hence, the design of lock components should incorporate concepts like design for recycling, design for disassembly to achieve reduction in the demand of raw materials, and mitigating the burden on ecosystem (soil contamination/land for waste disposal, air and water pollution) (Krajnc and Glavič 2003; Rizova et al. 2020). With increase in the percentage of products that can be recycled, reused, and free from hazardous substance, it is obvious that the organization is moving toward greater environmental performance (Veleva and Ellenbecker 2001). The other cause and effect relations discussed here have been acknowledged by researcher and industry professional in many studies (Boyden et al., 2016; Kai et al., 2016; Ocampo et al., 2015; Park & Kremer, 2017; Vinodh et al., 2014; Zarte et al., 2018).

6. Conclusions:

This study analyzed the interdependence among the environmental performance indicators in Indian Lock manufacturing industry belonging to the MSME sector. As it is not feasible to utilize large number of indicators for environmental performance assessment, the study focused on 15 critical environmental indicators identified from the literature. The interdependence relation was analyzed by taking into account the opinions of industry professional. Hence, the results highlighted the importance of incorporating sustainability at the product design level, which emphasized on the fact that Green product design (EN_{14}) has high driving power and significant impact 12 indicators out of 15 under consideration. It means by incorporating green concept in product design like reuse, recycling and disassembly will have the largest effect on other aspects of environmental performance.

The framework presented in this study not only provides a hierarchical structure for indicators based on their cause and effect relationships but also highlights the strength of driving and dependence power of indicators. The framework provides a structured and logical approach of decision making for improved environmental performance. The present framework will help managers and decision makers to understand the interaction between the indicators and enable them to obtain a detailed picture of environmental performance of the firm. This framework will allow the managers to better understand production activities of the firm in the context of environmental performance and make specific management interventions that would enhance firm's environmental performance. The framework presented will help decision makers to identify the priority areas and allocate resources for achieving maximum improvement in environmental performance. In a broader sense, this critical indicator-based framework may serve as a strategy development and monitoring tool for enhancing environmental performance of lock manufacturing units. The use of critical indicators combined with this framework will help sustainability practitioners, managers, and government agencies to formulate regulation, procedure, and establish assessment practices to evaluate the environmental performance of a manufacturing organization.

7. Limitations and Future Scope

The scope of the present work being limited to lock manufacturing units belonging to Indian MSME sector, the proposed framework can be expanded to include other areas of Indian MSME sector like the auto parts, foundries and metalwork industries, etc. This study utilizes the views of industry professional; hence, future works may also include views of researchers to understand the differences in the views of both the group. Further studies may also incorporate structural equation modelling within the framework given in this study to investigate the model and enhance the quality and authenticity of the results. Similarly, the fuzzy modelling techniques can also be incorporated into the framework.

Ethical Approval: Full Compliance with Ethical Standards policy of journal.

Consent to Participate: Not applicable.

Consent to Publish: Not applicable.

Authors Contributions: All Authors contributed in every stage including conception and design of this research. Questionnaire design, data collection and analysis were performed by Mr. Abdul Gani and Dr. Neeraj Bhanot, Results from the study were checked by Dr. Faisal Talib and Dr. Mohammad Asjad. The first draft of the manuscript was written by Mr. Abdul Gani and modified by Dr. Neeraj Bhanot and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Competing Interests: None.

Availability of data and materials: Not applicable.

Conflicts of Interest: None.

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Appendices

Appendix A1

Table A1: Environmental Indicators

S.N.	Indicators	Reference	Critical
1	Energy Consumption	Amrina & Yusof, (2011); Amrina & Vilsi, (2015); Bui et al., (2017); GRI, (2002, 2018)	✓
2	Reductions achieved due to Indirect Energy Consumption	Samuel, et al. (2013)	
3	Depletion of Non-Renewable Energy Resource	Vinodh, (2011)	
4	Renewable and Non-Renewable Energy Consumption	Amrina & Yusof, (2011); Amrina & Vilsi, (2015); Bui et al.,(2017); GRI, (2002, 2018); Lin et al., (2010)	✓
5	Energy Intensity	Kluczek,(2016); Krajnc and Glavič, (2003)	✓
6	Direct Energy Consumption By Primary Energy Source	GRI (2002)	
7	Contribution To Depletion Of Energy Resources	Veleva and Ellenbecker (2001a)	
8	Indirect Energy Consumption By Primary Energy Source	GRI (2002)	
9	Recycling and reuse of water	Anderson, (2003); GRI, (2002, 2016); Veleva & Ellenbecker, (2001a); Krajnc and Glavič, (2003)	✓
10	Total water withdrawal by source	Samuel, et al. (2013)	
11	Water sources significantly affected by the withdrawal	GRI (2002)	
12	Amount of Water Consumption	GRI, (2002, 2016); Samuel et al., (2013); Skerlos et al., (2008)	✓
13	Use of fresh water	Lin et al., (2010); Tseng, (2013); Tseng et al., (2009); Veleva & Ellenbecker, (2001a)	✓
14	Solid waste	Beekaroo et al., (2019); Park & Kremer, (2017); Shashi et al., (2018); Singh & Sultan, (2018); Tan et al., (2015)	✓
15	Waste generated before recycling	Tseng et al. (2013)	
16	Liquid Waste	Ziout et al.(2013)	
17	Waste Reduction and Management	Bour et al., (2019); GRI, (2002, 2016, 2018); Gupta et al., (2018); Veleva & Ellenbecker, (2001a)	✓

18	Hazardous waste	Ziout et al.(2013)	
19	Waste generated by contracted services/materials	Lin et al. (2010); Veleva and Ellenbecker (2001a)	
20	Water pollution (Discharge of effluent and pollutant)	Feil et al., (2019)	✓
21	Total weight of waste by type (scheduled and not scheduled)	Veleva and Ellenbecker (2001a); GRI (2002)	
22	Total number and volume of significant spills	GRI (2002)	
23	Recycled Materials	Azapagic et al., (2016); Fan et al., (2010); GRI, (2016)	✓
24	Reprocessed materials	GRI (2002)	
25	Packaging materials	Veleva and Ellenbecker (2001a)	
26	Hazardous Material Use	GRI (2002)	
27	Material consumption	Fan et al., (2010); GRI, (2016, 2002); Gupta et al., (2015); Krajnc and Glavič, (2003); Veleva et al., (2001); Winroth et al., (2016)	✓
28	PBT chemicals used	Veleva and Ellenbecker (2001a)	
29	Total Air Emissions	Ahmad et al., (2019); Amrina et al., (2016); GRI, (2002, 2016); Gupta et al., (2015); Singh et al., (2012)	✓
30	NO_X, SO_X, and other air emissions	Veleva and Ellenbecker, (2001a)	
31	Emissions of Acid Gasses	GRI, (2002, 2016)	
32	Emissions of ozone-depleting substances	GRI, (2002, 2016)	
33	Greenhouse Gas Emissions	Boyden et al., (2016); Kai et al., (2016); Park & Kremer, (2017); Zarte et al., (2018)	✓
34	Total direct and indirect greenhouse gas emissions	Samuel, et al.(2013)	
35	Design For Green Environment	Jayal et al. (2010)	
36	Reductions in GHG Emissions	Samuel, et al.(2013)	
37	6R concepts	Jayal et al. (2010)	
38	Green product design	Fan et al.,(2010); Veleva et al., (2001); Veleva & Ellenbecker, (2001a).	✓
39	Biodegradable packaging	Tseng, (2013)	
40	Green manufacturing	Vinodh et al. (2014)	
41	Products with take-back policies	GRI, (2002, 2016)	
42	Product innovativeness	Vinodh et al. (2014)	
43	Land use	GRI, (2002, 2016)	
44	Biodiversity	GRI, (2002, 2016)	
45	Environmental protection expenditure	Vinodh et al. (2014)	
46	Compliance with environmental laws and regulations	Ocampo et al., (2015)	
47	Significant environmental impacts of transportation of Products, Services, Material and Workforce	GRI, (2002, 2016)	
48	Initiatives to mitigate environmental impacts of products and services	Samuel et al.,(2013)	
49	Land pollution/Soil Protection	Veleva & Ellenbecker, (2001a)	✓

Appendix A2: Average matrix

$$
T_{av} = \begin{array}{r} \\ EN_1 \\ EN_2 \\ EN_3 \\ EN_4 \\ EN_5 \\ EN_6 \\ EN_7 \\ EN_8 \\ EN_9 \\ EN_{10} \\ EN_{11} \\ EN_{12} \\ EN_{13} \\ EN_{14} \\ EN_{15} \end{array}
\begin{array}{c}
\begin{array}{ccccccccccccccc} EN_1 & EN_2 & EN_3 & EN_4 & EN_5 & EN_6 & EN_7 & EN_8 & EN_9 & EN_{10} & EN_{11} & EN_{12} & EN_{13} & EN_{14} & EN_{15} \end{array} \\
\begin{pmatrix}
0 & 1.9 & 3.2 & 1 & 0.8 & 0.6 & 2.3 & 2.1 & 1.3 & 1.3 & 1.6 & 3.5 & 3.8 & 1.2 & 1.1 \\
1.8 & 0 & 0.9 & 1.7 & 1.8 & 1.7 & 2.5 & 3.2 & 2.4 & 1.7 & 1.8 & 3.5 & 3.8 & 0.7 & 2.8 \\
3.4 & 2.1 & 0 & 1 & 1.3 & 0.8 & 2.8 & 2.9 & 2.3 & 2.3 & 1.7 & 2.9 & 3.6 & 1 & 1.3 \\
1.2 & 1.3 & 1.4 & 0 & 3.6 & 3.5 & 2.3 & 2.8 & 2.9 & 2.3 & 2.7 & 1.9 & 2.3 & 1.8 & 2.3 \\
1.3 & 1 & 1.7 & 3 & 0 & 2.4 & 1.2 & 2.2 & 2 & 1.7 & 1.1 & 1.3 & 1.6 & 1.3 & 2.1 \\
1.2 & 1 & 0.2 & 3.8 & 2.5 & 0 & 1 & 1.6 & 1.7 & 0.7 & 0.8 & 0.9 & 1.3 & 0.9 & 3.1 \\
1.9 & 1.5 & 2.1 & 1.5 & 0.6 & 0.7 & 0 & 2.3 & 1.5 & 2.9 & 3 & 2.7 & 2.5 & 1.6 & 2.2 \\
2.1 & 1.6 & 2.6 & 2 & 1.4 & 2.1 & 3 & 0 & 3 & 2.4 & 3.3 & 3.4 & 3.5 & 2 & 2.5 \\
0.8 & 1.3 & 1.4 & 3.1 & 2.1 & 2.1 & 2.5 & 1.6 & 0 & 2.7 & 3 & 2.5 & 2.5 & 1.4 & 3.3 \\
1.6 & 1.3 & 2 & 1.5 & 1.4 & 0.6 & 3.6 & 3 & 2.7 & 0 & 2.8 & 2.7 & 2.7 & 2.1 & 2.4 \\
3.2 & 1.2 & 1.5 & 2.5 & 2.1 & 1.2 & 3.6 & 3.3 & 2.2 & 2.2 & 0 & 3.2 & 2.9 & 1.7 & 1.7 \\
2.9 & 3.2 & 2.7 & 1.5 & 1.1 & 0.9 & 2 & 3.3 & 1.6 & 1.7 & 2 & 0 & 3.6 & 1.7 & 1.9 \\
3.4 & 3.5 & 3.6 & 1.2 & 1.2 & 0.6 & 2.4 & 3 & 0.8 & 2.6 & 2.3 & 3.6 & 0 & 1.8 & 0.8 \\
3.5 & 2.8 & 3.4 & 3.2 & 2.9 & 2.3 & 3 & 3 & 3 & 3.2 & 3.3 & 3 & 2.6 & 0 & 2.5 \\
0.9 & 1.3 & 1 & 2.4 & 1.5 & 1.8 & 2.6 & 2.4 & 2.9 & 2.6 & 1.8 & 0.8 & 0.6 & 1 & 0
\end{pmatrix}
\end{array}
$$

Appendix A3: Cause and Effect analysis

Table A3: Cause and Effect analysis for Environmental Indictors

Factors	R	C	R + C	R - C
EN_1	2.177	2.456	4.633	-0.279
EN_2	2.497	2.13	4.627	0.367
EN_3	2.452	2.364	4.816	0.088
EN_4	2.636	2.361	4.997	0.275
EN_5	1.984	1.967	3.951	0.017
EN_6	1.706	1.739	3.445	-0.033
EN_7	2.285	2.896	5.181	-0.611
EN_8	2.885	3.034	5.919	-0.149
EN_9	2.496	2.48	4.976	0.016
EN_{10}	2.558	2.537	5.095	0.021
EN_{11}	2.699	2.625	5.324	0.074
EN_{12}	2.528	3.006	5.534	-0.478
EN_{13}	2.593	3.102	5.695	-0.509
EN_{14}	3.409	1.739	5.148	1.67
EN_{15}	1.974	2.443	4.417	-0.469

Figures

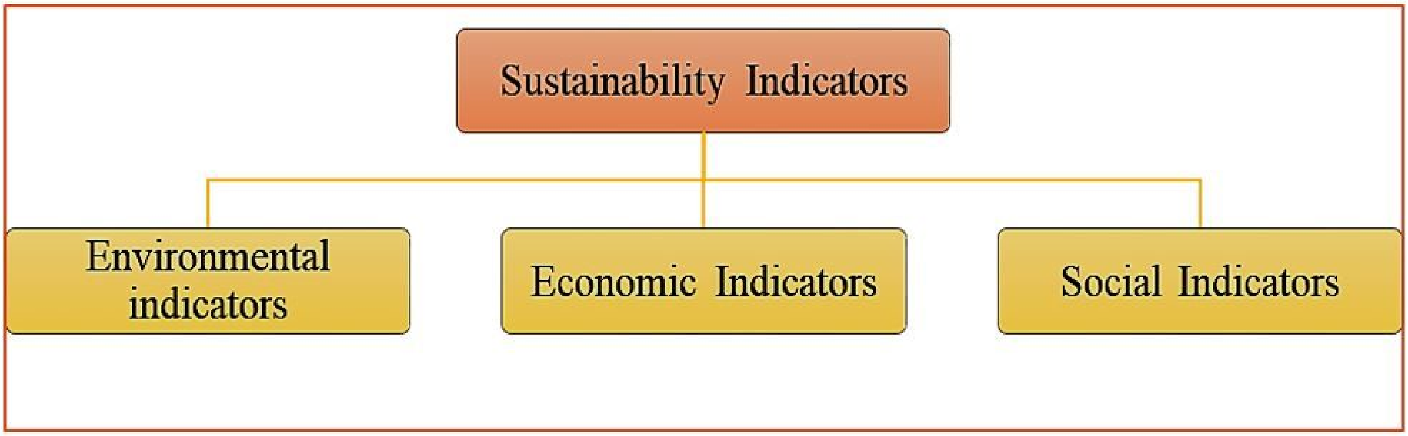

Figure 1

Classification of Sustainability Indicators (GRI 2002, 2016; Feil et al. 2015; Moldavska and Welo 2015).

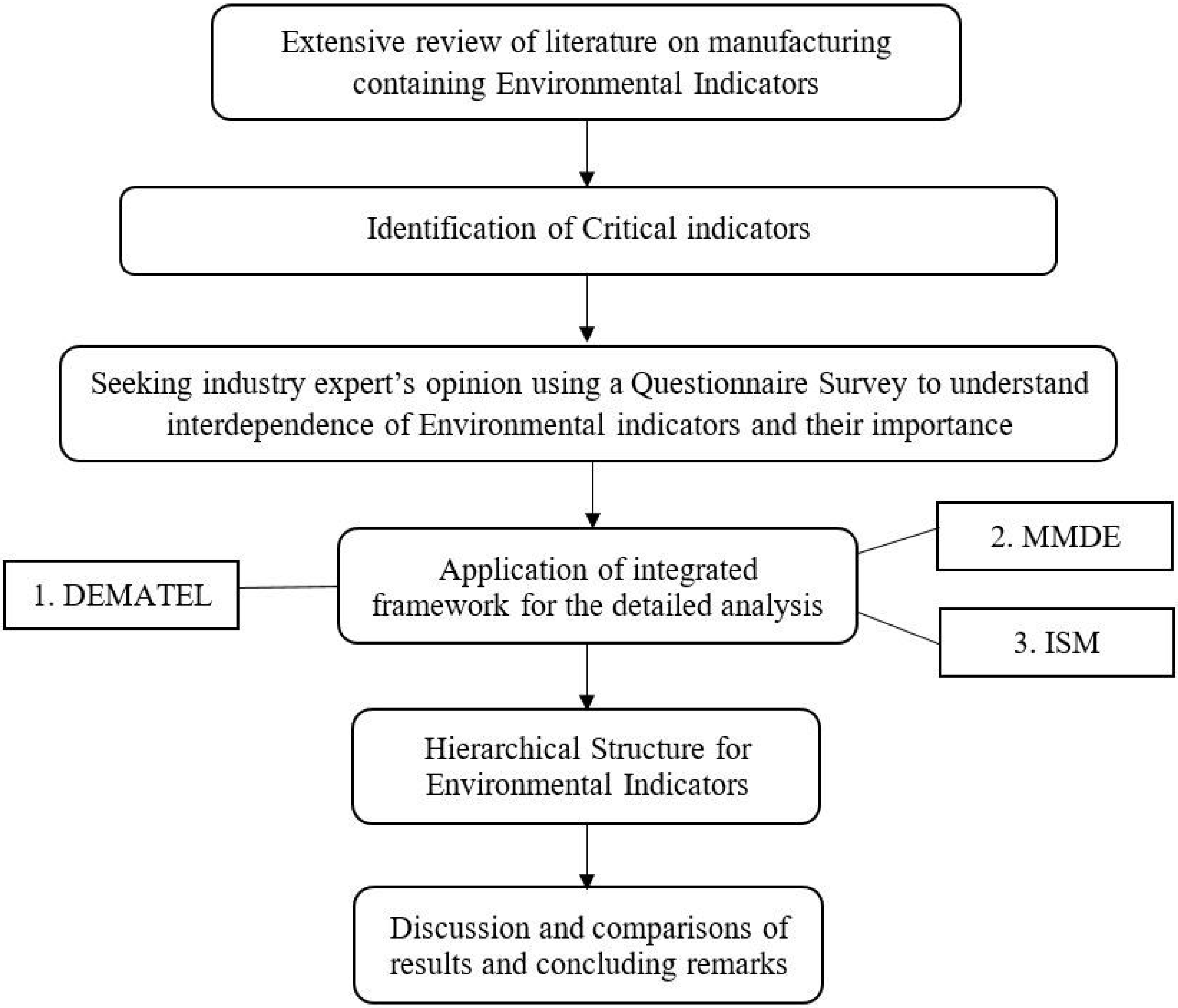

Figure 2

Methodology for identifying cause and effect relationship between critical indicators

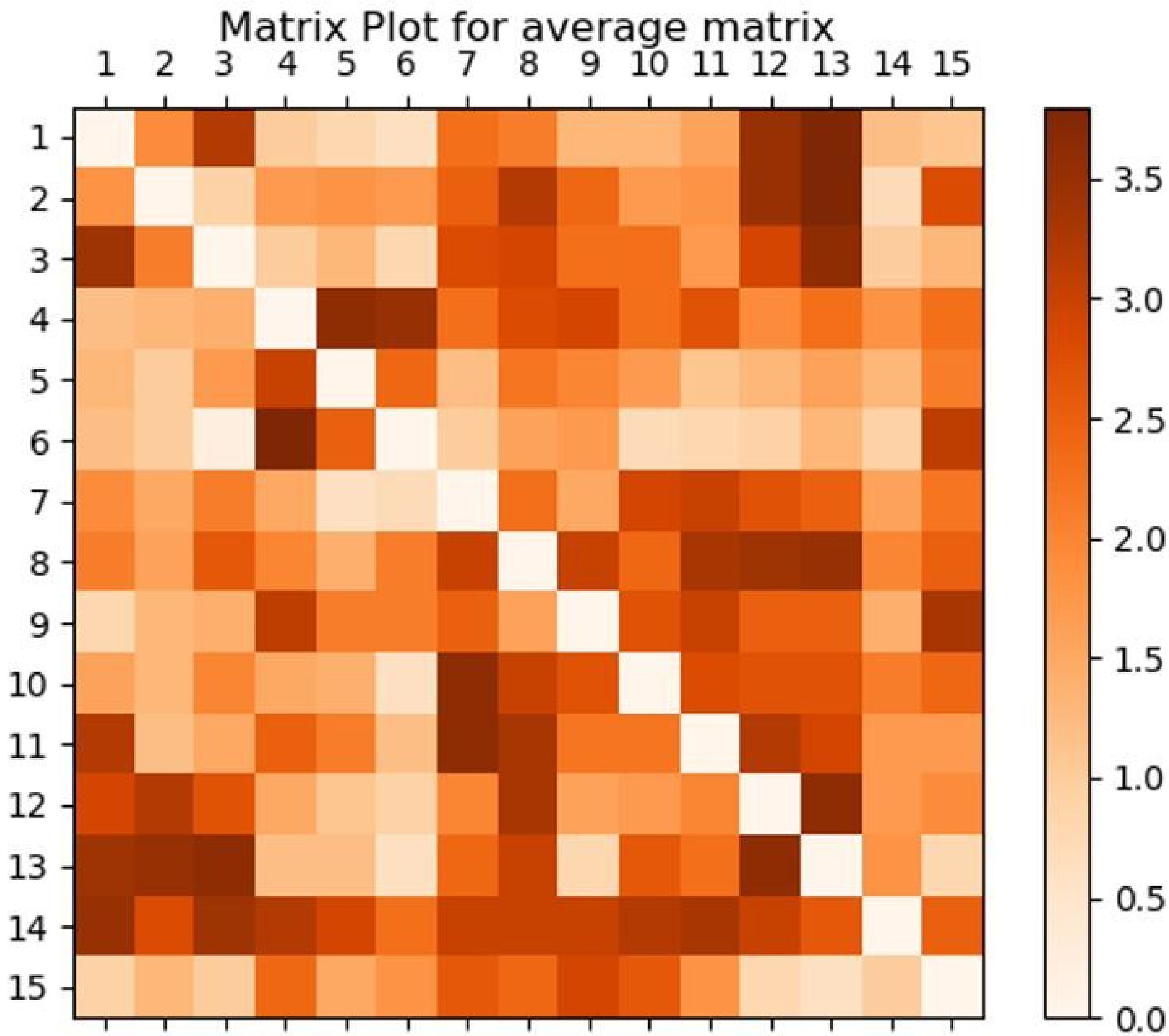

Figure 3

The Average Matrix plot for Environmental indicators

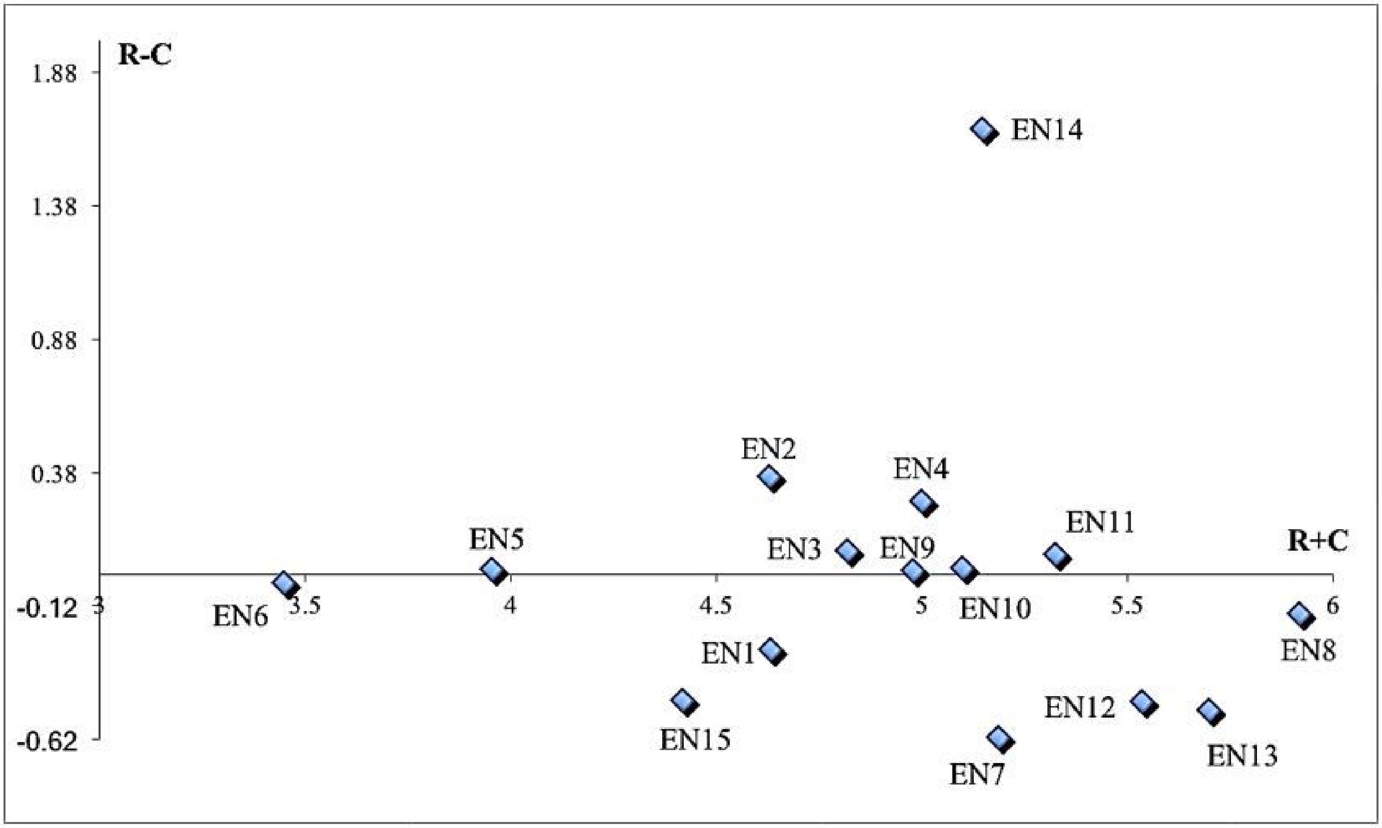

Figure 4

Casual Diagram for Environmental Indicators

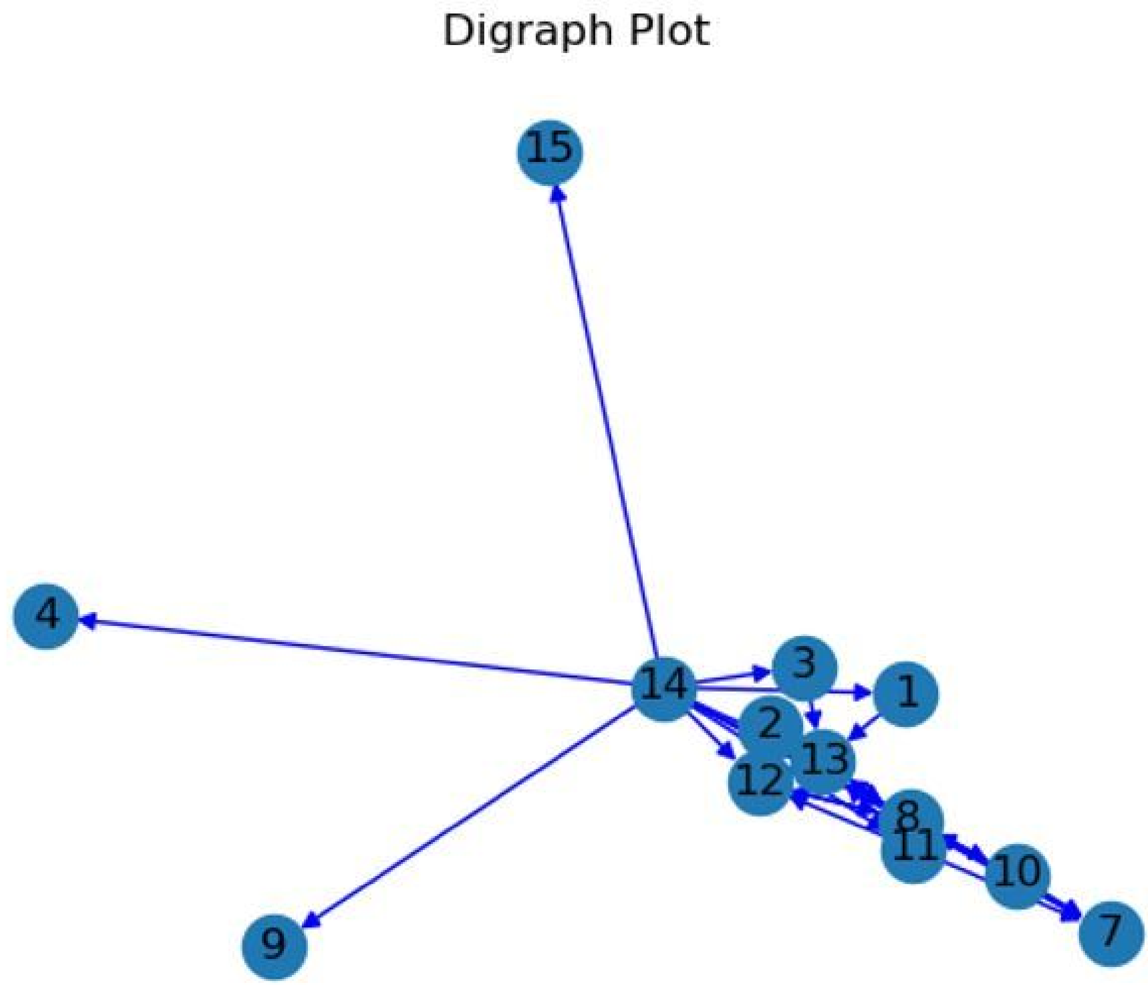

Figure 5

Digraph plot for Environmental Indicators

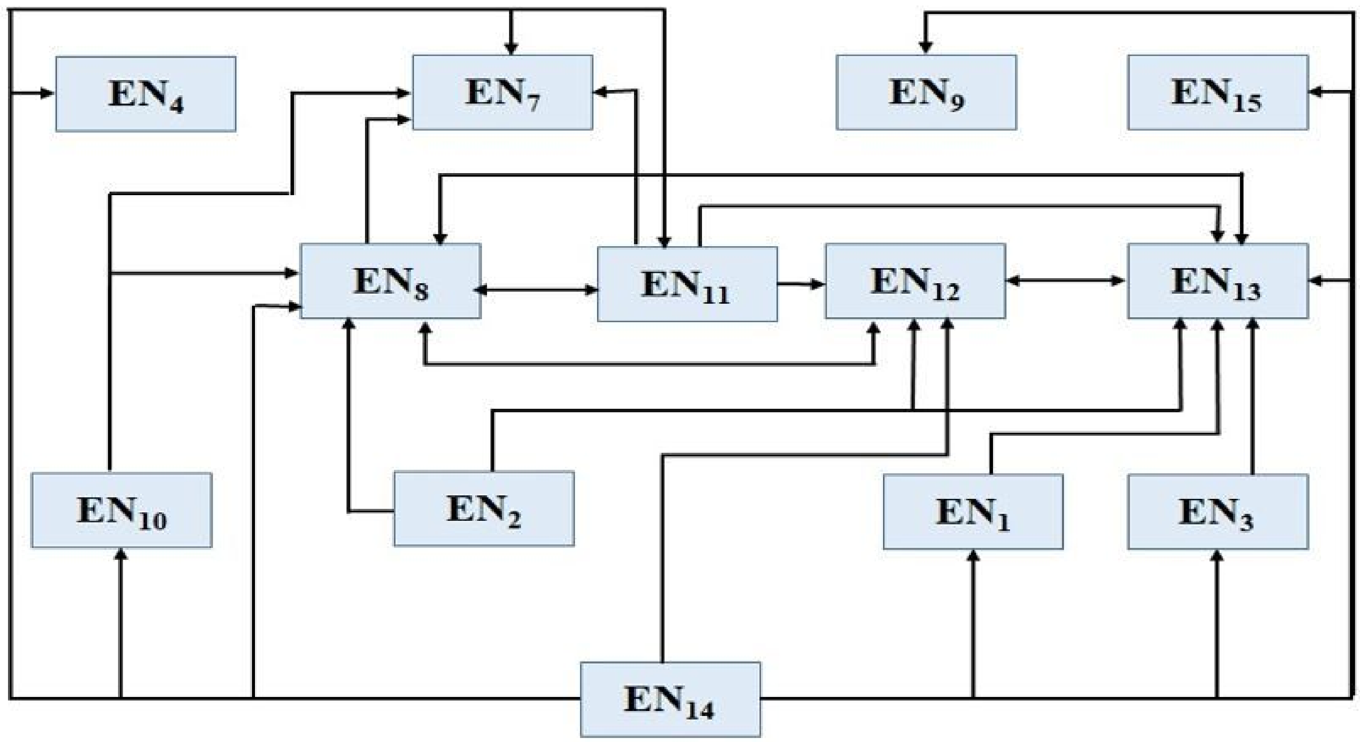

Figure 6

ISM model for Environmental Indicators

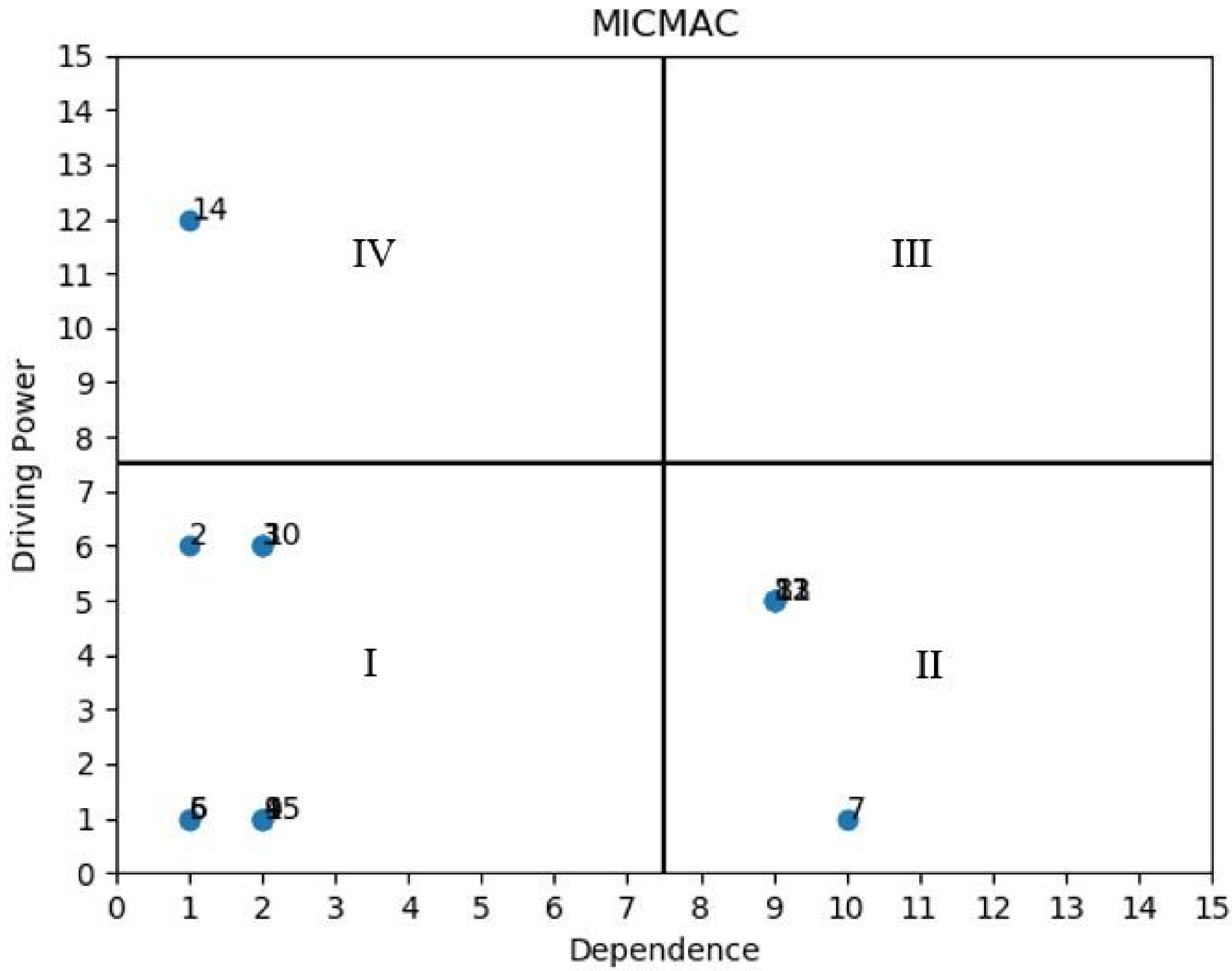

Figure 7

MICMAC Analysis of Environmental Indicators

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendices.docx