INVESTIGATIONS OF SUSTAINABLE MACHINING AND ULTRA-PRECISION MACHINING USING SOCIAL NETWORK ANALYSIS AND UNSUPERVISED LEARNING

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The Hong Kong Polytechnic University

2021

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Investigations of Sustainable Machining and Ultra-precision Machining using Social Network Analysis and Unsupervised Learning

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A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Philosophy

July 2020

CERTIFICATE OF ORIGINALITY

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Abstract

The manufacturing industry is one of the main contributors to greenhouse gas emissions and the consumption of natural resources. With an increasing demand for high technological products nowadays, the natural resource consumptions from ultra-precision machining (UPM) predictively go up and therefore sustainable machining has become progressively important in terms of reducing the induced negative environmental issues. On the other hand, sustainability includes three dimensions: economic sustainability, environmental sustainability, and social sustainability. However, the complicated interactive connections among the sustainable items of these three dimensions regarding UPM cause infeasibilities and difficulties to execute sustainable UPM practically. Up to now, it still lacks studies about the solutions or measurement for resolving interactive relationships between sustainable items of UPM. Therefore, it is necessary to develop a model to evaluate the sustainable UPM parameters considering their connections. In this study, the influential parameters of sustainable machining and their interactive relationships were identified. Several centrality metrics of social network analysis (SNA) were utilized to evaluate the role of each parameter from a systemic view. What's more, the calculation results of centrality metrics can be utilized as the feature data of some parameters to predict the feature of other parameters by using machine learning algorithms. By these steps, the SNA - machine learning model can be established for sustainable parameters investigation. Moreover, with the information from the obtained main metrics results, some managerial implications for improving the sustainability level of the UPM process were raised. In this study, it is the first time the SNA method was introduced in the research area of sustainable manufacturing and UPM. And the unsupervised learning approach was also applied firstly to classify the centrality metrics results. Moreover, the roles and importance of sustainable manufacturing and UPM parameters have been evaluated to help companies to achieve optimal settings of them. By using link prediction metrics of SNA, the

potential values of the undiscussed relationship between two sustainable machining factors in previous studies can be discovered to support the researchers to do the topic selection.

In the previous research on sustainable manufacturing, only a few factors were studied to find out their impacts on the overall sustainability level. It still lacks a study that can analyze the importance of various sustainable machining parameters in the same model with considering their influencing relationships. In this work, by using the method of SNA, this research gap can be resolved. Based on the evaluation of sustainable manufacturing factors, it was found that cutting quality is the parameter with the highest value of the centrality index, which is the overall measurement of centrality. It indicates that cutting quality should be considered as the key factor in the manufacturing system. In the case study of the UPM optimal setting, Material recovery was discovered as the UPM parameter which has the highest betweenness result, which shows that it performs as a gatekeeper to collect the impacts from the upstream UPM nodes and can be observed before getting machining outcomes. Thus, it plays a key role as one significant indicator for researchers to obtain optimized UPM output.

Besides, the influencing relationships among the sustainable machining parameters were selected based on relevant literature. As these relationships are performed as the "edges" in the SNA model, two non-adjacent nodes mean that their relationship is not discovered in current literature. In this work, the link prediction metrics were used to find out the probability of the existence of the hidden relationships between these two parameters. Therefore, this work can determine the undiscussed latent relationships among sustainable machining parameters with high potential values to be investigated. Thus, this work provides a reference for developing more research topics in the sustainable machining area.

List of Publications

Journal Papers

Yip, W. S., To, S., & **Zhou, H**. (2021), Current status, challenges and opportunities of sustainable ultra-precision manufacturing, accepted by *Journal of Intelligent Manufacturing*. (IF=**4.311**)

Zhou, H., Yip, W. S., Ren, J., & To, S. (2020). An Interaction Investigation of the Contributing Factors of the Bullwhip Effect Using a Bi-Level Social Network Analysis Approach. *IEEE Access*, 8, 208737-208752. (IF=**3.745**)

Yip, W. S., To, S., & **Zhou, H**. (2020). Social network analysis for optimal machining conditions in ultra-precision manufacturing. *Journal of Manufacturing Systems*, 56, 93-103. (IF=**5.105**)

Papers under review

Hongting Zhou, Wai Sze Yip, Jingzheng Ren, & Suet To (under review), Topic discovery innovations for sustainable ultra-precision machining by using social network analysis - machine learning approach, submitted to *International Journal of Production Research*.

Hongting Zhou, Wai Sze Yip, Jingzheng Ren, & Suet To (under review), Thematic analysis of sustainable ultra-precision machining by using text mining and unsupervised learning method, submitted to *Journal of Intelligent Manufacturing*.

Wai Sze Yip, **Hongting Zhou** , & Suet To (under review), Discover the trend and evolution of sustainable manufacturing: a thematic and bibliometric analysis, submitted to *Journal of Cleaner Production*.

Papers under preparation

Wai Sze Yip, **Hongting Zhou**, & Suet To (under preparation), Technology development, evolution and forecasting of ultra-precision machining technology: A bibliometric approach.

Wai Sze Yip, **Hongting Zhou**, & Suet To (under preparation), Sustainable performance of manufacturing: bibliometric and textual analyses of the triple bottom line.

Conference extended abstract

Hongting Zhou, Wai Sze Yip & Suet To (2019), An Interaction Analysis for Sustainable Machining Parameters Using Social Network Analysis Approach, The 9th International Conference of Asian Society for Precision Engineering and Nanotechnology (ASPEN2019), Matsue, Japan, 12-15 Nov 2019.

Acknowledgments

I would like to express my appreciation to the Hong Kong Polytechnic University, especially the Department of Industrial and Systems Engineering, for providing the resources and support necessary to complete this study.

My sincere thanks to my chief supervisor, Prof. Suet To who provided invaluable guidance, funding, encouragement, direction on procedures, and references on the adoption of ultra-precision machining studies specifically in the sustainable UPM area.

I extend my profound gratitude to Dr. Wai Sze Yip for being my co-supervisor, supporting me in the admission process, guidance on writing skills, and continuous encouragement throughout my study period. Also, I would like to thanks Dr. Jingzheng Ren for being my co-supervisor, his guide on the sustainable development area.

I am also grateful to my family and friends who provided support and encouragement throughout my studies.

Table of Contents

List of Figures

List of Tables

Chapter 1 Introduction

Due to the technological progress in industry and the growth of the population, environmental issues have become one of the main challenges for human beings. In 2000, the energy consumption causing CO2 equivalent emissions counted around 64% of the greenhouse gas emissions (Stern, 2006). Among the CO2 emissions, around 24 % and 14 % of CO2 emissions were caused by power generations and the manufacturing industry respectively. Thus, the energy used in manufacturing needs to be cut back in order to reduce CO2 emissions and therefore sustainable machining gets more and more attention. The measurement of sustainability includes three dimensions: economic dimension, environmental dimension, and social dimension. And each aspect also consists of various factors (parameters) that have complicated influencing relationships with each other (Vinodh, Ramesh, & Arun, 2016). This situation is one of the main causes of the difficulty to achieve and improve sustainability in manufacturing industries. Therefore, analyzing these influencing relationships among the parameters of sustainable manufacturing enables us to achieve a better understanding of the roles of each parameter.

Ultra-precision machining (UPM) is one of the advanced material processing technologies. Nowadays, ultra-precision products with nanometric-level surface roughness experience an increasing demand today. And the UPM process is one of the important and effective methods for manufacturing the components which can satisfy this demand. It has been widely used to produce ultra-precision objects such as medical equipment and lens, etc. And it can obtain the achievable level of the components' surface in the level of fewer than 1 nano and surface roughness at a level of less than 10 nano (Azulay, 2014). The resolution of the produced surface of UPM is less than 10 nano, whose surface level and form accuracy is 1000 times accurate compared with conventional machining. Though UPM has an extremely high capability of producing high-precision products with mirror surface finishing, the complex processing principle causes difficulties in practice. The nano-level surface production can be influenced by a lot of UPM parameters, and even some small changes in the UPM parameters could influence the optimal setting of machining. And it involves a large number of UPM parameters to achieve the optimal conditions of UPM setting and high sustainability.

1.1. Research gap

However, in previous work, there are still some research gaps in the area of sustainable manufacturing and UPM:

1. It still lacks the study about the sustainable manufacturing and UPM factors from the view of a whole system to evaluate the role and importance of each parameter by taking account of the interactive relationships among them.
2. It lacks the method to discover the potential value of undiscussed relationships between parameters of sustainable UPM.
3. Previous studies also lack a method to classify these parameters based on their importance to provide an overall concept of the centrality distribution.

1.2. Project objectives

To resolve the research gap mentioned in the above part, this project has three main objectives:

1. Study the role and importance of sustainable machining parameters considering their complicated influencing relationships.
2. Find the hidden relationships among sustainable machining parameters with high potential to be investigated to discover new potential topics and trends for the research area of sustainable UPM.
3. Classify the parameters based on the similarity of the role and importance in the

network of sustainable manufacturing and UPM to provide an overall concept of the importance distribution of the parameters.

1.3. Overview of Research Methodology

The whole working flow of the research methodology in this project was summarized in **Figure 1**. Firstly, the parameters of sustainable manufacturing and UPM can be identified from the literature. Moreover, influencing relationships are summarized in a matrix, which is called the adjacency matrix (McCulloh, Armstrong, & Johnson, 2013). Several types of graphs can be used to describe different social network models. According to the direction of the edges, they can be classified as undirected and directed graphs (Oliveira & Gama, 2012). According to the work of Zhou, Yip, Ren, and To (2020), the examples of directional networks and nondirectional networks and their adjacency matrices are shown in **Figure 2**. In this matrix, let a_{ij} be the value of the element in row i and column j. For the directional network, if $a_{ij} = 1$, it means the factor on the left-hand side (factor i) can influence the factor on the right-hand side (factor j); while if $a_{ij} = 0$ means the factor i cannot influence the factor j. For a non-directional network, $a_{ij} = 1$ representing the presence of an edge between factor i and j; and $a_{ij} = 0$ means the absence of an edge between node pair (i, j). Therefore, in a directional network, the adjacency matrix may not be symmetric. But all the adjacency matrices of the non-directional networks are symmetric, which means $a_{ij} = a_{ji}$ (Oliveira & Gama, 2012). As the influencing relationships among sustainable UPM factors have directions in this study, the SNA model will be constructed as a directional network in this work.

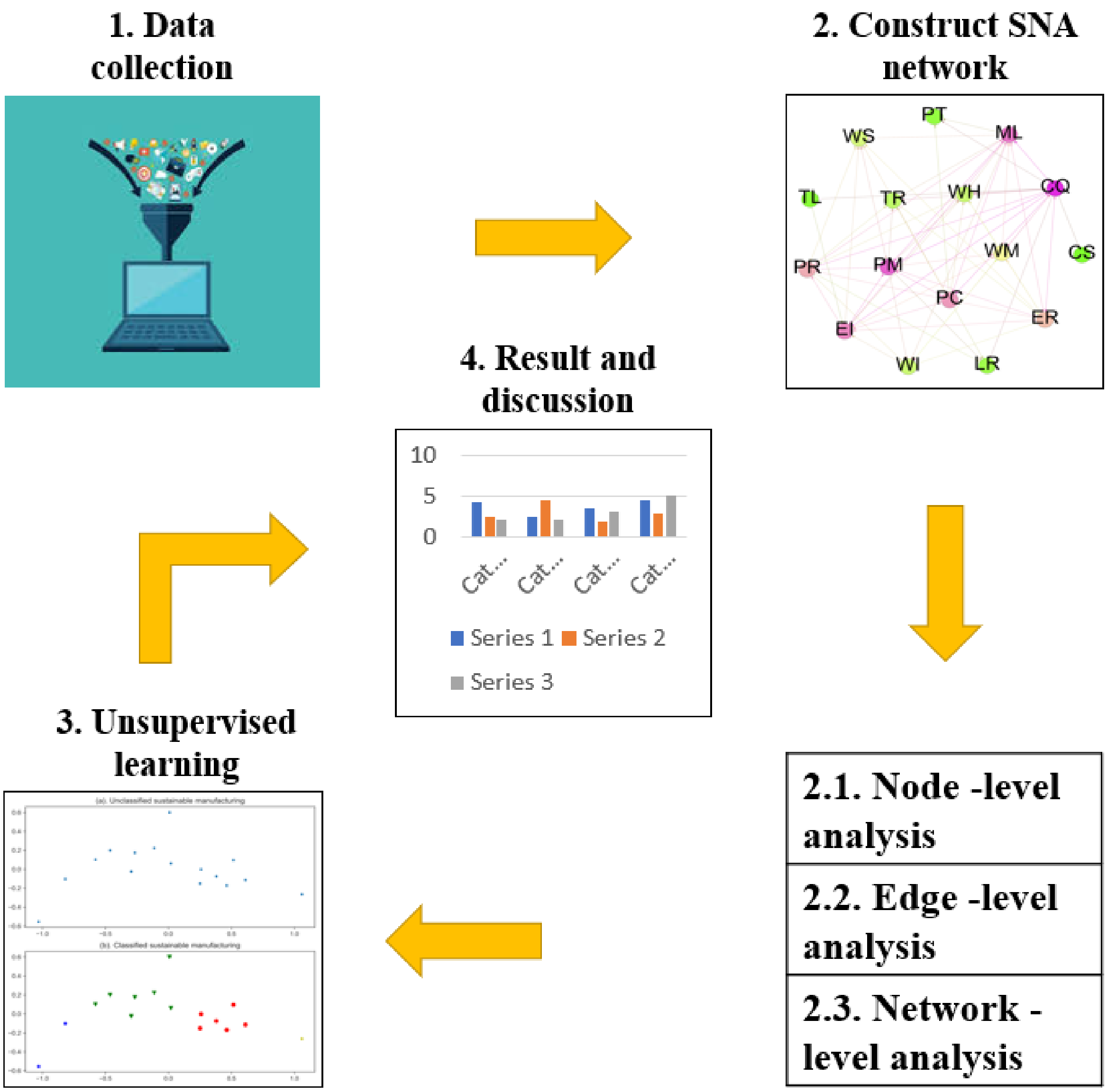

Figure 1 The working flow of the methodology

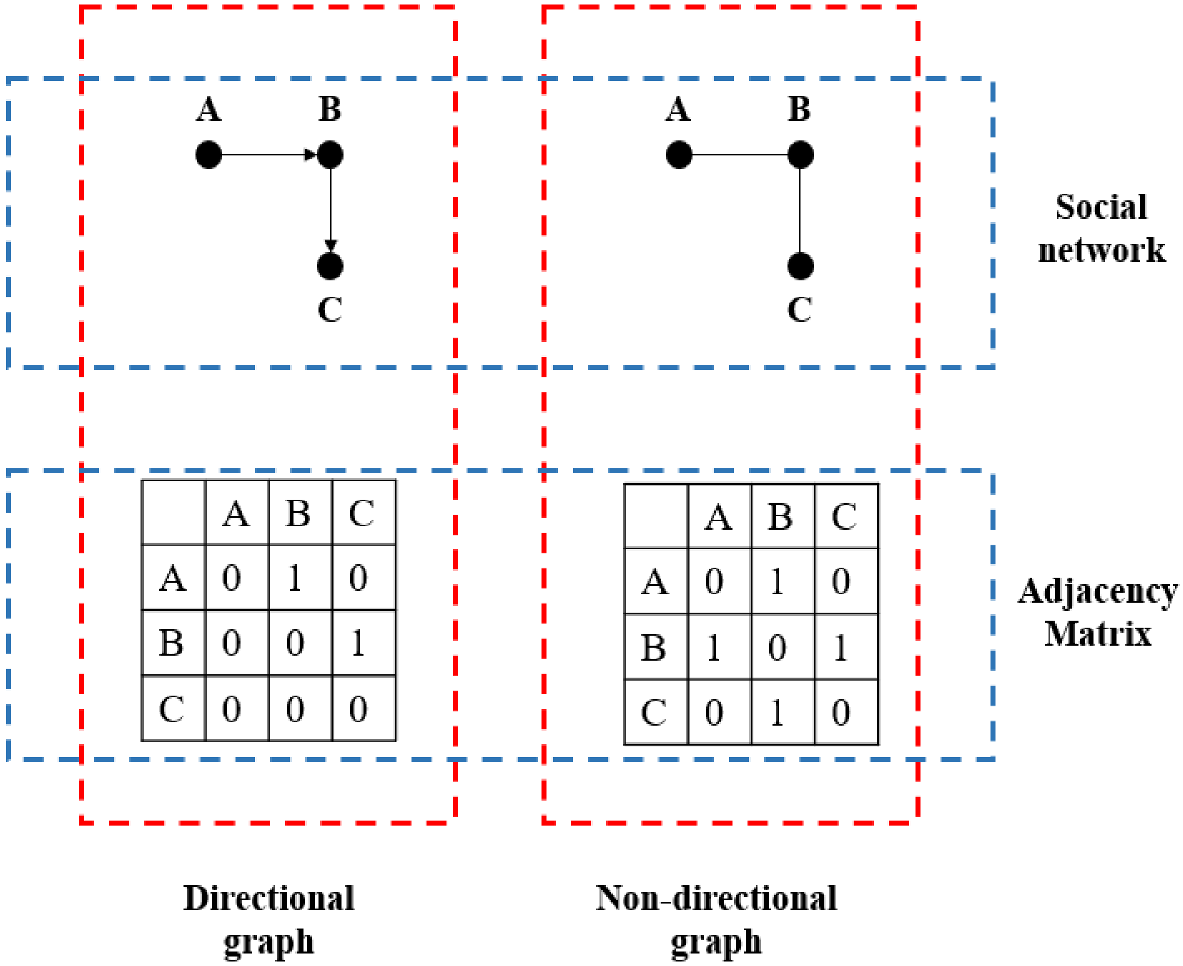

Figure 2 The illustration of the directional network, nondirectional network, and their adjacency matrix (Zhou et al., 2020)

After finishing the data collection, the parameters and relationships can be considered as the "node" and "edge" to construct a social network, which is a technology to discover the hidden pattern, structure in a system consisting of nodes and edges (Ryberg & Christiansen, 2008). After that, the social network can be evaluated in three levels: node level, edge level, and network level. The node-level analysis can utilize some metrics to measure the centrality of each node in this network, such as in-degree and out-degree. By doing so, the role and importance of the parameters of sustainable manufacturing or UPM could be measured. Then, the purpose of the edge-level analysis is to find out the probability of two non-adjacent nodes being linked together in the future. The link prediction metrics include the common neighbors, Jaccard coefficient, resource allocation, and so on. By utilizing them, the likelihood of linkages between the parameters can be recognized. It can assist the researchers to find out the valuable topics that have not been discussed in the previous study. The network-level analysis refers to the process to analyze the density and other features of the SNA network, which can provide researchers an overall concept of the whole research area. And one case study is not necessary to include all of these three levels of SNA analysis. The researcher can select supportive analysis partially from them according to the needs of the study.

Based on the SNA analysis results, the metrics results can be utilized as the raw data to be input into the unsupervised learning method such as k-means and principal components analysis (PCA) to do classification. It can help the researchers obtain the distribution and clustering of the parameters according to the similarity of centrality metrics results. By utilizing the k-means algorithm, the nodes are clustered according to the distance among them. It can minimize the internal distance of the parameters and maximize the external distance between the clusters.

1.4. Project significance

In this study, the new evaluation method was developed by using SNA and unsupervised learning algorithms. The SNA method was firstly applied in the sociology area to represent relationships between actors in a social setting and link prediction after it has been proposed. And it provides an efficient tool for various areas, such as supply chain management and knowledge management, to solve problems involving multiple stakeholders. By utilizing it, the roles of each parameter of sustainable manufacturing and UPM can be identified clearly, which can provide a guideline for researchers to find the optimal settings of UPM. And the inspiration from the influencing relationships among these parameters can be used to shows the potential values of undiscussed topics in the research area of sustainable manufacturing and UPM. Moreover, these results can provide a reference for researchers to determine the priority of different undiscussed topics as their future research.

1.5. Project organization

Besides the introduction, previous studies about sustainable machining, ultra-precision machining, the SNA method, and unsupervised method were reviewed and discussed in chapter 2; then, the details of the SNA and unsupervised learning methods were introduced in chapter 3; after that, two case studies are evaluated and discussed in chapter 4; finally, the conclusion was given in chapter 5.

Chapter 2 Literature review

This chapter consists of three parts: the previous studies about the application of SNA and some machine learning algorithms were discussed firstly; subsequently, the main methods used in relevant studies of sustainable machining and UPM were also reviewed in this chapter.

2.1. Social network analysis (SNA)

A social network is the pattern of linkages or relationships that exists among the parameters or nodes of a social system equipped with the mathematics foundation of graph theory (Wasserman & Faust, 1994). SNA has been applied to study social media data such as Tweeter (Cheong & Cheong, 2011) and information flow (Dekker, 2002). It also has been adopted to analyze disease transmissions such as HIV (Friedman, Neaigus, Jose, Curtis, & Des Jarlais, 1998) and even organized crime (McIllwain, 1999). More recently, researchers have also applied SNA in the knowledge management area, like human resource development (HRD), as well as knowledge mapping studies (Chan & Liebowitz, 2006). In the study of Zhong, Geng, Liu, Gao, and Chen (2016), the citation network of academic papers about natural resource accounting was constructed (shown in **Figure 3**). Besides that, SNA played a key role in the researches related to supply chain management (Wichmann & Kaufmann, 2016). Buccafurri, Fotia, Lax, and Saraswat (2016) applied SNA to do a case analysis of securing organizations against information leakage.

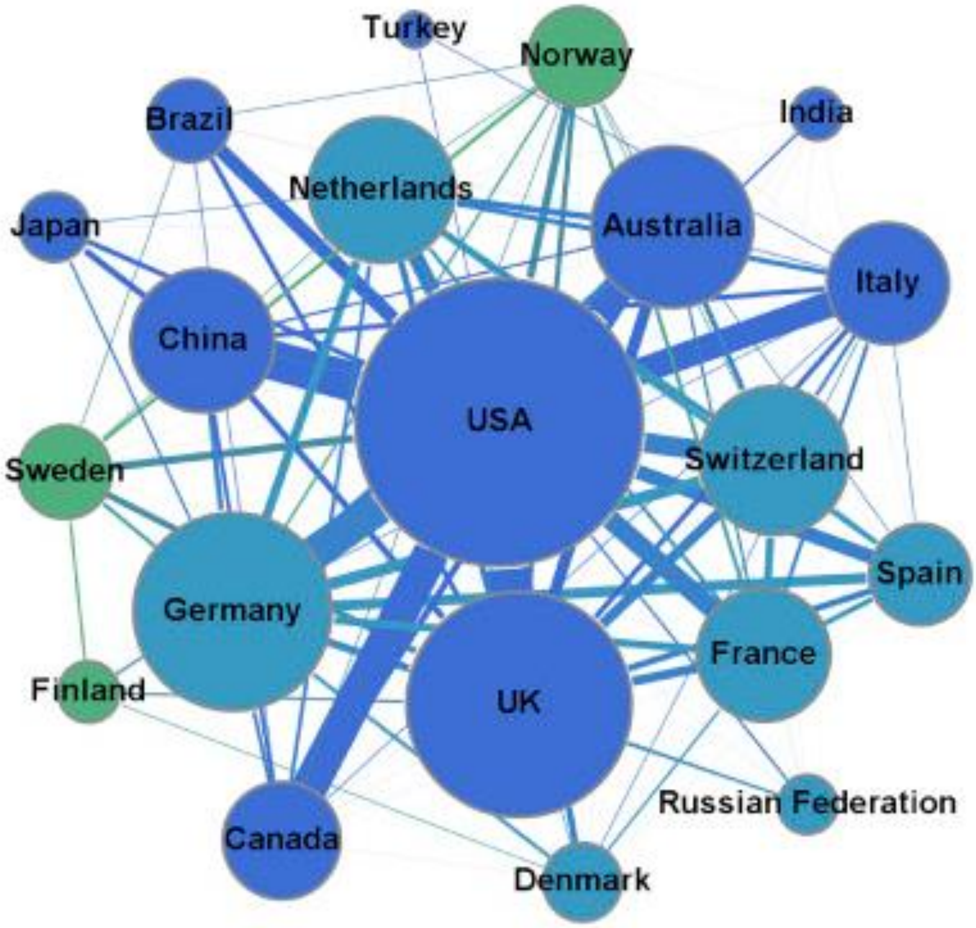

Figure 3 The academic collaborative network among the top 20 countries. (Zhong et al., 2016)

Within recent three years, the potential of SNA has been discovered in more problems and scenarios. For instance, some researchers have used SNA to identify the spread clusters of COVID-19 according to the inflection point (IP) and the spread pattern (Yie, Chien, Yeh, Chou, & Su, 2021). By using this model, three clusters from Eastern Asia and Europe to America were separated. Moreover, the most critical success factors have been identified based on the SNA method in the project management process (Nunes & Abreu, 2020). The centrality metrics were utilized to compare the email communication networks in the successful projects and unsuccessful projects. Besides, the SNA method has also been applied in the interdependence and relationship structure of the supply chain members (Han, Caldwell, & Ghadge, 2020). However, it still lacks studies of sustainable machining and ultra-precision machining by using the SNA approach currently.

2.2. Unsupervised learning algorithms

Unsupervised learning is a branch of machine learning which can achieve an outcome according to input without feedback or label from its environment (Suominen & Toivanen, 2016). While the supervised learning method can directly learn how to predict the correct results based on the label of training data. Unsupervised learning provides the approach which allows the algorithm to recognize patterns in the raw data. It contains a series of algorithms such as PCA and k-means and has a lot of real-life applications, including signal processing, natural language processing, image processing, and financial time series (D. Kumar, Rai, & Kumar, 2010). For instance, Kusuma and Chua (2011) have proposed an effective image classification method based on PCA. And the example of classification by this method is shown in **Figure 4**. However, as the best knowledge of the author, unsupervised learning methods have not been applied in the research area of sustainable UPM.

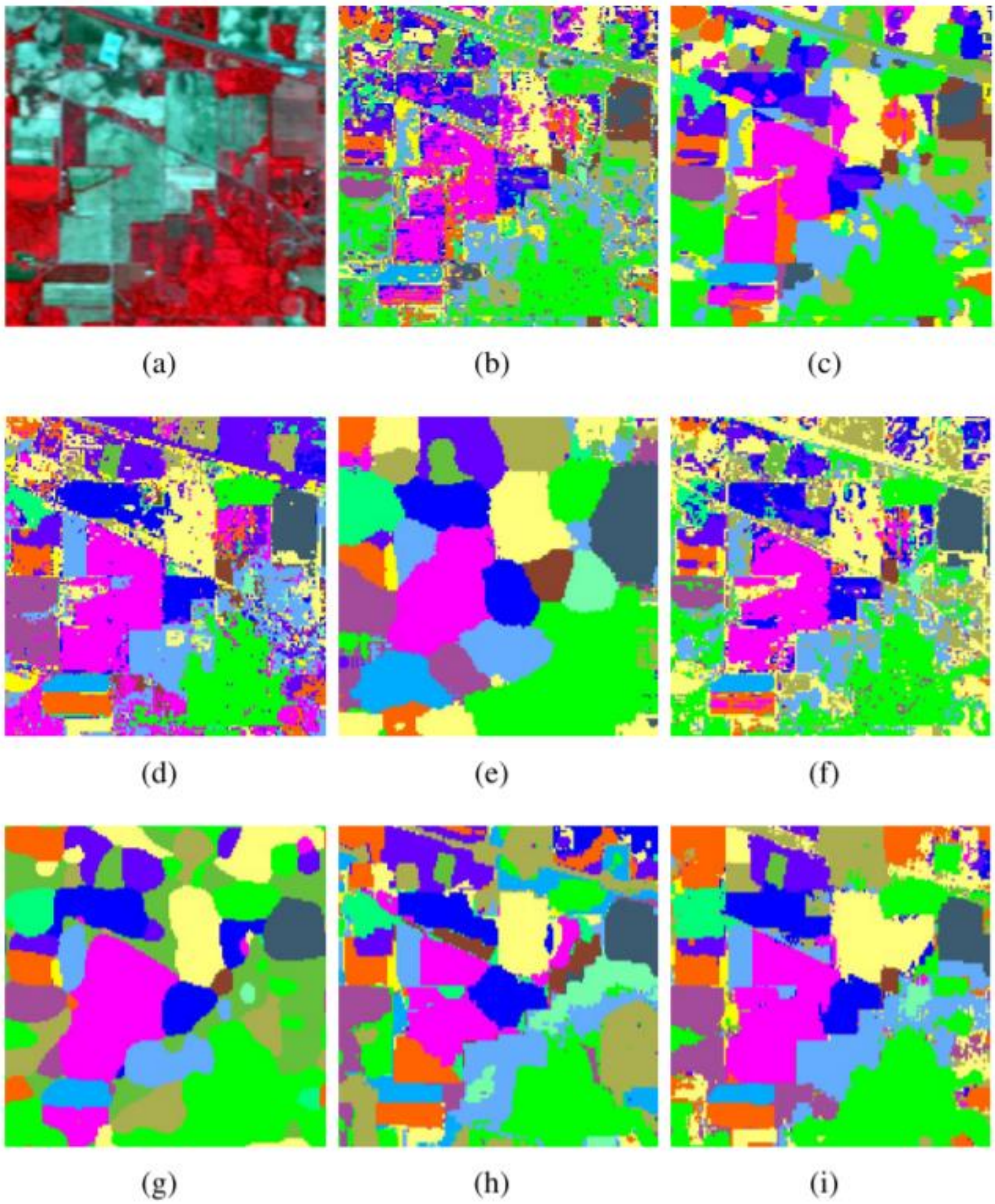

Figure 4 The example of image classification by using the PCA-based method (Kusuma & Chua, 2011)

2.2.1. K-means algorithm

For data classification, k-means is one of the simple unsupervised learning algorithms suitable for dealing with small data size (Kotsiantis & Pintelas, 2004). The working principle of this method is clustering the data based on the distance among them (Panda, Sahu, Jena, &

Chattopadhyay, 2012). And it shows the ability to find the patterns of clustering in multiple disciplines. For instance, A real-time system of sensor data for IoT has been built up with an illustration of geographical partitioning by Hromic et al. (2015). And Murray, Agard, and Barajas (2015) presented a system based on k-means to forecast the supply chain demand by classifying the customers according to their demand behaviors. What's more, Alsayat and El-Sayed (2016) have established a framework to study human social behavior by utilizing k-means to analyze the large-scale social media data in real-time. Besides, a recommendation approach utilizing k-means and genetic algorithms has been proposed to online customers' needs and utilize the Internet as a promotion platform more effectively (K.-j. Kim & Ahn, 2008). Also, G. Liu, Yang, Hao, and Zhang (2018) have proposed an energy efficiency assessment method of industry sectors in China according to k-means and the process was shown in **Figure 5**. In this study, the k-means method is the first time to be utilized to classify the sustainable manufacturing parameters based on the SNA metrics results similarity. It can privdes a overall concept of the centrality distribution.

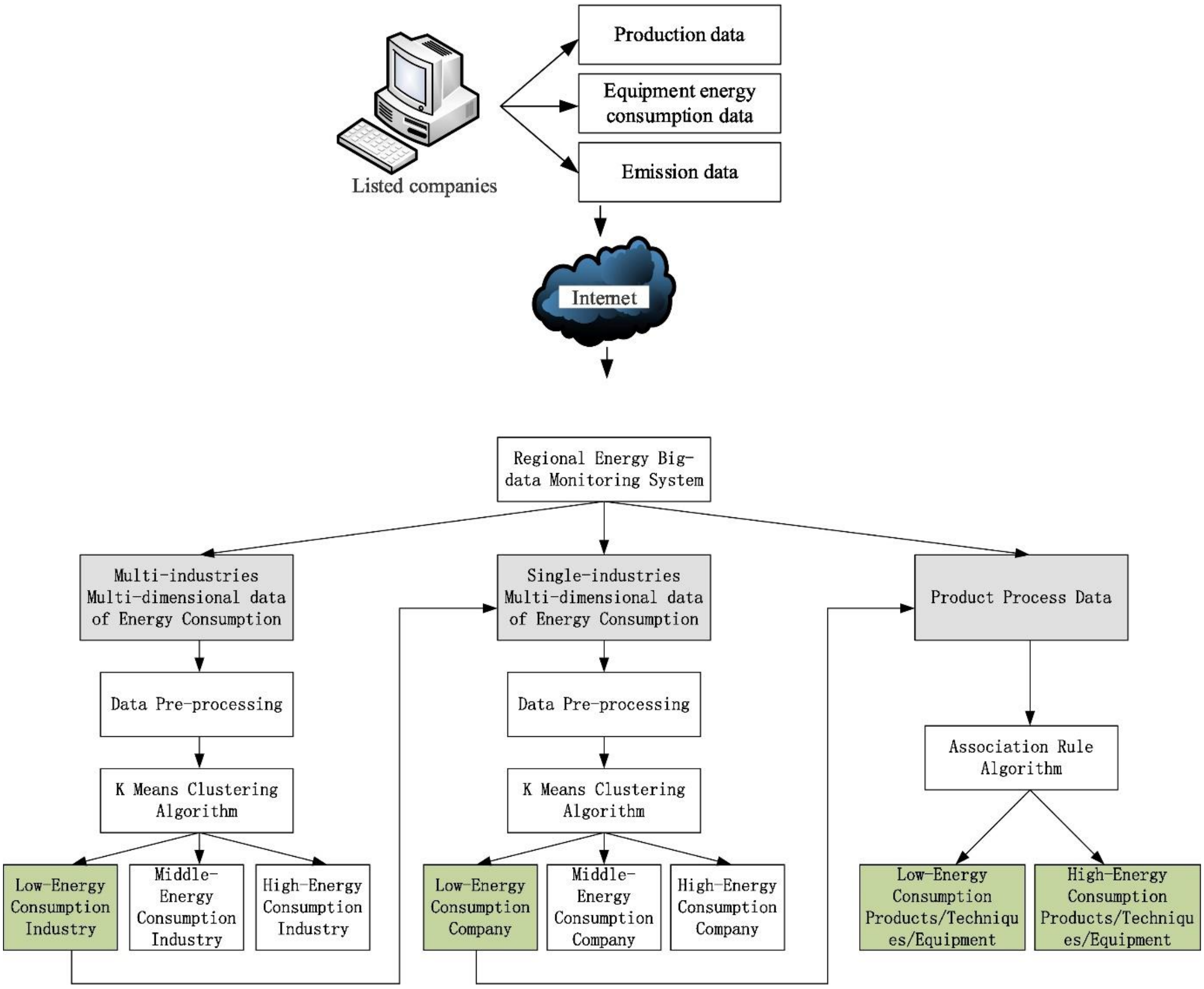

Figure 5 The approach of energy efficiency assessment model by G. Liu et al. (2018)

2.2.2. Principal components analysis

Principal component analysis (PCA) is a multivariate method that evaluates a data set in which the original data are represented by a few new orthogonal variables (Abdi & Williams, 2010). The target of it is to remain the most important dimensions from the raw data by representing it as a collection of few orthogonal variables and to discover the pattern of similarity of the original data (Tipping & Bishop, 1999). The calculation speed is faster compared with other dimension reduction technology like Linear Discriminant Analysis (LDA), which make it become a widely used method to reduce data size and saving storage resources without losing too much useful information by reducing high similarity dimensions. And it is also the main method to assistant data visulation because only 2 or 3 dimensional data can be ploted in a figure.

PCA has been applied in various disciplines to reduce dimensions, remove noises, and develop a new index. For example, A. Kumar and Goyal (2013) have developed an air quality index to predict the pollutant dispersion in urban areas based on Artificial neural networks (ANN) and PCA. And PCA has also been used to investigate the barriers to the development status of SMEs in South Africa by Olawale and Garwe (2010). Moreover, an alternative decision model to exam the relative performance of suppliers has been developed based on PCA (Petroni & Braglia, 2000). It can help retailers exam supplier performance to select the suppliers which meet their requirements in terms of multiple performance criteria. Besides, shen How and Lam (2018) have built up an optimization approach by combining PCA with the analytic hierarchy process (AHP) to conduct sustainability evaluation of the biomass supply chain (the workflow is in **Figure 6**). In this study, PCA can help to reduce the dimensions of centrality metrics result to make the distributions of factors can be visulatized in 2-D figures.

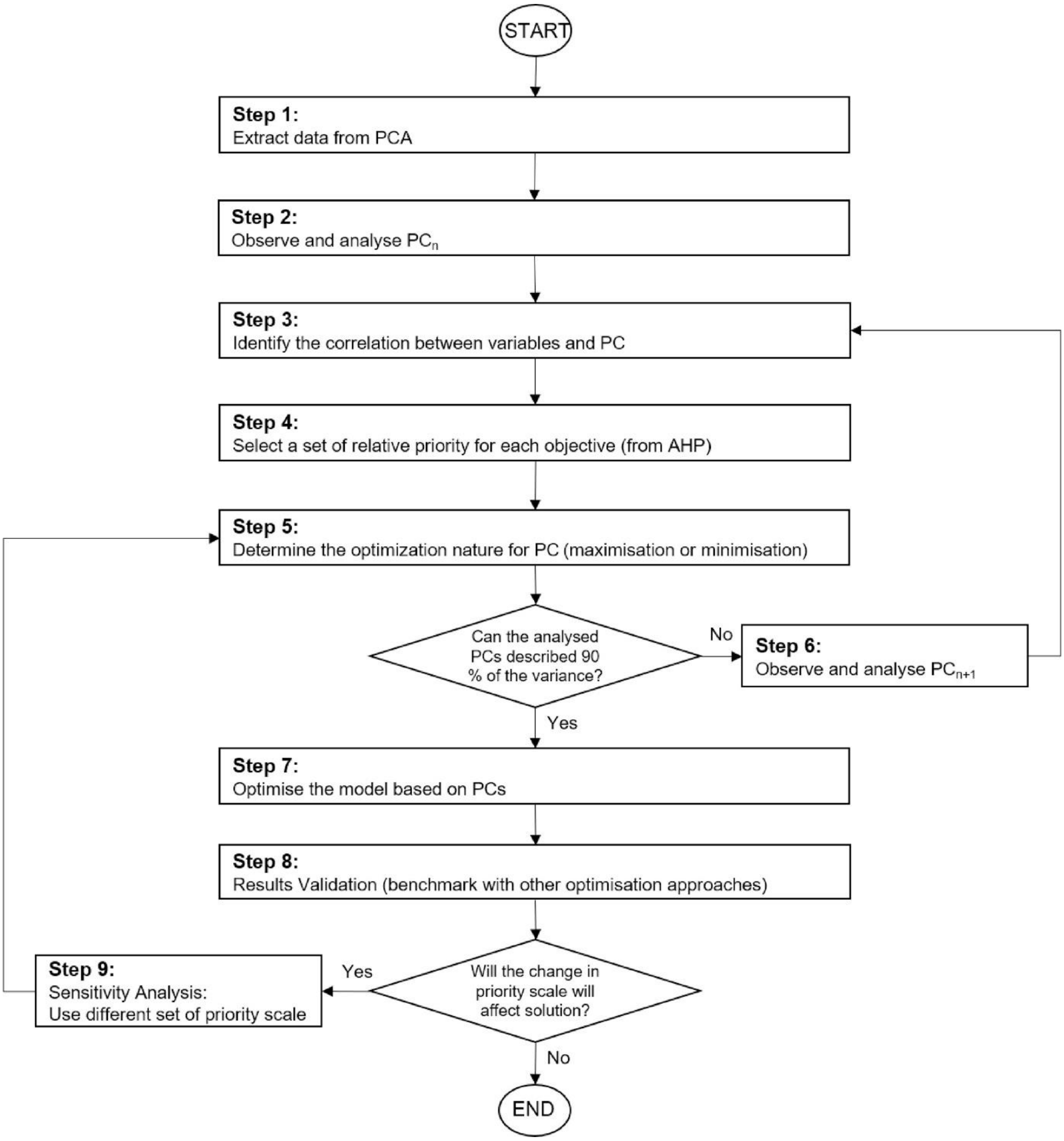

Figure 6 The sustainability assessment model based on PCA and AHP (shen How & Lam, 2018)

In the research area of sustainable manufacturing, PCA also shows its potential to assess the sustainability level (Jiang et al., 2018). A three-dimension sustainability assessment method has been proposed to measure the companies' performance (Jiang et al., 2018). And PCA has also enabled a new life cycle assessment method for ensuring sustainable manufacture (Vinodh, Ruben, & Asokan, 2016). T. Li, Zhang, Yuan, Liu, and Fan (2012) used PCA to conduct industry and academic surveys to obtain firsthand information on sustainability indicators. And a co-efficiency indicator in New Zealand was proposed based on PCA (Jollands, Lermit, & Patterson, 2004).

2.3. Sustainable manufacturing

Manufacturing refers to all the activities in the whole process from the raw material collection to the transformation process of the final product until sold to the customer, so it includes all the various types of services and products relative to the value chain (Garetti & Taisch, 2012). The importance of manufacturing to human society has been high in many regions. For example, the European Commission has reported that the manufacturing sector accounts for around 23% of the GDP in the EU, and 71% of jobs opportunity (Manufuture, 2004). Therefore, there is no doubt the manufacturing sector performs a key role in the three dimensions of sustainability (shown in **Figure 7**). And sustainable manufacturing becomes an increasingly important research area with the remarkable attention of both researchers and corporate.

As defined by Alting and Jøgensen (1993), sustainable manufacturing includes the management of the entire life cycle including designing, production, delivery to the disposal phase. It includes resource consumption and pollution reduction. Another dimension of sustainability is the social aspect. Gutowski (2007) reported four contributors including population, GDP per energy consumption, energy per capita, and the carbon intensity of energy to explain the causes of CO2 emissions.

The revolution towards sustainable manufacturing should consider different related aspects in terms of economics, society, and people, in which this concept can form one of the essential sustainability frameworks: triple bottom line (TBL). TBL comprises three components which are social equity, economy, and environment. TBL has been widely regarded as a framework for evaluating the sustainability level (Richardson & Henriques, 2013). These three dimensions need to be considered in the evaluation of sustainable manufacturing (S. Lee, Geum, Lee, & Park, 2012). Based on the concept of TBL, sustainable manufacturing parameters in this study are grouped into three communities: economic community, environmental community, and social community.

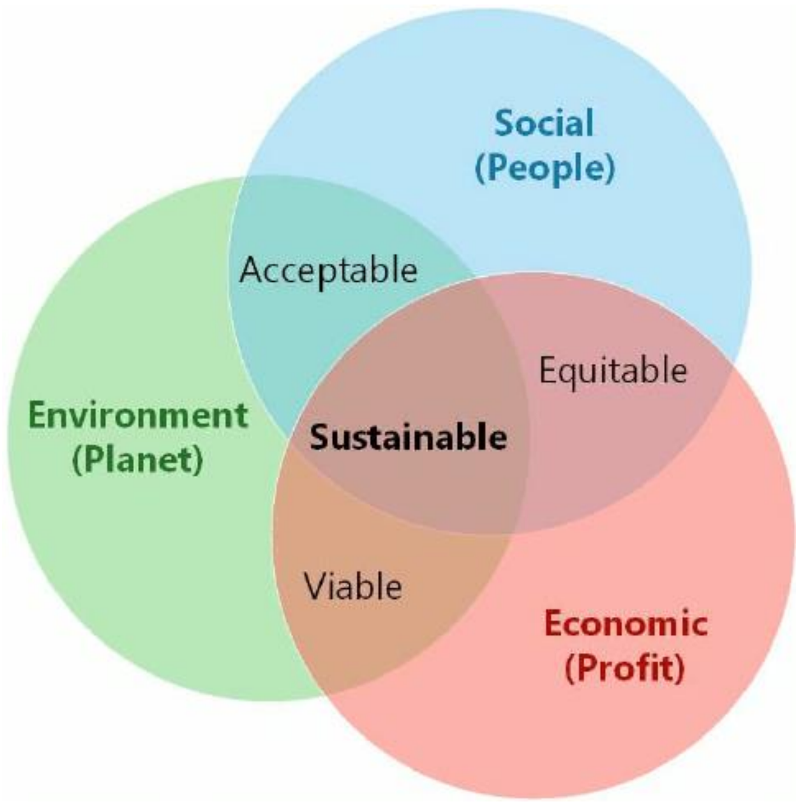

Figure 7 The three pillars of sustainability (Garetti & Taisch, 2012)

As the population grows, the demand for high-tech goods raises fast, and manufacturing productivity needs to be improved to fulfill the requirement (Westkämper, Alting, & Arndt, 2001). For factories, an increasing demand is a good signal of business expansion. However, the growth in demand could lead to more natural resource consumption. And the optimization of machining operations has been studied to minimized energy consumption (Rajemi, Mativenga, & Aramcharoen, 2010). Moreover, Rashid, Asif, Krajnik, and Nicolescu (2013) have proposed a new model of Resource Conservative Manufacturing (ResCoM) by studying the closed-loop systems of manufacturing companies. The updated concept of the manufacturing system with material flows is shown in **Figure 8**.

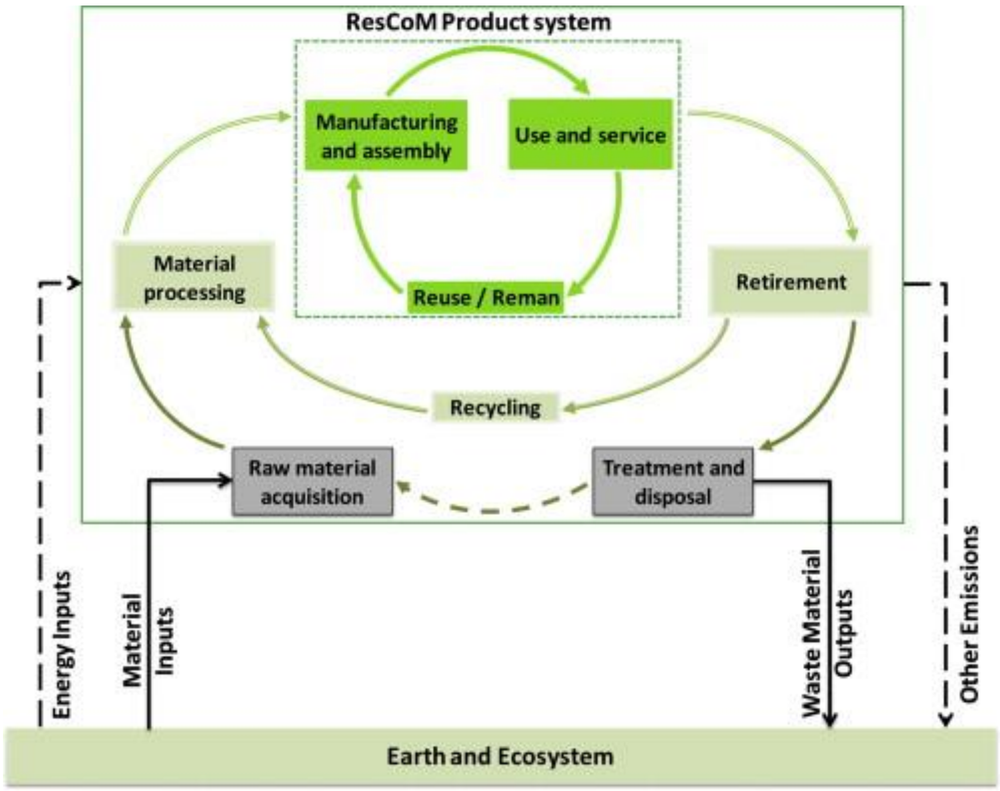

Figure 8 Modified manufacturing system with material flows (Rashid et al., 2013)

Some contributing factors of sustainable manufacturing have been studied by some researchers (Rosen & Kishawy, 2012), and a total of seven contributors has been identified in their study (as shown in **Figure 9**). However, the impacts of these factors on each other have not been investigated further in this study, which many leads to the difficulty to achieve the target of sustainable manufacturing. And the multiple dimensions system method has been developed to measure the sustainability level of the production process by C. Yuan, Zhai, and Dornfeld (2012). Based on this approach, a case study about semiconductor manufacturing has been conducted to illustrate how to improve its sustainability performance by using this system.

However, it does not include the upstream and downstream environmental impact assessment for the waste emission.

Figure 9 Key contributing factors to sustainable manufacturing (Rosen & Kishawy, 2012)

Recently, data-driven optimization methods have also been applied to improve the sustainability level in the manufacturing sector. For example, a manufacturing equipment service model was proposed to optimize the manufacturing schedule dynamically which is shown in **Figure 10**. This system can be driven by real-time energy consumption and production data to sustainable scheduling optimization (Xu, Shao, Yao, Zhou, & Pham, 2016). But as mentioned by the authors, this scheduling system only considers limited parameters of sustainable manufacturing. Moreover, a decision-making model based on the dynamic programming method has been proposed to achieve industrial energy optimization. However, the relationships among the parameters were not evaluated in that study.

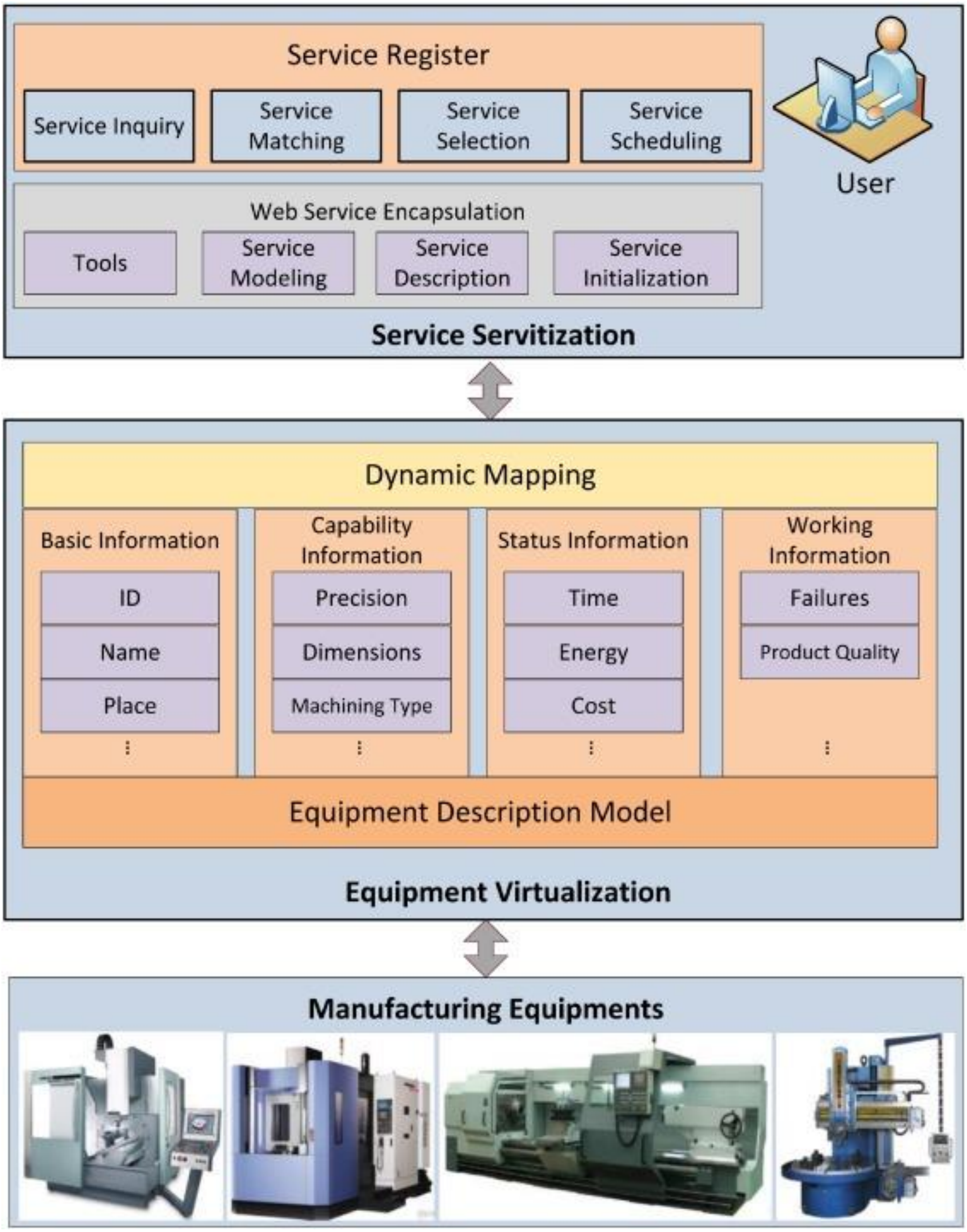

Figure 10 The manufacturing equipment service model

With the development of data mining technology, machine learning algorithms show their potential in the research area of sustainable manufacturing to do prediction and classification. To do the quality prediction of the rolling mill, supervised learning, as well as the unsupervised learning methods, have been utilized to identify the operational patterns by Lieber, Stolpe, Konrad, Deuse, and Morik (2013). And machine learning also enables cost savings, time savings, increased quality in manufacturing by predicting and managing human behavior (du Preez & Oosthuizen, 2019). Besides, a text mining approach was utilized to analyze the current research about sustainable manufacturing (Bhanot, Rao, & Deshmukh, 2016). Based on it, the critical issues for implementing sustainable manufacturing could be identified.

2.4. Ultra-precision machining

For the UPM process, surface topology is produced from the transformation between the UPM tool to the surface of raw material, and it consists of complex interactive relationships of workpiece deformations, which can be mainly denominated by the combining impact from UPM parameters. This complex impact of the parameters influences each other and is hard to be analyzed according to one single parameter. Thus, the interactive relationships among each parameter need to be identified, to evaluate the surface quality in terms of the machining process with the characteristics of the movement of machine tools.

Recently, a lot of studies have been done which focus on the evaluation of the impact of the UPM factors on surface accuracy. And the common UPM parameters consists of cutting condition, tool wear (Wada et al., 1980) tool geometry (C. F. Cheung & W. B. Lee, 2000), material properties (H. Wang, To, Chan, Cheung, & Lee, 2010b), machining system vibration (Takasu, Masuda, Nishiguchi, & Kobayashi, 1985), and tooltip vibration (H. Wang, To, Chan, Cheung, & Lee, 2010a). Tool geometry could remarkably influence chip formation, tool wear, surface roughness, and heat generation, etc. as shown in **Figure 11**, its impacts have been a key focus for studying cutting operation (Dogra, Sharma, & Dureja, 2011). Tool geometry includes radius of tool nose as well as tool profile, and commonly surface roughness can be reduced while the radius of tool nose raises. Nonetheless, the impact of other parameters associated with the parameter of tool geometry, which may lead to fast decisions of this parameter setting becomes extremely hard. What's more, material characteristics is another parameter with complex influencing relationships in UPM. It has remarkable impacts on surface generations in machining process as each type of material has the unique property influencing mchining, and it can also cause reversed effects under some working conditions to upstream UPM parameters. And tooltip vibration is one kind of vibration which can influence surface forming process. Its working mechanism is complicated and has been evaluated by researchers in a long period. And these material parameters do not individually transfer their impact on surface generation process. For UPM, their impacts are combined with each other as the perivous work reported, thus, a model with network structure with all relationships among parameters need to be constructed to provide a clear and effective strategy to conduct the machining.

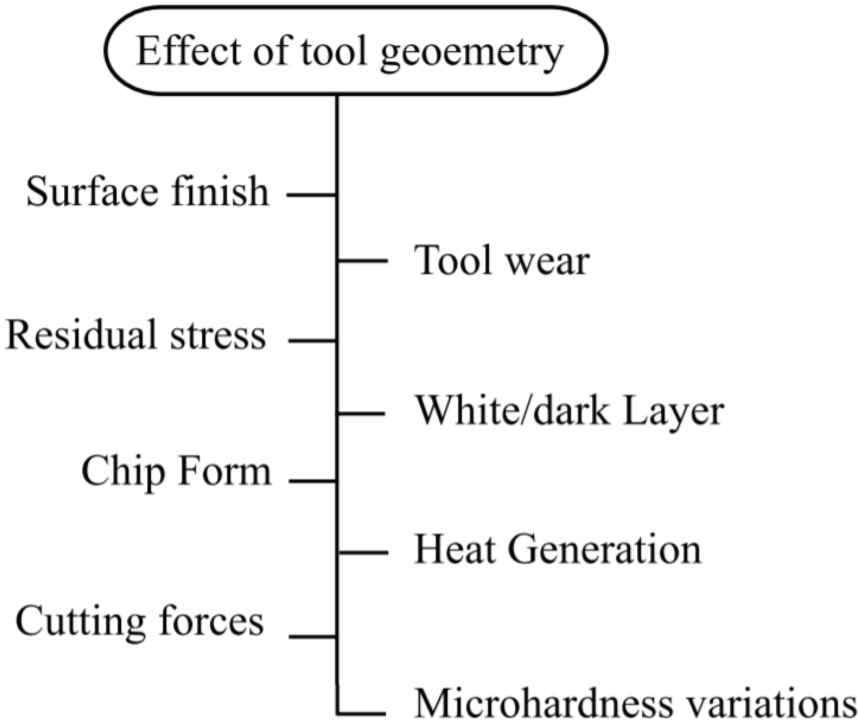

Figure 11 The effect of tool geometry on performance parameters in turning (Dogra et al., 2011)

The complexity of achieving optimal conditions of UPM may raise with the number of machining factors that involve the selection of tolerance allocation in machining processes (X. Zhang, Wang, Chen, & Huang, 2018). And a model-based simulation approach for the surface forming process has been developed by (SJ Zhang, To, Zhu, & Zhang, 2016). And The process of the simulation system is shown in **Figure 12**.

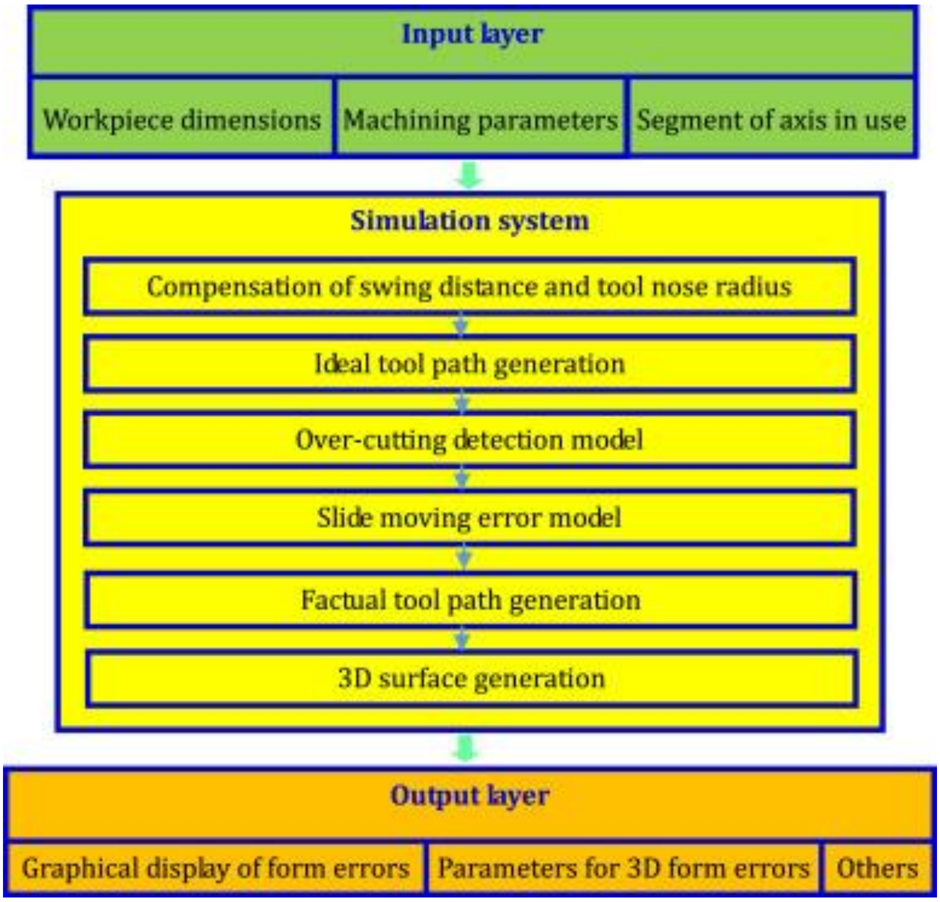

Figure 12 The process of the model-based simulation system (SJ Zhang et al., 2016)

Besides that, because of high machining costs and unstable machining environments during UPM, a lot of optimization methods are rarely utilized to detect the optimal processing condition during UPM. Conversely, conceptual modeling and simulation are frequently applied to study the optimal UPM parameters and conditions during the machining process. C. Cheung and W. Lee (2000) developed a computational simulation method that can consider the machining parameters to obtain the required surface generation during the ultra-precision turning. As presented in **Figure 13**, an influencing road map from the effect of material on surface roughness has been proposed after studied the causes of surface roughness (SJ Zhang, To, Wang, & Zhu, 2015). It illustrated an influencing path involves a lot of different UPM parameters such as cutting force and material removal rate. And Cheng, Cheung, Lee, To, and Kong (2008) developed a conceptual model for the evaluation of nano-level surface forming in milling. and the method can forecast the surface roughness of the final product and achieve the optimal condition when considering different UPM strategies. The simulation method has been utilized to study UPM commonly as the high machining costs caused in real-world experiments. But the simulation methods have been conducted with quite a lot of assumptions that are only available for the specific case, so they need to be updated if some small changes in the UPM process happen, and it can affect the forecasting result of the methods. Moreover, some numerical methods were also been applied to reduce or simplify of a few assumptions. Though the methods can be utilized to evaluate more significant parameters including the stress of material flow, the forecasting process still can underestimate the impacts of several certain machining parameters. Therefore, an influencing network consists of main UPM parameters need to be developed to offer an entire picture of relationship map showing the dependency, and it can provide the guidelines on how to set those parameters with consideration of the dependencies before starting the machining, and reducing the processing costs and computing time in the real-world system.

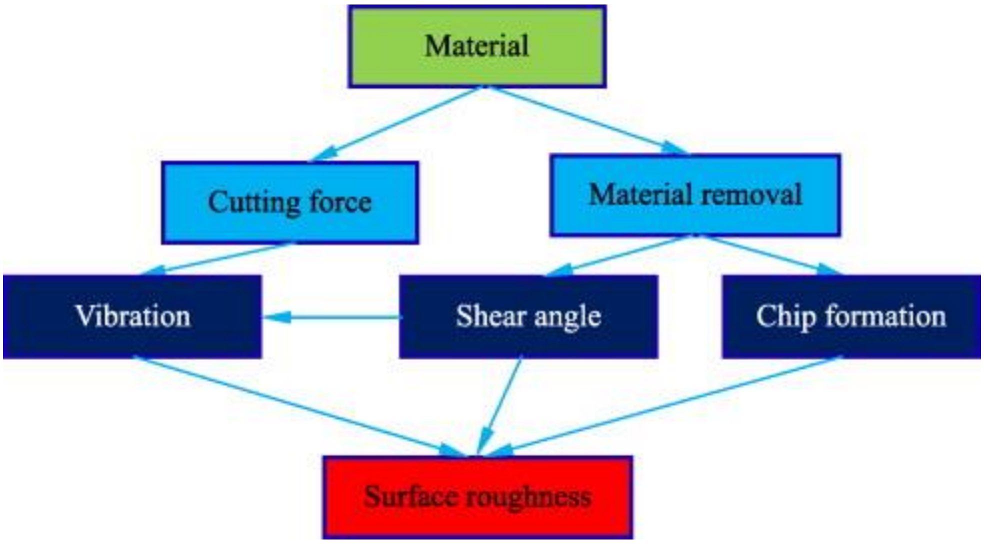

Figure 13 The roadmap of the impact of material on surface roughness (SJ Zhang et al., 2015)

Currently, the UPM optimization methods are normally including an orthogonal experiment and gray relational analysis combined with the Taguchi method. It is helpful to be adopted in situations involving various inputs, uncertainty, and discrete data in experimental design (Yu, Zhang, Yu, Yang, & Sun, 2019). Nonetheless, there is a specific drawback of this method, in which the calculation method rarely relies on the input. For UPM, some machining parameters are commonly presented in descriptive ways. Two examples are tool wear and chip formation, which are normally shown in descriptive forms to analyze the machining principles. Thus, these parameters can not be evaluated by applying the statistical method including the gray relational analysis. And the Taguchi method utilizes statistical models considering the evaluation of variance, while the parameters in the experiments can be recognized as the essential parameters leading to declines in machining performance. The main focus of the Taguchi method is the significance of the parameters in the overall designing flow. Thus, the parameters need to be identified before utilizing the Taguchi method. And then, a set of experiments with different values of parameters to show the influences on the performance are conducted. Thus, researchers need to find out the necessary parameters of the machining which may influence the expected experimental result. It indicates that the researchers are required to know the selection of the involved parameters in advance. Because of that, the model with a network structure using SNA can perform as an instruction for researchers to prepare themselves with the machining factors before a large number of experiments are made. Traditional optimization methods utilized in UPM have their advantages, and this project can offer new insight into applying the SNA method to equip the optimization approach.

2.4.1. Data-driven optimization method for UPM

According to the study of Kucukoglu, Atici-Ulusu, Gunduz, and Tokcalar (2018), a deep neural network (DNN), which is developed according to the working principle of neuron cells has also been applied to optimize the UPM parameters (as shown in **Figure 14**). It achieves great success in many targets including classification, prediction, and a certain range of accuracy (Kucukoglu et al., 2018). However, it also has some limitations, such as long training time and power consumption. To solve these issues, a dendritic neuron algorithm has been developed with the consideration of the nonlinearity of synapses, which provides an efficient method for concrete problems. And, the methods in the dendritic neuron model consist of particle swarm optimization, evolutionary strategy, genetic algorithm (Gao et al., 2018). The outputs achieved from the dendritic neuron algorithm are described to be accurate. Authors adopt a big bang-big crunch optimization method coupled with particle swarm optimization to reduce the negative impact of the problem of the large raw data size, where the hybrid optimization method can transform the overall approach into a feed-forward training process (J. Wang & Kumbasar, 2019). Additionally, network-based analysis is commonly utilized in projects to study machining systems. For instance, a networked method was proposed to evaluate advanced manufacturing systems based on a literature review (Y. Li, Tao, Cheng, Zhang, & Nee, 2017). Some scientific papers were used to find out the current research gaps and utilized them to construct a complex network of machining parameters to shows the potential research chances in this area in further study. What's more, Chankov, Hütt, and Bendul (2018) studied the synchronous stability of the network in a machining system according to the feature of the network. It was the first time the synchronization-oriented design of the machining process concerning the structure characteristics was adopted. Besides, it was presented the reliability assessment of machining processes with various production lines according to the machining network (Y.-K. Lin & Chang, 2013). They utilized the graphical approach to transform the production system into a complex network to discover the general machining paths in this process. It shows that academic attention on network-based method is increased remarkably.

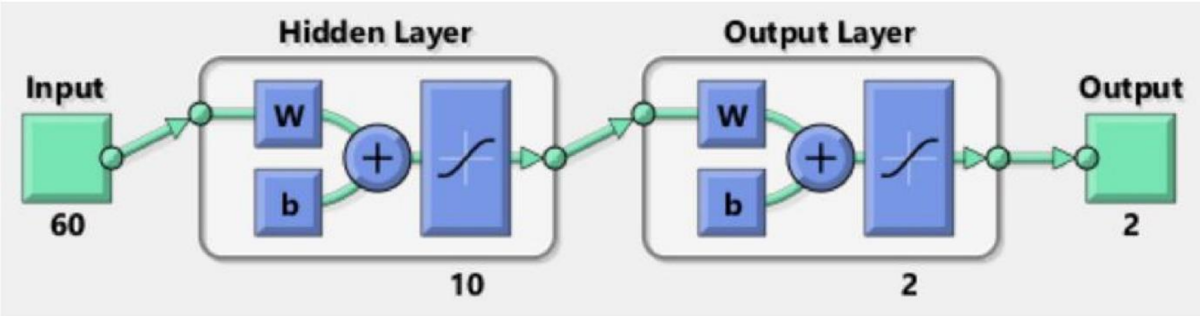

Figure 14 The ANN structure for the digital assembly glove (Kucukoglu et al., 2018)

2.5. Summary of literature review

From the current literature, it shows the applications of SNA and unsupervised learning methods in the sustainable UPM area remain insufficient. It still lacks studies of sustainable machining and ultra-precision machining by using the SNA approach in current research work. The interactive relationships among the sustainable manufacturing factors are still a research gap to be fulfilled. In this work, the SNA-unsupervised learning model was proposed for the first time to improve the research area of sustainable UPM.

Chapter 3 Methodology

As shown in **Figure 15**, the overall methodology in this project consists of four levels: node-level analysis, edge level analysis, network-level analysis, and classification unsupervised learning. The first three levels belong to the method of social network analysis (SNA) and the third level is unsupervised learning. This section has two main parts: the social network centrality metrics were presented in section 3.1, and the deep learning method was introduced in section 3.2.

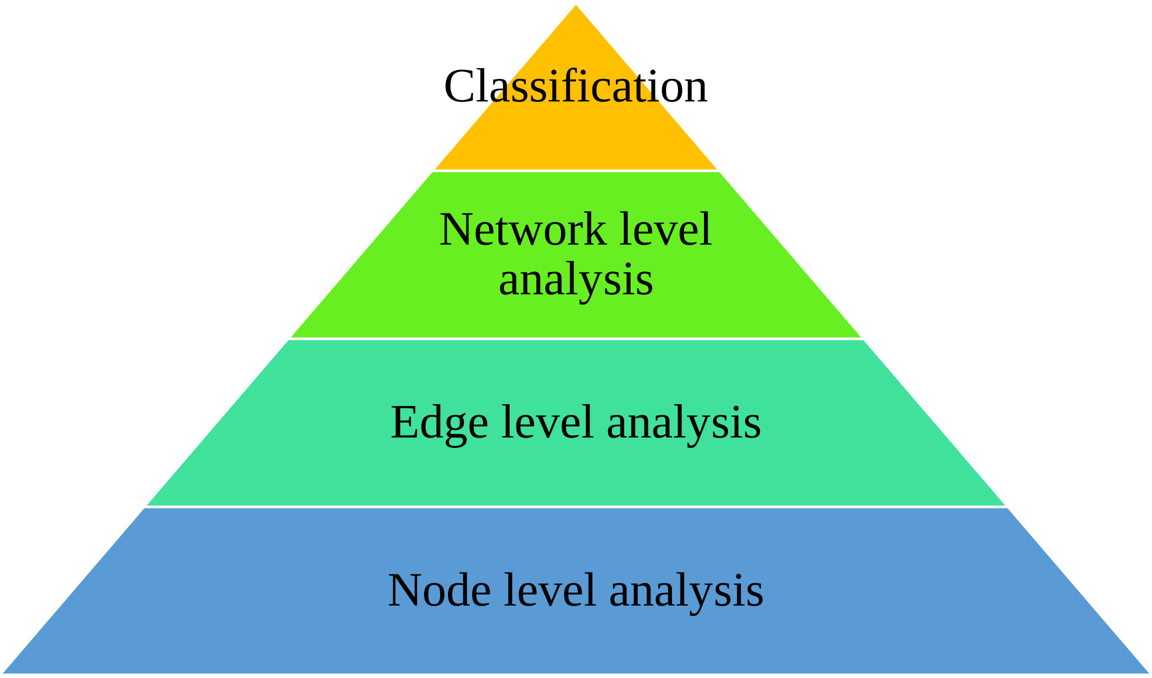

Figure 15 The structure of the three-level SNA-ML model

3.1. Social network analysis centrality metrics

The centrality metrics drawn from graph theory seek to represent and analyze the patterns of nodes and relationships in networks (Pavlopoulos et al., 2011). As mentioned by Clemente, Martins, Wong, Kalamaras, and Mendes (2015), centrality metrics are measurements of importance and power. And there are four most common metrics in SNA were chosen: degree, betweenness, closeness, and eigenvector. The definition and description of these centrality metrics are summarized in **Table 1**. The centrality metrics were ulized as the node-level analysis because they can evalute the roles and importance of each parameters.

Table 1 the definition and description of centrality metrics

Centrality metrics	**Definition**	**Description**	**Comparison between directional and non-directional networks**
In-degree centrality	The number of incoming edges pointing to one node divided by the possible maximum number of edges.	Measure the degree of nodes influencing a given node (Y. Kim, Choi, Yan, & Dooley, 2011).	Non-directional networks only have the degree centrality as the number of incoming edges is equal to the outgoing edges.
Out-degree centrality	The number of outgoing edges starting from one node divided by the possible maximum number of edges (Zhou et al., 2020).	Measure the degree of nodes influenced by a given node (Y. Kim et al., 2011).	Non-directional networks only have degree centrality as the number of incoming edges is equal to the outgoing edges.
Betweenness centrality	The number of shortest paths between a pair of non-adjacent nodes where a node lies (Y. Kim et al., 2011).	Measure the ability to "control" the shortest path in a network.	In a non-directional network, betweenness centrality is normalized by $2(g-1)(g-2)$; while it is normalized by $(g-1)(g-2)$ in a directional network. And g is the total number of nodes.
Closeness centrality	Reciprocal of the distance between a given node to all other nodes (Y. Kim et al., 2011).	An index of "center" in a network according to the distance.	In a directional network, the shortest path's distance from n_i to n_j may not equal to that from n_j to n_i, there may be more than one shortest path between n_i and n_j.
Eigenvector centrality	Centrality based on the level of connectedness of a node's connections, taking the	Measure the connectivity of a node according to its neighbors' connectivity.	It has the same concept in both directional and non-directional networks

	whole network structure into account.		
Centrality Index	A weighted average of the above metrics by scaling all other metrics' results.	A scaler of other centrality metrics.	It has the same concept in both directional and non-directional networks

3.1.1. Degree distribution

Degree centrality is a measure of immediate relationships only (Lusher, Koskinen, & Robins, 2013). In a non-directional network, the degree of a node is the number of edges accident to it. As for the directional networks, the in-degree of a node is the number of edges pointing to the node while the out-degree is the number of outgoing edges starting from the node. In a directional network, the in-degree centrality $C_I(n_i)$ and out-degree centrality $C_O(n_i)$ of n_i are calculated by the number of direct edges of n_i. These metrics are defined as below (Shaw, 1954):

$$C_I(n_i) = \frac{\sum_j x_{ji}}{g-1} \quad (1)$$

$$C_O(n_i) = \frac{\sum_j x_{ij}}{g-1} \quad (2)$$

where x_{ij} is the number of edge from n_i and n_j while x_{ji} is the number of edge from n_j to n_i, which can only be 0 or 1. And g is the total number of nodes. Therefore, the possible maximum number of edges of n_i is $g-1$. In non-directional network, the number of links started from n_i to n_j is equal to the number of links from n_j to n_i. Therefore, the degree centrality in a non-directional network is defined as below:

$$C_d(n_i) = \frac{\sum_j x_{ji}}{g-1} = \frac{\sum_j x_{ij}}{g-1} \quad (3)$$

It is the most basic measurement of the centrality based on the direct relationships with other nodes comparing with other centrality metrics. However, it cannot consider the indirect relationships among nodes.

3.1.2. Betweenness centrality

Betweenness is a metric according to the chance that a vertex distributes on the shortest path (which is called geodesic) between other nodes in the network (Newman, 2005). Normally, this metric is calculated according to the fraction of geodesic between two vertices that pass through the target vertex. Thus, it can indicate the ability to control the communications within the network. The betweenness centrality of n_iw as expressed as (Freeman, 1977):

$$C_B(n_i) = \sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}} \quad (4)$$

where g_{jk} is the total number of shortest paths between n_j and n_k. And $g_{jk}(n_i)$ is the number of these shortest paths through n_i. In a directional network, it is normalized into the range from 0 to 1 by:

$$C_B{}'(n_i) = \frac{C_B(n_i)}{(g-1)(g-2)} \quad (5)$$

However, in a non-directional network, betweenness centrality is normalized by $2(g-1)(g-2)$:

$$C_B{}'(n_i) = \frac{C_B(n_i)}{2(g-1)(g-2)} \quad (6)$$

Betweenness value can measure the capability of "gatekeeping" of specific factors for the other factors (Yip, To, & Zhou, 2020). The factors with high betweenness scores perform as hubs and transport the impacts through the SNA network. If the parameters with high betweenness scores are removed, the paths of impacts are stoped and not able to come to downstream UPM parameters smoothly. This metric measures the centrality from the view of the impacts on the connectivity of the whole network, which does not focus on the direct relationships with the neighbors of the node compared with degree distribution.

3.1.3. Closeness centrality

Closeness measures how close a node is to all other nodes in a network (Zhao, Lui, Towsley, & Guan, 2014). In a directional network, the shortest path's distance from n_i to n_j may not equal to that from n_j to n_i, there may be more than one shortest path between n_i and n_j. Thus, the determination of the geodesic between a pair of factors is necessary as several paths from n_j to n_i. The closeness can be calculated as :

$$C_C(n_i) = [\sum_{j=1}^{g} d(n_i, n_j)]^{-1} \quad (7)$$

where $i \neq j$, and g is the number of vertices in the network. Therefore, $\sum_{j=1}^{g} d(n_i, n_j)$ is the total distance from n_i to all other nodes. The closeness centrality measures the centrality from the view of the total distance of the "information flow" from one node to all other nodes, which is not being considered in other metrics.

In this study, closeness shows the ability of parameters to influence the overall performances in the view of a whole system. It indicates that the machining parameters with high closeness value could lead to important impacts on the system performance. And the nodes with a shorter overall path to other nodes can be regarded as the main concern to achieve the target of performance. This accessibility could increase the capability to obtain specific aims, for instance, achieving high machining quality and removal rates, make it possible to achieve fewer machining costs.

3.1.4. Eigenvector centrality

Eigenvector centrality is a metric of centrality considering the connectivity of the node's neighbors (Ruhnau, 2000). The eigenvector centrality of n_i was expressed as below:

$$C_E(n_i) = \frac{1}{\lambda}\sum_{n_j \in M(n_i)} n_j \quad (8)$$

where $M(n_i)$ is the collection of the neighbors of n_i , while λ is the largest eigenvalue of the adjacency matrix. The main idea behind eigenvector centrality is that the importance of a node is larger if this node is linked to more important vertices (Perra & Fortunato, 2008). That indicates the parameters with high eigenvector score performs as the “bridge” of other nodes in the sustainable UPM network. Compared with other metrics, eigenvector centrality can take into account the connectivity of the node's neighbors.

3.1.5. Centrality index

To provide an overall measurement, all the centrality metrics result can be normalized into the range 0 to 1 firstly by the below equation:

$$c_{ij} = \frac{c_{ij}^{(0)} - c_{j,min}^{(0)}}{c_{j,max}^{(0)} - c_{j,min}^{(0)}} \quad (9)$$

where $c_{ij}^{(0)}$ and c_{ij} and are the sequences before and after the data normalization; $i = 1,2,\dots,m$ and $j = 1,2,\dots,n,$ where m and n stands for the number of parameters and the number of metrics; thus, $c_{j,min}^{(0)}$ and $c_{j,max}^{(0)}$ represent the minimum and maximum of the results of metric

j. Then, the normalized metrics results can be summed up to get the overall measurement called "centrality index".

3.2. Social network analysis linkage prediction metrics

To find some hidden linkages among different parameters, several technologies were introduced in this section, including common neighbors, Jaccard coefficient, resource allocation, Adamic-Adar Index, Pref. attachment, community common neighbor, community resource allocation. With the comparison of centrality metrics, edge-level analysis analyze the network from the view of the relationships among the sustainable manufacturing and UPM factors. It can help to detect the non-adjacent factor pairs that have a high potential to be linked in the future.

3.2.1. Common neighbors

The common neighbor is a metric to predict the linkage between two nodes according to the number of their common adjacent nodes (F. Tan, Xia, & Zhu, 2014). the common neighbor between n_i and n_j is calculated by:

$$cn(n_i, n_j) = |N(n_i) \cap N(n_j)| \quad (10)$$

where $N(n_i)$ and $N(n_j)$ are the collections of the neighbors of n_i and n_j. It is the most basic measure of the chance that two nodes be linked in the future. It is developed from the fact that people who have more common friends have a higher probability to know each other.

In the study of sustainable machining, it can be utilized to measure the probability that two parameters have a hidden relationship. If a pair of nodes have a high common neighbors score, it may be valuable to be explored.

3.2.2. Jaccard coefficient

Jaccard coefficient is a measurement developed based on the common neighbors (Barbour, Graves, Plafkin, Wisseman, & Bradley, 1992). The Jaccard coefficient is expressed as:

$$jc(n_i, n_j) = \frac{|N(n_i) \cap N(n_j)|}{|N(n_i) \cup N(n_j)|} \quad (11)$$

where $|N(n_i) \cup N(n_j)|$ is the total number of neighbors of n_i and n_j. It measures the chance based on comparing the percentage of common neighbors in the total number of their neighbors. If common neighbors count low percentages of neighbors, these two nodes may have less chance to be linked through the number of common neighbors is large.

3.2.3. Resource allocation

Resource allocation is a metric based on the share of one unit of "resource" that a node can send to another node through a middle node. It was proposed based on the resource flow. The resource allocation is formulated as (De et al., 2011):

$$jc(n_i, n_j) = \sum_{n_k \in N(n_i) \cap N(n_j)} \frac{1}{|N(n_k)|} \quad (12)$$

where $N(n_k)$ is the collection of the neighbors of n_k. As shown in **Figure 16**, if node k has n neighbors, when n_i sends 1 "resource" to n_j through n_k, then n_k distributes the resource equally to every neighbor of it. Therefore, the n_j can only receive $1/n$ unit from n_i through node k. In this study, this metric can measure the hidden relationship between two parameters based on the share of flow capacity in the whole network.

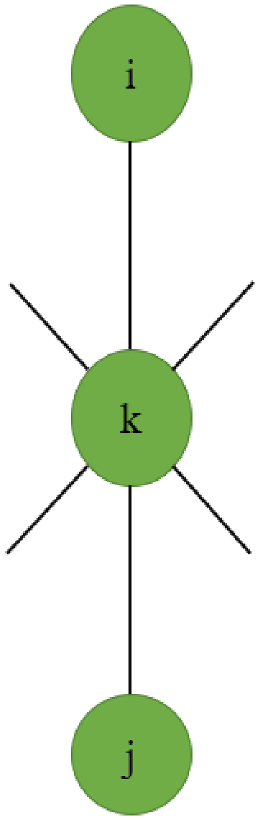

Figure 16 Resource allocation model

3.2.4. Adamic-Adar Index

The Adamic-Adar index is similar to resource allocation, but it has a log function in its denominator (Bliss, Frank, Danforth, & Dodds, 2014). The formula of Adamic- Adar index is expressed:

$$aai(n_i, n_j) = \sum_{n_k \in N(n_i) \cap N(n_j)} \frac{1}{\log(|N(n_k)|)} \quad (13)$$

According to the experiment, this index can give a better performance between the actual mail network and predicted linkages. Therefore, It was used to be one metric to predict the relationships among parameters in this study.

3.2.5. Preferential Attachment

According to some studies (Alamsyah, 2014), the nodes with a high degree get more neighbors. Therefore, the preferential attachment can be calculated as:

$$pa(n_i, n_j) = |N(n_i)||N(n_j)| \quad (14)$$

where $|N(n_i)|$ and $|N(n_j)|$ are the number of neighbors of n_i and n_j. It is proposed based on that the two people with a large number of friends have a higher chance to be introduced.

3.2.6. Community common neighbors

Some measures consider the community structure of the link prediction. Assume two nodes in the network belong to different communities (sets of nodes). Pairs of nodes who belong to the same community and have many common neighbors in their community are likely to form an edge. The community common neighbor defined by Soundarajan and Hopcroft (2012):

$$ccn(n_i, n_j) = |N(n_i) \cap N(n_j)| + \sum_{n_k \in N(n_i) \cap N(n_j)} f(n_k) \quad (15)$$

where $f(n_k) = \begin{cases} 1, & n_k \text{ in the same community as } n_i \text{ and } n_j \\ 0, & otherwise \end{cases}$, which could give a bonus for a common neighbor in the same community. As the example shown in **Figure 17**, node A, B, C, D form community 1 and the nodes E, F, G, H, I form community 2. The community common neighbor value between node A and node C is 2+2=4 as both community common neighbors and A, C belongs to community 1. And community common neighbor value between node E and node I is equal to 1+1=2.

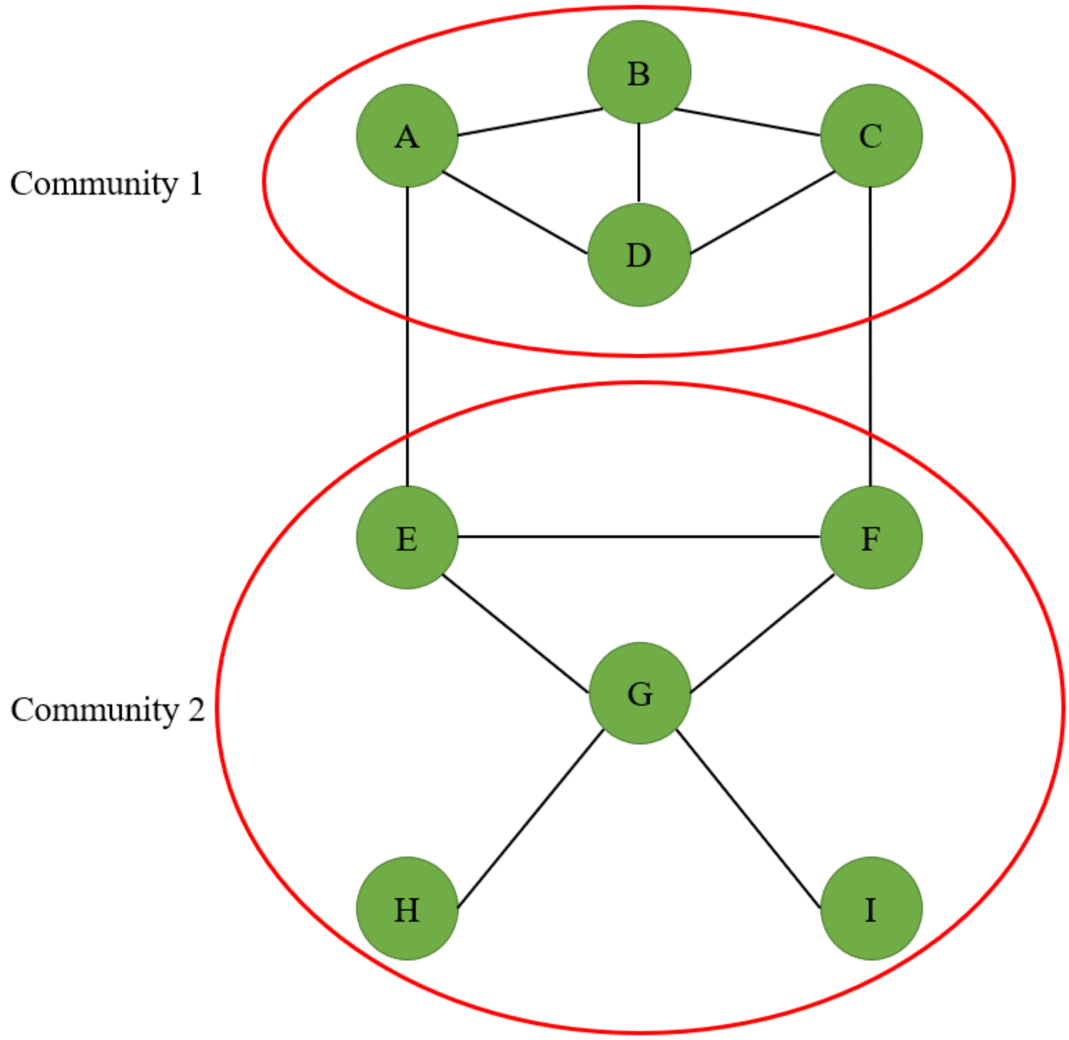

Figure 17 The community common neighbor example

3.2.7. Community Resource Allocation

The community resource allocation is developed based on resource allocation, but it only considers the nodes in the same community (Afolabi, Dadlani, & Kim, 2012). And it is calculated as:

$$ccn(n_i, n_j) = \sum_{n_k \in N(n_i) \cap N(n_j)} \frac{f(n_k)}{|N(n_k)|} \quad (16)$$

For the example shown in **Figure 16**, the community resource allocation between node A and node C is calculated as below:

$$cra(A,C) = \frac{1}{3} + \frac{1}{3} = \frac{2}{3}$$

Node A and C have two common neighbors in the same community, which are nodes B and D. And nodes B and D have three neighbors. Therefore, community resource allocation is $\frac{1}{3} + \frac{1}{3} = \frac{2}{3}$.

3.3. Network-level analysis metrics

The network-level analysis metrics are presented in this section, which includes centralization and density of a network. The definition and description of the network-level analysis metrics were summarized in sections. Compared with node-level analysis and edge-level analysis, the network-level analysis metrics focus on the overall structure of the whole network. Thus, the SNA approach including three types of metrics can evaluate the sustainable manufacturing and UPM parameters from the individual factor aspect, relationship aspect as well as integral structure aspect. In this way, this model can provide a comprehensive analysis of the problems of sustainable UPM involving multiple parameters and complicated inter-relationships.

3.3.1. Centralization in SNA method

Centralization C_D is calculated according to the maximum $C_D(n^*)$ and its formula is shown below:

$$C_D = \frac{\sum_{i=1}^{g}[C_D(n^*) - C_D(n_i)]}{max \sum_{i=1}^{g}[C_D(n^* - C_D(n_i)]} \quad (17)$$

where the total number of nodes is g, and the denominator is $(g-1)(g-2)$. The value of C_D is 1 if the parameters are connected to all other factors, thus, other factors can only reach other nodes through a specific one. The value of C_D will be 0 if the degrees of all vertices in this network are equal. In this study, centralization indicates the ability that can be exercised by the core parameters over other parameters.

3.3.2. Density in SNA method

The density is measured by the number of nodes and the degree of interdependency among other nodes in a network. In this study, a raised number of parameters means that more parameters are required to deal with in the manufacturing, so the optimization is hard to conduct effectively due to the interactive relationships caused by other parameters. Besides, more linkages in a network reflect a higher chance of barriers in evaluating the parameters, leading to more challenging in cooperation among every parameter. For instance, for a parameter with more than one upstream node, the parameter makes large impacts on aligning with the upstream machining parameters compared to the parameters with only one upstream parameter in the network.

3.4. Unsupervised learning method

Unsupervised learning refers to a kind of machine learning algorithm, including k-means and Principle components analysis (PCA), to classify unlabeled data. In this study, k-means can be used for classifying the machining parameters according to the similarity of the centrality metrics and PCA can reduce the dimension to plot the classification result. In this study, the metrics result of the node-level analysis is a small dataset that can help to classify the sustainable UPM factors to provide an overall view of the centrality distribution. According to the research of Soni and Patel (2017), the K-means algorithm can perform efficiently in a small dataset for classification problems compared with other machine learning algorithms like Support Vector Machine (SVM). Therefore, it is selected in this study to classify the sustainable manufacturing and UPM parameters. After getting the clustering results, the dimensions of metrics results should be reduced to 2 or 3 dimensions to visualize the clusters. As mentioned by Onat, Kucukvar, and Afshar (2019), PCA has been used commonly as a dimension reduction technique in literature. In this study, the metrics result of sustainable manufacturing and UPM parameters have more than 3 dimensions. Therefore, PCA was suitable to reduce metrics results to 2 or 3 dimensions before plotting the classification results.

3.4.1. K-means algorithm

And similarly, it can also be utilized to clustering the relationships among the parameters. As the data size is small, k-means is the most suitable method to do the classification. The process of this algorithm is shown in **Figure 18**.

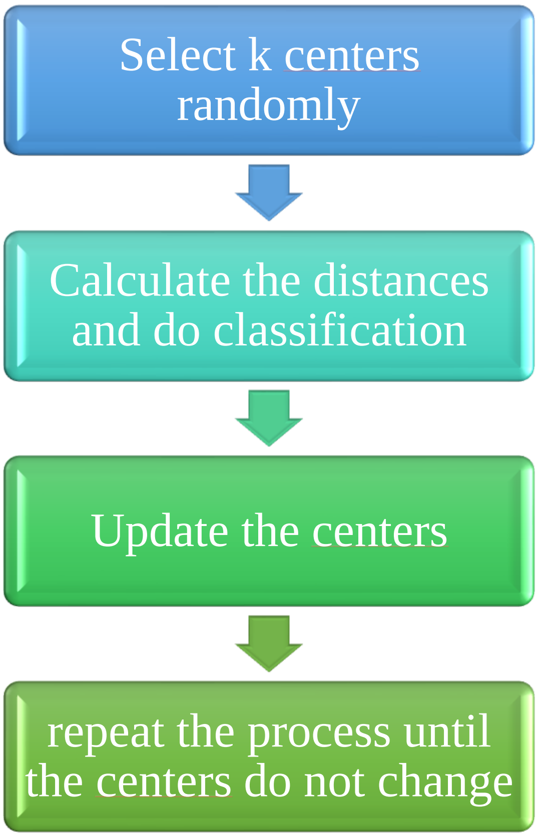

Figure 18 The main process of the k-means algorithm

However, before utilizing this method, the value of k, which stands for the number of clusters should be determined first. In order to do so, two measurements can be used based on the main purposed of classification, including the sum of square error (SSE) and the silhouette coefficient. Normally, a “good” classification means the internal distances among the points in the same clusters should be minimized and the external distances between different clusters should be maximized. Therefore, SSE and the silhouette coefficient are the indicators of the internal and external distances. To find the suitable value of k, different values of k can be tried and run k-means algorithm once for each k, for example, 2 to 9. By observing the decreasing rate of SSE, it can be found that starting from a certain value of k, the rate becomes very small. If the silhouette coefficient for this k is also close to the maximum value, this k can be chosen as the number of clusters. From the classification according to the centrality metrics results, the whole distribution of the parameters can be presented. And it can provide a reference for topics selection, importance evaluation, and so on.

3.4.2. Principal components analysis

The PCA algorithm can find the direction with the most variance and adjust the axis by using the linear combinations of each dimension (Roweis, 1998). And it consists of 5 main steps as shown in **Figure 19**. And the working principle of PCA was illustrated in **Figure 20**. It is widely to be utilized to reduce the dimension of data without losing too much information (Metsalu & Vilo, 2015).

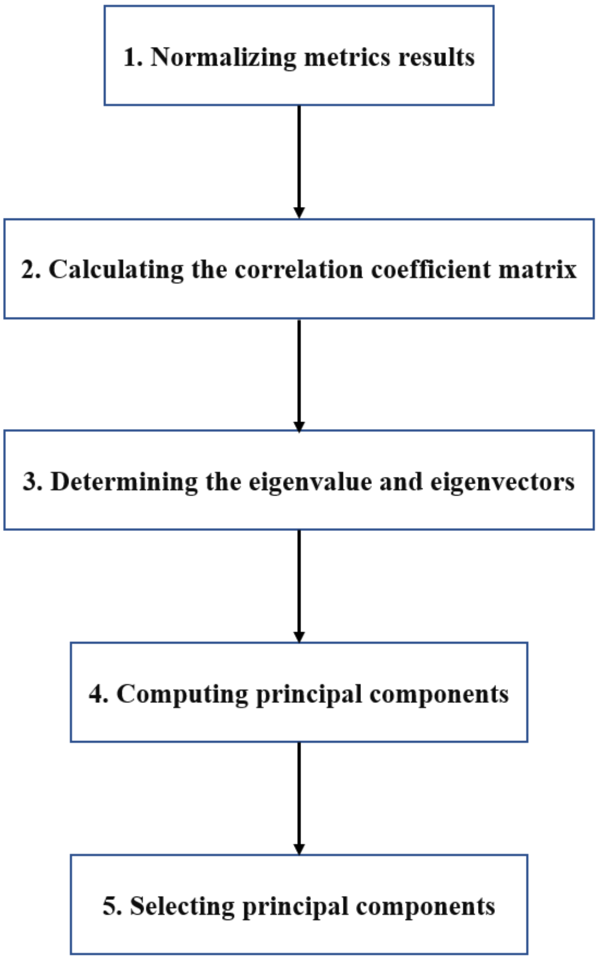

Figure 19 The steps of the PCA algorithm

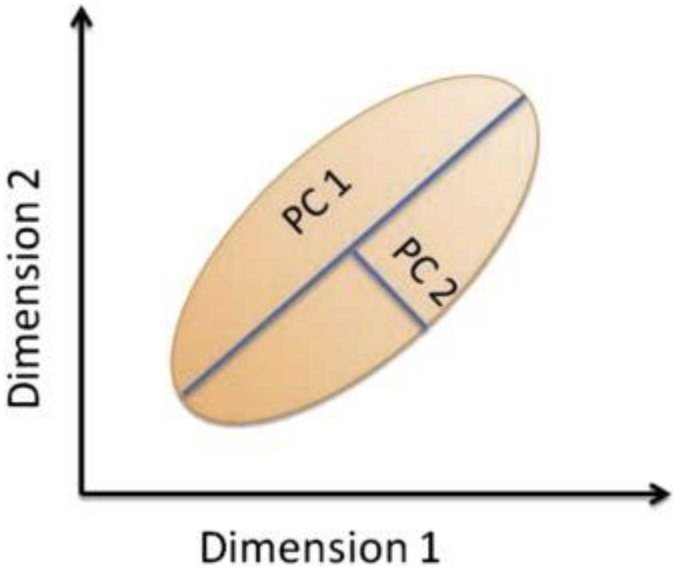

Figure 20 An illustration of the working principle of PCA (Park, Egilmez, & Kucukvar, 2015)

According to the work of Lu, Chang, Hwang, and Chung (2009), The details of the calculation are described below:

1. Normalizing raw data.

To make the data in all dimensions distributed in the same range, the raw data needs to be normalized by the below equation:

$$x_{ij} = \frac{x_{ij}^{(0)} - x_{j,min}^{(0)}}{x_{j,max}^{(0)} - x_{j,min}^{(0)}} \quad (18)$$

where $x_{ij}^{(0)}$ and x_{ij} and are the data in dimension j before and after the data normalization; $i = 1,2,\ldots,m$ and $j = 1,2,\ldots,n$, where m and n is the number of rows and the number of dimensions; thus, $x_{j,min}^{(0)}$ and $x_{j,max}^{(0)}$ are the minimum and maximum of the data in dimension j.

2. Computing the correlation coefficient matrix

The correlation coefficient matrix is calculated as below:

$$R_{jl} = \left(\frac{Cov(x_{ij}, x_{il})}{\sigma(x_{ij}) \times \sigma(x_{il})}\right) \quad j, l = 1,2, \ldots, n \quad (19)$$

where $Cov(x_{ij}, x_{il})$ is the covariance of data in dimension j and l; while $\sigma(x_{ij})$ and $\sigma(x_{il})$ are the SD of data in dimensions j and l.

3. Finding the eigenvalue and eigenvectors:

The eigenvalues and eigenvectors are computed from the correlation coefficient matrix by the following formula:

$$(R - \lambda_k I_m)V_{ik} = 0 \ (20)$$

where λ_k is the eigenvalue of the correlation coefficient matrix; and $V_{ik} = [v_{k1}\ v_{k2}\ \ldots\ v_{kn}]^T$ is the eigenvector corresponding to the eigenvalue λ_k.

4. Calculating the principal components:

Firstly, it needs to rank the eigenvalue λ_k in descending orders, the corresponding principal component can be calculated by this equation:

$$Y_{mk} = \sum_{i=1}^{n} x_{mi} \cdot V_{ik} \quad (21)$$

where γ_{m1} is the first principal component because it is corresponding to the largest eigenvalue, and γ_{mk} is called the kth principal component.

5. Selecting principal components:

An equation called the explained variation ratio is developed to measure the percentage of one principal component accounts for:

$$r_k = \frac{\lambda_k}{\sum_{i=1}^{n} \lambda_i}, i = 1,2, \ldots, n \quad (22)$$

where the r_k is the explained variation ratio of kth principal component.

In this study, the PCA algorithm was used to treat the centrality metrics results to reduce the 5-dimension data to 2-dimension data. In this way, the classification results by k-means can be presented more directly to do further analysis.

Chapter 4 Results and discussion

To illustrate the applications of this model, two case studies have been conducted in this chapter. In the first case study, some main general sustainable manufacturing parameters have been selected based on the TBL. Then, the node-level analysis and edge-level analysis, as well as the unsupervised learning method, were utilized to provide an overall concept of the roles of sustainable manufacturing parameters. In the second case study, the model was utilized to help to solve a more specific problem in the sustainable manufacturing field: how to achieve optimal conditions of the UPM process. As the UPM process involves complicated interaction among the UPM parameters, this situation causes a lot of barriers to obtain the optimal settings. The SNA model in this project provides an effective tool to shows the guideline for researchers to study the optimal conditions. These two case studies show the ability of this SNA-unsupervised learning method to evaluate the roles of parameters in complicated sustainable manufacturing scenarios. It offers a powerful tool to represent, analyze, and uncover the features of parameters and their relationships in sustainable manufacturing.

The definition, description, and interpretation in sustainable manufacturing and UPM of the centrality metrics, link prediction metrics, and network-level analysis metrics were shown in **Table 2**, **Table 3**, and **Table 4** respectively.

Table 2 Centrality metrics and their interpretations in sustainable parameters analysis

Centrality metrics	Definition	Description	Interpretation
In-degree centrality	It can measure how many other factors which have	The factor with a high value of in-degree centrality indicates it	Machining factors be influenced (Yip et al., 2020)

	impacts on a specific sustainable manufacturing factor	can receive more influences from other parameters.	
Out-degree centrality	It can measure the number of other factors that can be influenced by one specific sustainable manufacturing factor.	Sustainable manufacturing factor with high out-degree centrality has more ability to distribute its influences across other machining factors	Machining factors influence others (Yip et al., 2020).
Betweenness centrality	The number of the shortest path between a pair of non-adjacent sustainable manufacturing factors where the target factor can control (lies in).	To mediate the influences among the sustainable machining factors, perform as the "gateway" to transfer the knowledge in other disciplines.	Machining factors lie between a pair of non-adjacent parameters (Yip et al., 2020).
Closeness centrality	The measurement according to the distance from a certain sustainable manufacturing	The ability to reach and change the system performances by modifying the sustainable	parameters could affect manufacturing performances without relying on other

	factor to all other factors	manufacturing factors with high closeness	parameters (Yip et al., 2020)
Eigenvector centrality	Centrality taking the whole network structure into account (Ruhnau, 2000).	Measure the connectivity of sustainable manufacturing parameters according to its neighbors' connectivity.	The measurement of factors' influences according to their neighbors' influences in a sustainable UPM network

Table 3 Link prediction metrics in sustainable machining parameters analysis

Link prediction metrics	**Definition**	**Description**
Common neighbor (F. Tan et al., 2014)	A metric to predict the likelihood of two non-adjacent factors to be linked based on their common neighbors	The metric from the fact that people who have more common friends have a higher chance to know each other.
Jaccard coefficient (Niwattanakul, Singthongchai, Naenudorn, & Wanapu, 2013)	A measurement of possible linkages by normalizing common neighbors.	It measures the chance of potential linkage based on the number of common neighbors and their total neighbors

Resource Allocation (Harberger, 1995)	A metric based on the share of a "resource" that a sustainable manufacturing factor can send to another through a middle factor.	It was developed and inspired by the process of resource flow by adding the node degree information of the common neighbors (S. Liu, Ji, Liu, & Bai, 2017).
Adamic-Adar index (Lü, Jin, & Zhou, 2009)	Based on the resource allocation, but using a log denominator.	It is found to get better prediction performance in the MIT email network (Adamic & Adar, 2003).
Preferential attachment (Newman, 2001)	A metric based on the importance of the factors' neighbor.	It is proposed based on the fact that the two famous people have a higher probability to be connected. And this metric requires less information than all the others, but it considers less about the structure (Zeng, 2016).
Community common neighbors (Yang, Hu, & Zhang, 2016)	A metric considers the community structure based on common neighbors.	Compared with the common neighbor index, it gives a bonus to the common neighbor in the same community
Community resource allocation (Krzysik, 1979)	A metric is calculated by summing up the number of common neighbors in the same community divided	It has a similar concept to resource allocation, but only considering the nodes in the same community.

	by the number of common neighbors.	

Table 4 Network level metrics in sustainable machining parameters analysis (Yip et al., 2020)

Metrics	Definition	Description
Centralization	The measurement of core factors to transfer their influences to the system performance.	The machining performances/ outcomes are influenced by few machining factors (Yip et al., 2020).
Density	The number of sustainable manufacturing and UPM factors in a network that has already established a relationship with other factors.	Low efficiency in adjusting machining factors in the optimization of the process at the network level due to a large amount of noise involved from the upstream parameters to the system outcomes.

4.1. Case study 1

According to several previous works (Bhanot, Rao, & Deshmukh, 2015; Yip & To, 2018), the interactive relationships among 16 parameters of sustainable manufacturing are identified. These 16 parameters can be divided into the economic dimension (shown in **Table 5**), environmental dimension (shown in **Table 6**), and social dimension (shown in **Table 7**) based on the TBL. In addition, the inter-relationships are summarized in an adjacent matrix shown in

Table 8. In this table, "1" means the left-hand side parameter has an impact on the top right-hand side parameter. And "0" means the left-hand side parameter has no impact on the top right-hand side parameter. This matrix data were input into the IPython Jupyter notebook to do the programming of SNA. The programming is shown in the **Appendix**.

Table 5 Economic parameters in sustainable manufacturing analysis

No.	Parameter	Description
1	Production Cost (PC)	• Consists of various types of costs caused during the machining process including equipment costs, land or renting costs, energy costs, as well as labor costs, and so on. • Multiple parameters have an impact on the production cost, such as cutting quality and process management (Proietti et al., 2016).
2	Cutting Quality (CQ)	• Quality requirements are regarded as one of the most significant qualities needed for the final product (Correa, Bielza, & Pamies-Teixeira, 2009). • The cutting quality has a large influence on production costs. For example, if the cutting standards are set to be extremely high, it will lead to higher standards of surface roughness, tool capability, labor skills, and higher machine expenses (Bhattacharya, Das, Majumder, & Batish, 2009).
3	Production Rate (PR)	• Relevant to material removal rate and machining conditions including the feeding rate, depth of cut, and

		cutting speed also has a lot of influence on the economic dimension of machining processes (Debnath, Reddy, & Yi, 2016). • It requires selecting the optimal setting of machining variables to improve the material removal rate (J. Lin & Lin, 2002).
4	Process Management (PM)	• It refers to various methods to discover, model, analyze, measure, improve, optimize, and automate business processes (Camargo, Dumas, & González-Rojas, 2020) • It was found that process management has impacts on resource consumption like water, energy (Peng, Kellens, Tang, Chen, & Chen, 2018).
5	Profit (PT)	• Several factors have an impact on product profit, including the machining cost and the selling price (Alsyouf, 2007). • The suppliers normally utilize the “high quality, high price” policy (Yip & To, 2018).

Table 6 Environmental parameters in sustainable manufacturing analysis

No.	**Parameter**	**Description**
1	Water Intensity (WI)	• It refers to the consumption of water in the manufacturing processes. The water is utilized directly or indirectly for cooling, heating, or washing (Sanders & Webber, 2012).

		• It is significant to replan the amount of water used for machining processes, if no, it could lead to damage to the ecosystem (Scheren, Zanting, & Lemmens, 2000). • Water conservation methods including recycling the used water for some other functions by cleaning it should be adopted (Willis, Stewart, Panuwatwanich, Williams, & Hollingsworth, 2011).
2	Energy Intensity (EI)	• It refers to the consumption of energy per unit of final products during the machining processes. And it is a measurement of the energy inefficiency of manufacturing activities (Filleti, Silva, da Silva, & Ometto, 2017). • High energy intensity also leads to running out of non-renewable resources, emissions of GHGs, and ecosystem damage (Paramati, Sinha, & Dogan, 2017). • It is a critical problem for manufacturing companies because even if the energy intensity of the world's manufacturing activities is continuously increasing, the amount of demand is still rising faster (Zheng et al., 2018).
3	Materials (ML)	• Material is a significant parameter of process planning consists of hazardous materials, chemicals, raw materials, material composition, packaging reusability, and so on.

		• It is advised to find out suitable "kinds of materials" which can reduce the negative influences on the environmental aspect (P. Tan, Liu, Shao, & Ni, 2017). • It has been mentioned that material has a direct impact on cutting quality, production cost, and several parameters (Yip et al., 2020).
4	Waste Management (WM)	• It was defined as the activities and actions to manage waste from its inception to its final disposal (LaGrega, Buckingham, & Evans, 2010). • It requires taking account of the concepts of "reuse, recovery, and recycle" for all kinds of wastes caused by manufacturing activities (Choudhury, 2017).
5	Environmental Regulations (ER)	• Consider the large necessity to establish a process to set up the environmental regulations and laws for the companies (B. Yuan, Ren, & Chen, 2017). • Set up standards for sustainability analysis requiring considering the approach, strategies, and outcomes in the manufacturing industries (Abdul-Rashid, Sakundarini, Ghazilla, & Thurasamy, 2017).
6	Tool Life (TL)	• Tool life is defined as the time period between two successive grinding of tools and two successive replacement of tools (Sahin, 2009). • Tool life is one of the main factors influencing energy consumption in the machining process (Yip & To,

		2018).

Table 7 Social parameters in sustainable manufacturing analysis

No.	Parameter	Description
1	Worker Health (WH)	• It refers to the employees' health condition with consideration of the pollution released and wastes generated from machining processes, which can influence the exposed labor (Huang & Badurdeen, 2018). • It was reported that more attention and training should be paid to improve worker health by both industry and academia (Schneider, Das, Kirsch, Linke, & Aurich, 2019).
2	Worker Safety (WS)	• It is widely classified into operational safety and personnel safety. • Operational safety focuses on the amount of human involvement in the manufacturing process and the protecting precautions offered against unpredicted accidents (Maurino, Reason, Johnston, & Lee, 2017). • Personnel safety focuses on compliance with and the suitable implementation of safety regulations (Yiu, Sze, & Chan, 2018). • It is found that primary prevention plays a key role in environmental protection and worker health and safety

		(Armenti, Moure-Eraso, Slatin, & Geiser, 2011).
3	Labour Relations (LR)	• It refers to the relationship between employers and employees in the industry (Streeck, 1987). • It can be affected by working duration, workload, organization culture, and local employment, and so on (Zhang and Haapala, 2012). • For the situation nowadays, this problem has not been paid adequate attention by most manufacturing companies while it performs a key role to achieve social sustainability (Amui, Jabbour, de Sousa Jabbour, & Kannan, 2017).
4	Training and Education (TR)	• It can benefit the workers to improve the work and life quality, and it can also help the companies to reach their strategic goals. • It can benefit the employees, and managers in improving working skills which can bring increased efficiency through updates in the manufacturing processes on time (Reid & Sanders, 2019). • It performs a key role in achieving companies' sustainability level by involving in such problems through appropriate training of workers, and managers (Chandra, 2009).
5	Customer satisfaction (CS)	• It is defined as the measurement that determines how happy customers are with a company's products,

		services, and capabilities (Fečiková, 2004). • Customer satisfaction highly depends on product quality. The top two determinants of overall customer satisfaction are the perceived quality and value of customers (Yip & To, 2018).

Table 8 Interactive relationship among the sustainable manufacturing factors

	PC	CQ	PR	PM	PT	WI	EI	ML	WM	ER	TL	WH	WS	LR	TR	CS
PC	0	1	1	1	1	0	1	1	0	0	0	1	1	1	1	0
CQ	1	0	1	1	1	1	1	1	1	1	0	1	0	1	1	1
PR	1	1	0	1	0	1	1	1	0	0	0	1	1	1	1	0
PM	1	1	1	0	0	1	1	1	1	1	0	1	1	1	1	0
PT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WI	0	1	0	0	0	0	1	0	1	1	0	0	0	0	0	0
EI	1	1	1	1	0	0	0	1	1	1	0	1	1	0	0	0
ML	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	0
WM	0	1	0	1	0	0	1	1	0	1	0	1	0	0	0	0
ER	1	1	0	1	0	0	1	1	1	0	0	1	1	0	0	0
TL	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
WH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WS	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
LR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TR	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
CS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The parameters and relationships would be imported into Python to construct a network of sustainable manufacturing parameters as the nodes and edges. After that, the centrality metrics and link prediction metrics can be calculated. Then, the metrics result can be normalized into the range from 0 to 1 to avoid the overall result is dominated by several extreme values. By summing up the normalized metrics results, the overall measurements of the centrality and link prediction can be achieved to do the node-level and edge-level analysis. And the centrality metrics results perform as the raw data of the unsupervised learning algorithm to classify the sustainable manufacturing parameters.

4.1.1. Centrality metrics analysis

The calculation results of centrality metrics are shown in **Table 9**. And the visualization of the SNA network is shown in **Figure 21**.

Table 9 Calculation result of centrality metrics

Parameter	In degree centrality	Out degree centrality	Betweenness centrality	Closeness centrality	Eigenvector centrality	Centrality Index	Rank
CQ	0.667	0.867	0.174	0.672	0.342	5.000	1
PM	0.533	0.800	0.047	0.576	0.325	3.801	2
EI	0.600	0.600	0.040	0.621	0.315	3.667	3
ML	0.467	0.800	0.027	0.538	0.293	3.434	4
PC	0.467	0.667	0.030	0.538	0.294	3.300	5
ER	0.467	0.533	0.030	0.538	0.273	3.082	6
PR	0.400	0.667	0.020	0.504	0.260	2.994	7
WH	0.533	0.000	0.000	0.600	0.335	2.672	8
WM	0.400	0.400	0.004	0.504	0.246	2.551	9
WS	0.400	0.200	0.001	0.504	0.251	2.320	10
TR	0.333	0.133	0.002	0.475	0.216	2.002	11
WI	0.267	0.267	0.002	0.448	0.174	1.894	12
LR	0.267	0.000	0.000	0.480	0.174	1.623	13
PT	0.200	0.000	0.000	0.457	0.133	1.368	14
CS	0.067	0.000	0.000	0.400	0.049	0.838	15

TL	0.000	0.133	0.000	0.000	0.000	0.154	16

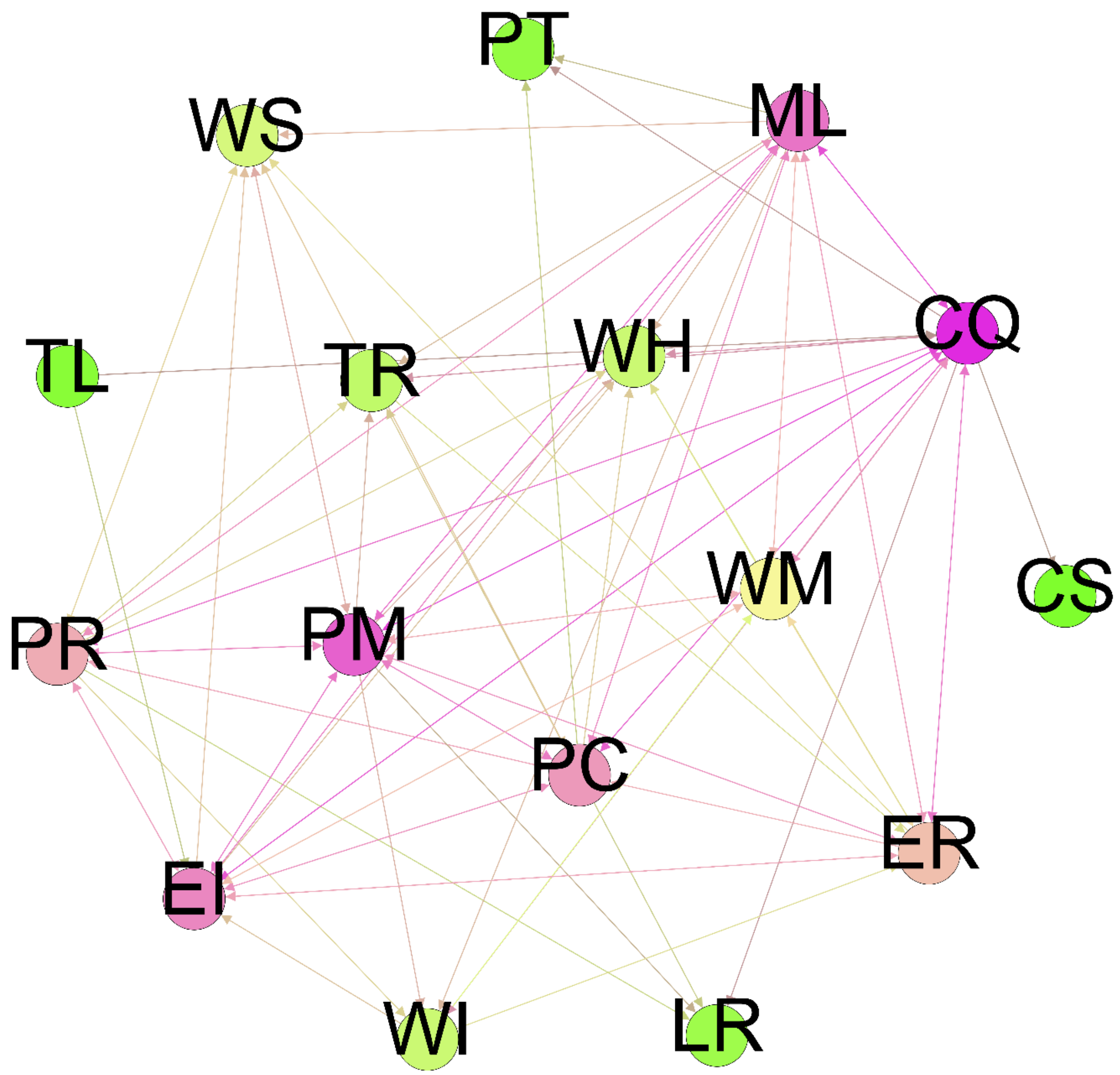

Figure 21 The visualization of the sustainable manufacturing network

According to **Table 9**, cutting quality and energy intensity are the top two factors with the highest in-degree value in the sustainable machining analysis. It means these two factors perform as collectors in the sustainable machining concept. This result shows cutting quality is one of the most complicated factors to manage in a sustainable machining process. Cutting quality is determined by ten other sustainable machining parameters, such as production cost and environmental regulations. When cutting quality increases, manufacturers need to improve the production cost to upgrade tools.

This result shows cutting quality is a key factor in sustainable machining improvement. The high in-degree centrality value shows the tradeoffs need to be balanced among cutting quality, production cost, tool life as well as other parameters to improve the sustainable level and cutting quality.

According to **Table 9**, cutting quality, process management, and materials have the highest out-degree centrality values which are 0.867, 0.8, and 0.8. This result shows cutting quality is the "influencer" in the sustainable machining network. The cutting quality has a direct impact on worker health, water intensity, waste management, and other parameters. And this impact could bring a complicated chain reaction to the whole machining process.

Cutting quality, process management, and energy intensity have the highest betweenness centrality values, which are 0.174, 0.047, and 0.04. It shows that the cutting quality, process management, and energy intensity perform as the bridges of influences from upstream factors to downstream factors. This result indicates that making controlling the process of cutting is complicated and important for the whole system. These three parameters are the gateway for the factors of system-level to transform their impact on sustainable machining factors.

According to the result of closeness centrality, cutting quality, energy intensity and worker health have the highest value, which is 0.672, 0.621 and 0.6, which imply that these factors perform as the "controller" among the sustainable machining process and has a most direct impact on the whole system's performance. That indicates energy, quality, and workers can control the integrated effectiveness and sustainability of the machining system by delivering its impact to all downstream factors through the shortest path. Thus, when designing or modifying the machining system, it requires strategic analysis of the influence of energy, worker, and cutting quality firstly.

Cutting quality, worker health, and process management have the highest eigenvector centrality scores, which are 0.342, 0.335, and 0.325. It indicates that these three factors have the highest importance when considering its neighbors' importance and perform as the "connector" of the influences among important factors in this sustainable machining system.

Among all sustainable machining parameters, the top four parameters with the highest average value are cutting quality, process management, energy intensity, and material. The top two factors belong to the economic aspect and the other two belong to the environmental dimension. It indicates that the key aspect of sustainable machining is the economic dimension.

According to **Table 9**, the node of cutting quality has the highest value of the centrality index, which is 5. As there are only five centrality metrics and each of them has been normalized into the range from 0 to 1, the upper bound of the centrality index is 5. Therefore, cutting quality has the highest value for every centrality metric. This result implies that cutting quality is the most influencing factor in the sustainable manufacturing network. It shows the cutting quality, which belongs to the economic dimension, is still the main concern of the overall manufacturing performance.

4.1.2. Link prediction analysis

The link prediction metrics were calculated by considering the network as an undirected network. And the calculation result is shown in **Table 10**.

Table 10 Calculation result of link prediction metrics

Non-edge	common neighbors	Jaccard coefficient	resource allocation	Adamic Adar index	preferential attachment	community common neighbors	community resource allocation	LP index	Rank
(ER, PR)	9	0.818	1.021	4.129	100	9	0	5.935	1
(WH, WI)	7	0.875	0.672	2.983	56	7	0	4.487	2
(PR, WM)	6	0.545	0.597	2.596	70	6	0	3.864	3
(PC, WM)	6	0.5	0.554	2.516	77	6	0	3.822	4
(WH, WS)	6	0.75	0.548	2.508	48	6	0	3.804	6
(CQ, WS)	6	0.429	0.548	2.508	84	6	0	3.804	6
(PC, WI)	6	0.500	0.529	2.469	77	6	0	3.786	7
(WH, TR)	6	0.75	0.529	2.469	48	6	0	3.776	8
(EI, TR)	6	0.546	0.529	2.469	66	6	0	3.726	9
(TR, WS)	5	0.714	0.458	2.090	36	5	0	3.229	10
(WI', WS)	5	0.625	0.458	2.090	42	5	0	3.188	11
(TR, WI)	5	0.625	0.438	2.052	42	5	0	3.160	12
(PT, PM)	3	0.250	0.246	1.198	36	5	0.162	3.052	13

(PT, PR)	3	0.300	0.246	1.198	30	5	0.162	3.048	14
(LR, TR)	4	0.667	0.346	1.633	24	4	0	2.609	15
(WM, WS)	4	0.444	0.358	1.656	42	4	0	2.556	16
(TR, WM)	4	0.444	0.338	1.618	42	4	0	2.528	17
(LR, WH)	4	0.500	0.346	1.633	32	4	0	2.500	18
(LR, ML)	4	0.333	0.346	1.633	48	4	0	2.473	19
(EI, LR)	4	0.364	0.346	1.633	44	4	0	2.467	20
(LR, WS)	3	0.429	0.274	1.254	24	3	0	1.953	21
(PT, TR)	3	0.500	0.246	1.198	18	3	0	1.932	22
(TL, WI)	2	0.286	0.162	0.796	14	3	0.091	1.916	24
(TL, WM)	2	0.286	0.162	0.796	14	3	0.091	1.916	24
(LR, WI)	3	0.375	0.255	1.216	28	3	0	1.904	25
(LR, ER)	3	0.272727	0.246	1.199	40	3	0	1.897	26
(TL, ML)	2	0.166667	0.162	0.796	24	3	0.091	1.882	27

(TL, ER)	2	0.200	0.162	0.796	20	3	0.091	1.880	28
(PT, WH)	3	0.375	0.246	1.198	24	3	0	1.851	29
(ER, PT)	3	0.300	0.246	1.198	30	3	0	1.826	30
(EI, PT)	3	0.273	0.246	1.199	33	3	0	1.826	31
(LR, PT)	2	0.400	0.162	0.796	12	2	0	1.355	32
(LR, WM)	2	0.222	0.155	0.781	28	2	0	1.305	33
(PT, WS)	2	0.286	0.174	0.819	18	2	0	1.303	34
(PT, WM)	2	0.250	0.155	0.781	21	2	0	1.265	36
(PT, WI)	2	0.250	0.155	0.781	21	2	0	1.265	36
(TL, WH)	2	0.250	0.162	0.796	16	2	0	1.225	37
(TL, PM)	2	0.167	0.162	0.796	24	2	0	1.211	38
(TL, PR)	2	0.200	0.162	0.796	20	2	0	1.208	39
(TL, PC)	2	0.182	0.162	0.796	22	2	0	1.208	40
(CS, TL)	1	0.500	0.071	0.379	2	1	0	0.955	41

(CS, PT)	1	0.333	0.071	0.379	3	1	0	0.775	42
(TL, PT)	1	0.250	0.071	0.379	6	1	0	0.710	43
(CS, LR)	1	0.250	0.071	0.379	4	1	0	0.690	44
(TL, WS)	1	0.143	0.091	0.417	12	1	0	0.678	45
(TL, LR)	1	0.200	0.071	0.379	8	1	0	0.674	46
(TL, TR)	1	0.143	0.071	0.379	12	1	0	0.649	47
(CS, TR)	1	0.167	0.071	0.379	6	1	0	0.615	48
(CS, WI)	1	0.143	0.071	0.379	7	1	0	0.598	50
(CS, WM)	1	0.143	0.071	0.379	7	1	0	0.598	50
(CS, WH)	1	0.125	0.071	0.379	8	1	0	0.588	51
(CS, ML)	1	0.083	0.071	0.379	12	1	0	0.581	53
(CS, PM)	1	0.083	0.071	0.379	12	1	0	0.581	53
(CS, ER)	1	0.100	0.071	0.379	10	1	0	0.580	55
(CS, PR)	1	0.100	0.071	0.379	10	1	0	0.580	55

(CS, PC)	1	0.091	0.071	0.379	11	1	0	0.580	57
(EI, CS)	1	0.091	0.071	0.379	11	1	0	0.580	57
(CS, WS)	0	0.000	0.000	0.000	6	0	0	0.041	58

According to **Table 10**, it shows the relationship between environmental regulations and production rate has the highest common neighbor value, which is 9. That means these two parameters have more interactive relationships with the same other parameters. If the relationships among them can be investigated in the future, the whole network can be denser, which means the area of sustainable manufacturing can get a better understanding. By studying the impact of Environmental Regulations on production rate, lawmakers can propose and update the environmental law to minimize the negative impact on the production rate when protecting the environment and saving natural resources.

According to **Table 10**, the relationship between worker health and water intensity has the highest Jaccard coefficient, which means they have the highest percentage of common neighbors among all the relationships which have not been studied. This result shows the value of the indirect relationship between these two parameters. It indicates that the studies about the relationships among worker health and water intensity and their common neighbor can bring some inspiration about the environmental and social aspects. For example, waste management has impacts on both worker health and water intensity, it can be considered as a key factor in reducing water consumption and improving employee's working conditions.

From **Table 10**, the relationship between environmental regulations and production rate has the highest score of resource allocation and Adamic-Adar index, which are 1.02 and 4.13. It indicates that the study about the influencing relationship between these two parameters can help to control the influences flow from the upstream parameters and downstream parameters. After that, by modifying the environmental regulations, the downstream parameters of production rete such as water intensity and worker safety can be changed. It shows that the interactive relationship between environmental regulations and production rate is highly important for improving resource consumption and workers' benefit.

From **Table 10**, it can be found that the relationship between environmental regulations and production rate has the highest score of preferential attachment, which is equal to 100. As preferential attachment is measured by multiplying the degree of the two vertices, both these two factors have a high degree, which presents high importance and centrality. This result indicates that the study about the relationship between environmental regulations and production rates can help to improve the network's integration and increasing the controllability of the whole researcher area.

For the result of community common neighbors, the relationship between environmental regulations and production rate still has the highest score, which is equal to the value of common neighbors. As environmental regulations and production rate belongs to different communities, no bonus was given to the relationship between them.

Among the relationship between parameters in the same community, the relationship between profit and process management and the relationship between profit and production rate has the highest value, which is 5. It means these two linkages perform as the local bridges inside the economic community. By studying these two relationships, the optimal condition of the economic dimension of sustainable manufacturing can be achieved easily.

According to **Table 10**, the relationship between profit and process management and the relationship between profit and production rate has the highest community resource allocation value, which is 0.1623. Thus, these two hidden linkages need to be investigated to gain a more clear concept about the influencing paths among the economic parameters in this SNA network.

Therefore, these two linkages perform as the local hub of influencing in the economic community.

From **Table 10**, the relationship between environmental regulations and production rate has the highest LP index, which is 5.935. Thus, this linkage is considered as the most significant hidden relationship in the sustainable manufacturing network with the highest potential value to investigate. For a manufacturing company, it needs to balance its social responsibility and production rate under environmental regulations and laws. For researchers, by modeling the impacts of environmental regulations on production rate, a better planning method to improve sustainability could be proposed.

4.1.3. Classification of parameters

By checking the SSE and silhouette coefficient, it was found that starting from 4, the declining rate of SSE value becomes slow (as shown in **Figure 22**). Therefore, the value of k is set as 4, which means the parameters should be classified into 4 groups. Then, by running the k-means algorithm, the sustainable manufacturing factors were clustered as shown in **Table 11**. From the correlations among the centrality results (shown in **Figure 23**), some metrics have a considerably high correlation, which means high similarity. For example, the eigenvector centrality and in-degree centrality correlate 0.98. Therefore, the PCA method can be utilized to reduce the dimension of the data effectively. In this way, the centrality metrics data can be reduced from 5 dimensions to 2 dimensions without losing too much information. By doing so, the classification can be visualized in a 2-dimension figure (as shown in **Figure 24**).

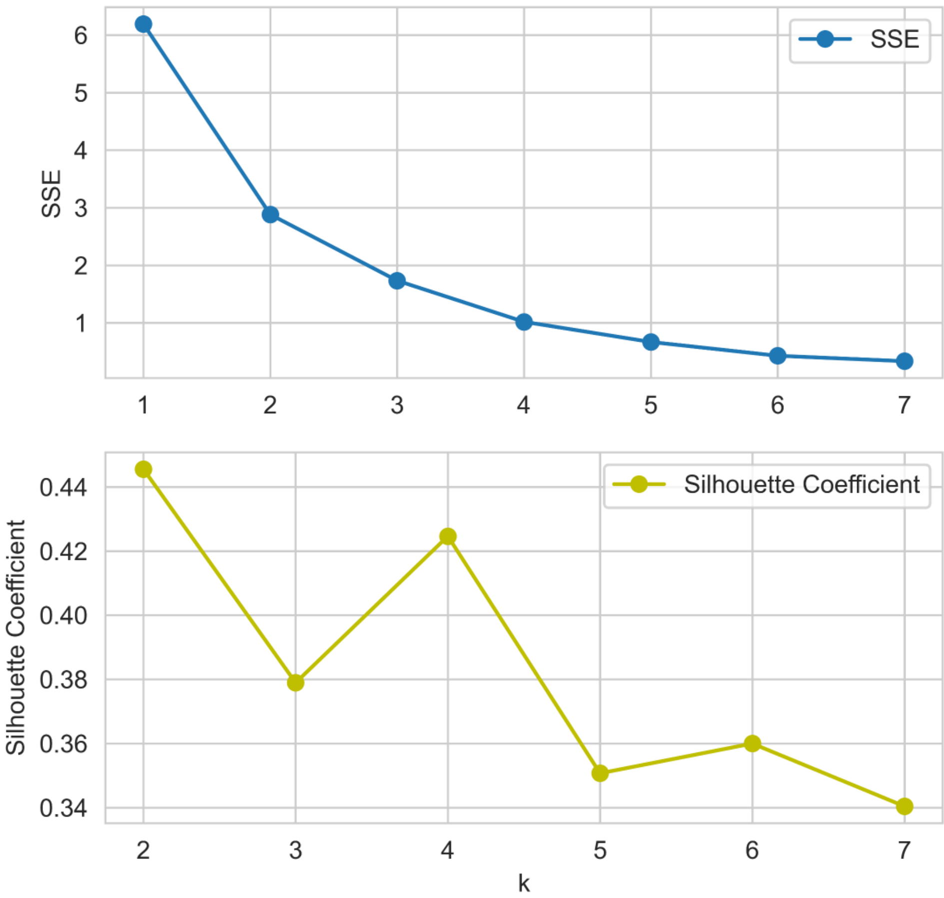

Figure 22 SSE and Silhouette coefficient of the k-means algorithm

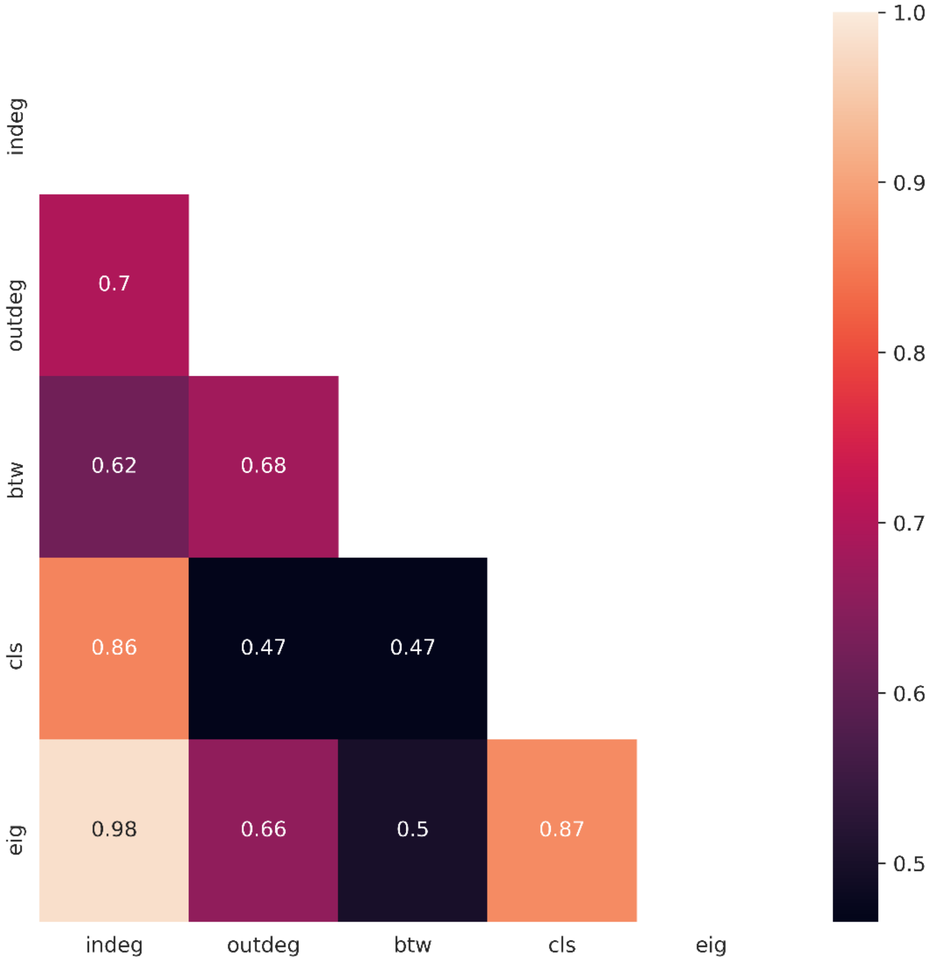

Figure 23 The correlation heatmap of the centrality metrics

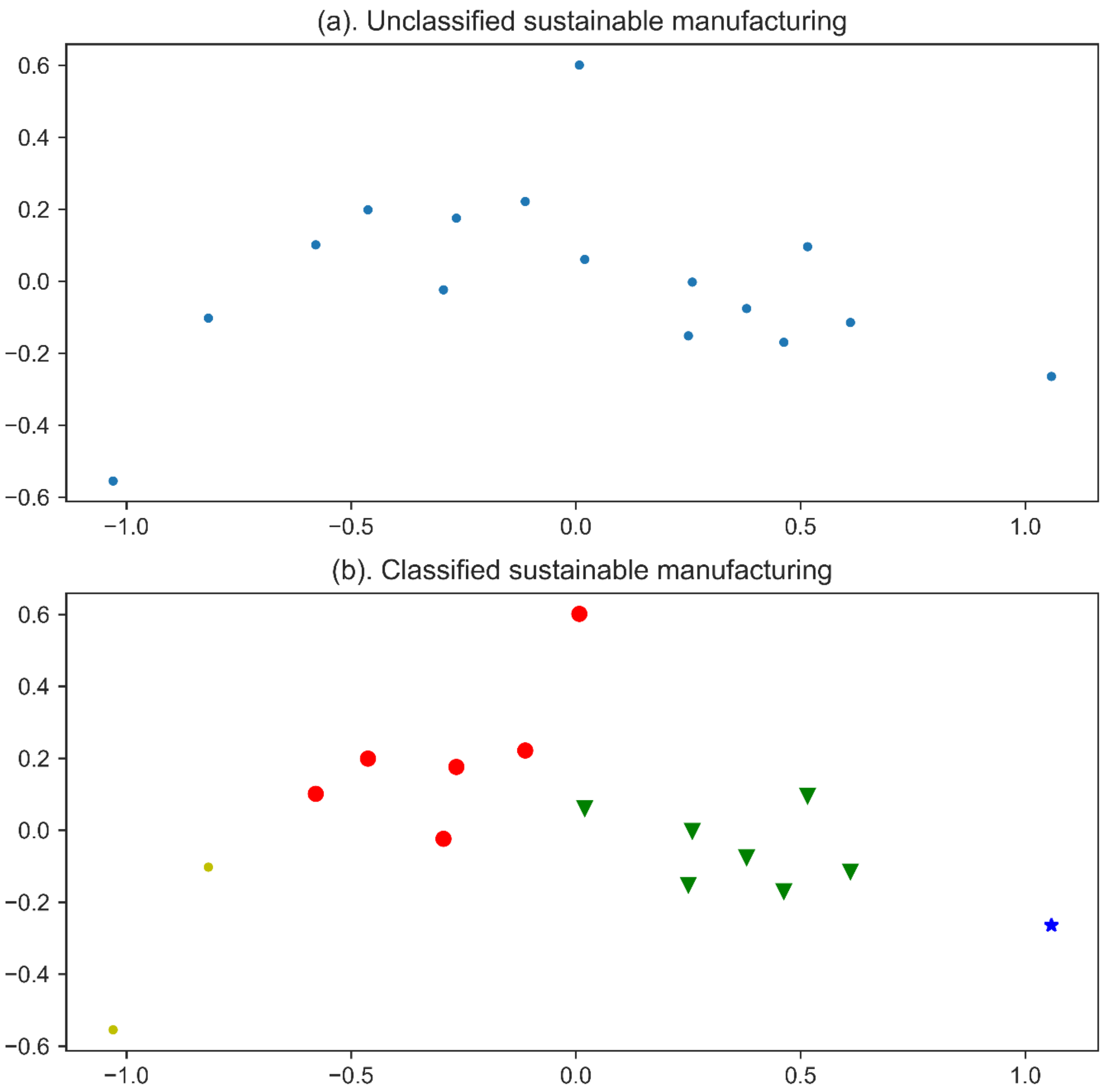

Figure 24 The sustainable manufacturing parameters before and after the classification (cluster 1,2,3,4 are represented by green, red, yellow, and blue)

Table 11 The classification results of sustainable manufacturing parameters

Parameters	**Centrality Index**	**Clusters**
CQ	5.000	4
PM	3.801	1
EI	3.667	1

ML	3.434	1
PC	3.300	1
ER	3.082	1
PR	2.994	1
WH	2.672	2
WM	2.551	2
WS	2.320	2
TR	2.002	2
WI	1.894	2
LR	1.623	2
PT	1.368	2
CS	0.838	3
TL	0.154	3

From **Table 11**, it shows that cluster 4 only includes one parameter which is cutting quality. And it can be found its centrality index ranking in the first place, which is 5 and much higher than the parameter with the second-highest value. It indicates that cutting quality is the core factor with the highest importance. It is the key consideration when establishing a sustainable manufacturing system. Besides that, six factors including process management and energy intensity belong to cluster 1. Their centrality index values are distributed in the range from 2.99 to 3.80. these factors also have quite high centrality values. All the factors in clusters 4 and 1 belong to the economic and environmental dimensions, which shows the economic and environmental parameters are still the main concern. Therefore, researchers could pay more attention to the study of the social aspect of sustainable manufacturing. Moreover, for the companies that need to build up or modify their manufacturing system to improve the sustainability level, they should evaluate the impacts of the parameters in clusters 1 and 4 firstly.

4.1.4. Summary of case study 1

Sustainable manufacturing attracts increasing attention from academia nowadays. To achieve higher sustainability in the manufacturing process, the parameters involved and the complicated influences among them need to be considered. Thus, this situation leads to difficulties to improve the sustainability level. To help to eliminate these difficulties, the method of SNA was utilized to conduct the node-level and edge-level analysis. In this case study, the main parameters (factors) of sustainable manufacturing and the influencing relationships among them were selected from the literature. Then, the sustainable manufacturing network was established by considering the parameters as nodes and relationships as edges. After that, the centrality metrics and link prediction metrics were utilized to analyze the roles of the parameters and the potential value of the hidden relationships. And these results can offer some guidelines to build up a sustainable manufacturing system for companies and the direction of finding new research topics for researchers. After that, the centrality metrics result was used as the raw data of the k-means algorithm to classify parameters. By calculating the SSE and Silhouette Coefficient, it is determined that four is the appropriate number of clusters. According to the classification result, an overall picture of the centrality distribution of sustainable manufacturing can be given. The main findings of this case study are summarized below:

1. Cutting quality is the parameter with the highest value of the centrality index, which is the overall measurement of centrality. It indicates that cutting quality should be considered as the key factor in the manufacturing system. The manufacturing companies should evaluate the impact on it before change any setting of other variables.

2. The relationship between environmental regulations and production rate has the highest link prediction index, which means this relationship has the highest potential value to be investigated by the researchers in the future study.
3. The sustainable manufacturing parameters can be classified into four clusters by using the k-means method. And the parameters in clusters 1 and 4 have high centrality. Therefore, these parameters should be treated as the main considerations when designing a new manufacturing system.

This chapter illustrates the application of node-level analysis and network-level analysis of this SNA method in UPM to provide a guideline for researchers to obtain optimal settings.

4.2. Case study 2

A systematic literature review was conducted and data from the PolyU SKL laboratory was obtained as the raw data in this section. The method uses the relevant scientific literature and experimental data to ensure the transparency and reliability of the raw data. In this project, the SNA method was used to conduct the evaluation and present the analysis result. To collect the data of UPM parameters from papers, influencing relationships among the parameters of literature in detail were also needs to be identified. In this project, the relevant previous work was found by some keywords in the electronic scientific databases of several scientific publishers, and these electronic databases mostly belong to Elsevier. And then, the literature was filtered based on the knowledge of the researchers. Finally, specific literature was chosen to develop the network. The machining parameters are defined as the nodes and edges in the UPM network. And the linkages among each node were added according to the relationship among the parameters.

The UPM parameters are represented by the vertices in the UPM network, and they can be presented as the row in the adjacent matrix. Two vertices are linked if there is an influencing relationship between them. And in this case, the UPM network is a directed one as the influencing relationship from one parameter to another has a direction. After the data of the UPM network is collected, it would be imported into MS Nodexl which can do the visualization of the UPM network and calculate the metric of different levels. The MS NodeXL is equipped with the functions of collecting data from Facebook and Twitter. It is a useful tool to do SNA metrics computation.

The network-level metrics results were summarized in **Table 12**. And network visualization was shown in **Figure 25**. While the SNA results of the node-level analysis, as well as network-level analysis, were summarized in **Table 13** and **Figure 26**. The parameter "material" in **Figure 25** stands for the workpiece materials, instead of tools'. The tool used in UPM commonly is diamond, which is normally utilized to produce high-quality products with a nano-level surface (SJ Zhang et al., 2016). In the research area of UPM, the common material of the tool is a single-crystal diamond because of its excellent characteristics, such as high hardness, and relevant strong resistance to wear (Zong et al., 2010). Thus, because the tool for UPM is normally diamond in the research as well as the manufacturing industry, the tool material is considered as fixed and does not input as a parameter in this work.

Table 12 The results in the network-level analysis.

Network-level metrics	Results
Graph Type	Directional
Nodes	13
Edges	60
Maximum Edges in the Connected Component	78
Average Distance of the Shortest Path	1.195266

Density	0.378205

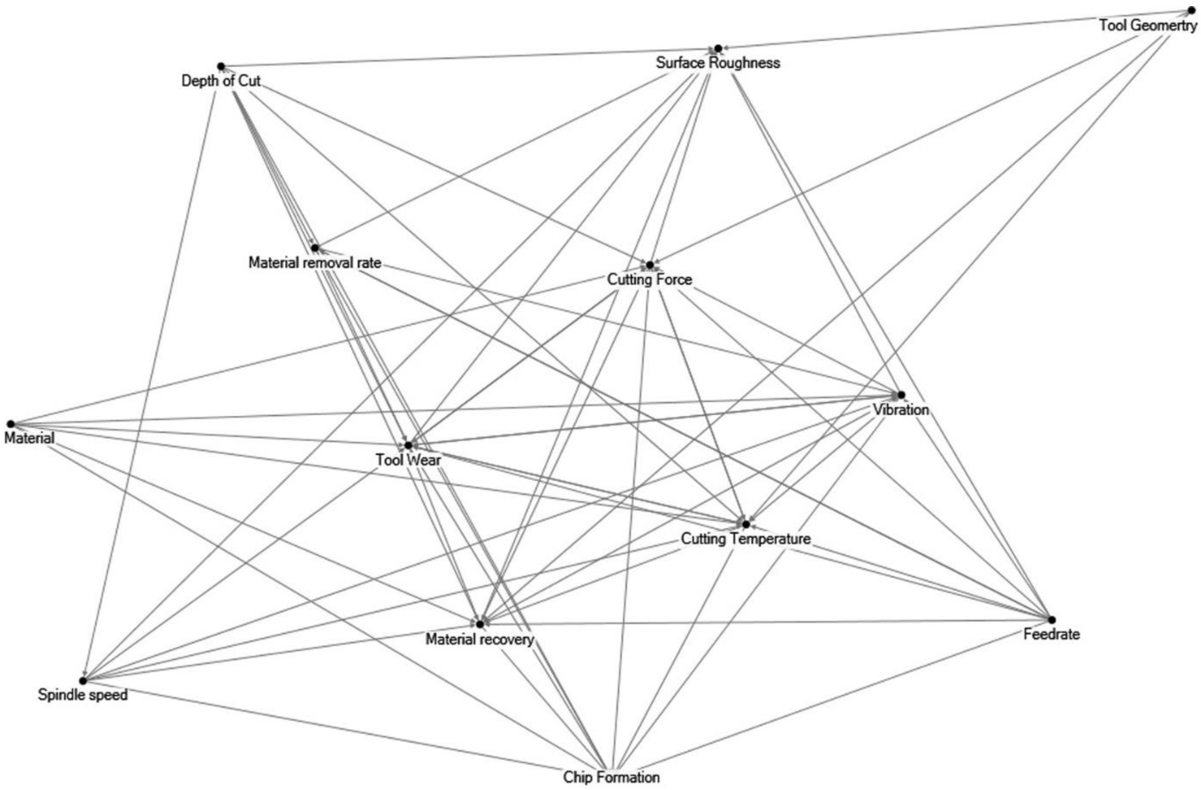

Figure 25 UPM network consists of different UPM parameters

Table 13 Centrality metrics of UPM factors

UPM factors	In-Degree	Out-Degree	Betweenness Centrality	Closeness Centrality	Degree Centrality
Depth of Cut	0	8	2.252	0.063	0.074
Chip Formation	10	0	4.421	0.071	0.089
Surface Roughness	9	0	6.888	0.067	0.077
Tool Wear	9	5	5.421	0.077	0.097
Spindle speed	1	6	0.750	0.059	0.068

Material removal rate	2	4	0.786	0.056	0.057
Material recovery	7	4	7.288	0.077	0.095
Cutting Temperature	8	4	6.288	0.071	0.088
Cutting Force	7	5	5.602	0.071	0.088
Feedrate	0	8	1.567	0.063	0.076
Vibration	6	5	4.486	0.071	0.090
Material	0	6	0.000	0.056	0.061
Tool Geomertry	0	4	0.250	0.050	0.039

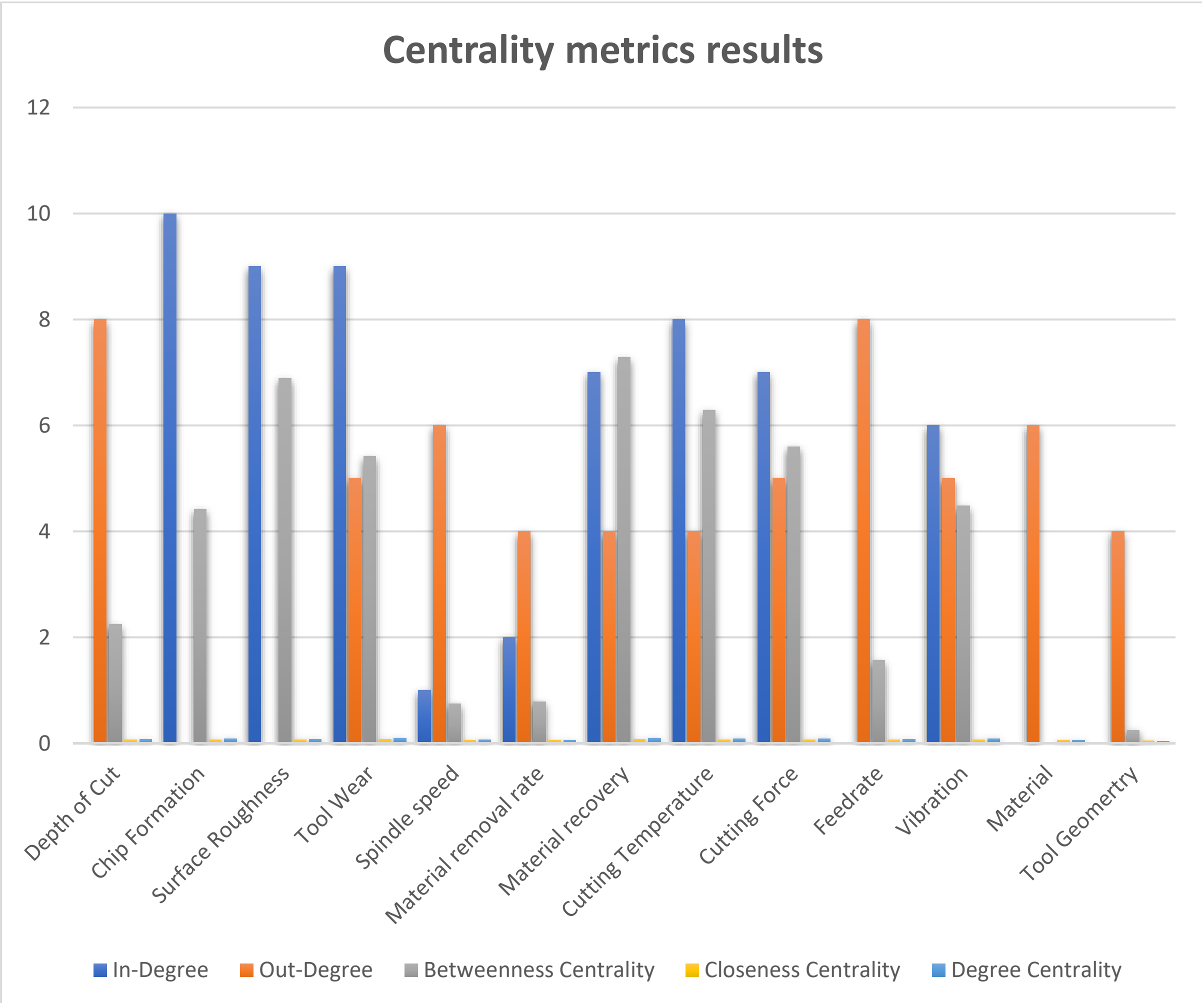

Figure 26 Distribution of centrality metrics of UPM factors

4.2.1. Node-level analysis

4.2.1.1. In-degree

From **Figure 26**, the parameters that have the top three in-degree values are chip formation, tool wear, as well as surface roughness, and they are 10, 9, and 9. And they are the machining parameters that can be affected by most of the other UPM parameters in the UPM network. Any minor modification in other UPM parameters individually in the machining operation could influence them significantly, thus, they can be considered as an independent study topic for optimization of machining condiction. Surface roughness and tool wear are regarded as normal targets and provide the index of the UPM final product, therefore, they are the parameters that obtain the impact from other UPM parameters. Chip formation is another UPM index that can reflect the rightness of the setting of the UPM parameter (Shaojian Zhang, Guo, Xiong, & To, 2020). Because tool wear and surface roughness are different types of chip shape changes, thus, chip formation has higher in-degree them. It shows that without the constructed SNA network, the important role of chip formation has been underrated. The continuous chips formed in the UPM could be the signals collecting the impacts from upstream UPM parameters to the downstream parameters.

4.2.1.2. Out-degree

The value of the out-degree of each factor is summarized in **Error! Reference source not found.**. The factors that have the largest out-degree value include cutting depth as well as feed rate, and their out-degree are both 8. Therefore, they can be considered as the influencers which can influence the other UPM parameters in the networks the most. Any minor changes of them individually can lead to a large impact on other UPM parameters in UPM dramatically. Thus, they are always regarded as dominating factors in the conceptual modeling discussed in the literature about optimization due to their large influential abilities. Depth of cut, feed rate, as well as spindle speed is the UPM factors that are adjusted relying on a lot of other machining parameters including surface roughness, and worked materials, etc. These three UPM factors (depth of cut, feed rate, and spindle speed) can be considered as equally significant as they are at the same level in the UPM network, but only the depth of cut and feed rate were found with the highest out-degree score beside spindle speed. And the role of the spindle speed could be overestimated without the model of the SNA. The centrality metric results provide the guideline of the priority of managing UPM variables in the production planning stage.

4.2.1.3. Betweenness centrality

From **Figure 26**, the parameter that has the largest value of betweenness is material recovery. The nano-level surface machining is considered as a complex process because of the combined effects of elastic recovery and plastic deformation of the product. Unsimilar to conventional machining, the parameter of material has a large impact on the material removal process as the depth of cut is normally smaller than the grain size of the workpiece in the UPM process (Furukawa & Moronuki, 1988). If the cutting process is conducted on a necessarily small depth of cut and feed rate, the principle of machining would turn to single-crystal cutting (W. Lee & Zhou, 1993). Undercutting at the point-shaped edge with small cutting depth, burnishing and material recovery necessarily occur. Thus, swelling as well as material recovery are two special characteristics of UPM. The fact that material recovery has the highest betweenness score reflects the uniqueness of its property, which can be considered as the major gate to the performance indicators: surface roughness, which performs as the main and dominating parameter which can influence the surface roughness directly. It can be found the majority of upstream UPM parameters need to transfer their impact by influencing material recovery to change the factor of surface roughness. If the connection to the gatekeeper is stopped, the upstream UPM parameters can not deliver the impacts or information to the downstream UPM parameters. Besides that, another result showed by the betweenness metric is that the parameter of material that dominates the degree of material recovery of the produced surface can be one of the mediators to facilitate the UPM outcomes across multidisciplinary paths.

The unique characteristics of “gatekeeper” for the problematic material recovery in machining offer opportunities to seek development from other disciplines. No matter how the upstream UPM parameters are changed, their impacts should be transferred to the gatekeeper (material recovery) to access the final performance. Thus, these new methods integrating with knowledge of other disciplines can focus on the study of material recovery effect, in this way, the positive impacts can be effective in a shorter path. If the designed methods concentrate on other UPM parameters, the positive influences are scaled and normalized by other UPM parameters distributed in the upstream, or, the modification of the UPM factor does not enable to achieve in the optimal setting as there are a few downstream UPM parameters, and they are influenced by the chain effects, which leads to a lot of unwanted impacts and recompensing the advantages of novel methods.

4.2.1.4. Closeness centrality

From **Figure 26**, tool wear and material recovery are the two factors with the top two closeness scores, and their closeness value is both 0.77. This result reflects these UPM parameters can reach the impacts to the UPM performance and the shortest path to having significant impacts on the UPM outputs. And the tool wear’s result of the closeness metric reflects that it has the most direct impact on surface integrity. Thus, to obtain great surface finishing, the UPM parameter with the priority that needs to be considered early is tool wear, thus, the method to reduce tool wear is a hot academic topic. Similarly, material recovery also gets the largest closeness score, which means it has the shortest influencing path to impact the UPM performance. And it performs as the navigator to reach and gather influences from the upstream UPM parameters and can provide the integrating function to the UPM performance. Besides that, it is the only UPM parameter with the highest scores of betweenness as well as closeness metrics. It reflects the value of putting efforts to study this parameter can improve the UPM performances.

As the material recovery has the highest closeness and betweenness value in the UPM network. Therefore, it can be considered as the gatekeeper, which can receive the influences from upstream parameters and distribute the influences to downstream parameters (Yip et al., 2020). It can provide more opportunities to apply interdisciplinary knowledge in the UPM areas to improve machining performance. For example, Yip and To (2017) have applied a magnetic field in the cutting process to resolve material recovery of titanium alloys, which belongs physic field. This experiment shows the approach to utilize the advantage of the gatekeeper role of material recovery in the UPM network.

4.2.2. Network-level analysis

4.2.2.1. Degree centralization

For network-level analysis, all of the metric results are evaluated aggregately. If some metric result is dominantly high compared with others, there should be a certain UPM parameter that can dominate other UPM parameters. The UPM performances are affected by the parameters with a high degree centralization score. According to **Figure 26**, there is no UPM parameter with an extremely high degree centralization score. A network with high centralization has one limitation, which is the effectiveness to optimize parameters is not high, the reason is that the chain effect among different parameters is high. Thus, more investigation needs to be conducted to transform the impacts from upstream to downstream UPM parameters. On the other hand, high centralization can also bring some benefits to the network just like high stability. And that stands for a large ability to avoid the uncertainty caused by the outside.

4.2.2.2. Network density

According to **Table 12**, the density of this network is 0.378, which indicates that the number of potential parameters that have established a linkage to others counts only around 0.378. And the average distance of the shortest path in this network is 1.195. Because this network has 13 nodes in total, the number of 1.195/ vertex is considerably high as every UPM parameter can get an adequate path to transfer impacts on other UPM parameters as well as the system performance. If a network has an extremely large density score in practical situations may cause various problems because the factors could have too many ways of accessing the other factors, any adjustment in a certain parameter can lead to instability for the system. What's more, checking the source of influences will become extremely hard as there are too many possibilities. In this study, the density of the UPM network has a middle-level value, which reflects an assessable control of the machining process.

4.2.3. Validation and application 1: Experimental setup precedence design

As reported by Su, Jia, Niu, and Bi (2017), depth of cut has a significant impact on chips formation and surface quality through a complicated reaction with other UPM parameters including material, tool geometry. It makes the influence of depth of cut on chip formation one of the difficulties to measure in UPM research. From the metrics results shown in **Table 13**, all of the depth of cut, material, and tool geometry have zero in-degree value. It means that the settings of these parameters get little impact from other factors. On the other hand, depth of cut and material also have considerably high out-degree scores, which are 8 and 6 respectively. This result indicates that depth of cut and other factors with zero in-degree value and high out-degree values can be considered in the earliest stage when determining the experimental setup precedence. In this way, the order of experimental setup for the machining parameters can be decided according to the in-degree and out-degree results.

4.2.4. Validation and application 2: surface roughness reduction

Surface roughness is the main target and the indicator of the machining performance of UPM outcomes, therefore, various relevant parameters have been optimized for minimizing surface roughness. However, this situation causes underestimation of the dominating factor of surface quality. For example, as mentioned by S. Wang, To, and Cheung (2012), the influence of the workpiece material on surface roughness was ignored by some previous studies especially the modeling of surface generation (Cheng et al., 2008). And in this project, surface roughness was also reported as one of the parameters with the highest in-degree, which means it is the main receiver of complicated influences from downstream factors. Therefore, in order to reduce surface roughness effiectively, the influencing map of experimental setup for the machining parameters should be provided for the modeling process of UPM so that important parameters are not ignored.

Besides that, the influencing map could also help to build up more complicated experiments for researchers. For example, some researchers have designed experiments to investigate the impacts of different parameters, such as federate and surface roughness reduction (Q. Lin, Liu, Zhu, Chen, & Zhou, 2020). Based on the influencing path shown in **Figure 25**, more parameters can be considered as variables, like the depth of cut, in the experiment design stage. In this way, this work can provide more ideas for the variables of experiments of surface roughness reduction. Moreover, it also provides a guideline for manufacturing companies if they want to improve their cutting quality by changing parameters setting.

4.2.5. Summary of case study 2

UPM is a cutting-edge technology to produce components with nanometer-level and complex geometry. As a lot of UPM parameters with complex influencing relationships are involved in the machining process, it is considerably hard to obtain the optimal machining conditions. Besides that, a high tool wear rate can cause various experimental costs in the machining process. Thus, the whole picture of UPM composing of the detailed relationships of major UPM parameters need to be formed, it offers the instruction for the researchers to avoid missing important parameters in experimental design and setup. It is the first time that the SNA method was applied to the UPM area to establish the network structure in this project. Based on the UPM network, a detailed evaluation was conducted according to the SNA metrics relevant to a collection of UPM parameters. An overall figure of the impact relationships among the UPM parameters was exploded based on the calculation results. Moreover, the UPM strategies concentrating on the different properties with applications were also presented. The main findings in this section are summarized below:

1. The UPM parameters which have the top in-degree centrality include chip formation, surface roughness, and tool wear. It shows they are more sensitive to the changes from other parameters. Besides, the top parameters with the highest out-degree score are the depth of cut and feed rate. These two factors should be considered as the parameters which can deliver the most influence to other UPM factors in the SNA model.
2. Material recovery is the UPM parameter that has the highest betweenness result. This result shows that it performs as a gatekeeper to collect the impacts from the upstream UPM nodes and can be observed before getting machining outcomes. Thus, it plays a key role as one significant indicator for researchers to obtain optimized UPM output.
3. What's more, material recovery is the UPM parameter which has the top closeness score. Thus, it is strongly suggested for these downstream UPM parameters to be paid

particular attention and further investigation because it has the shortest influence path to the final UPM outputs.

4. The density and centralization of the SNA analysis offer the whole picture of the UPM parameters model. In this project, No UPM parameter was found with a relevantly high score in centralization. It indicates that no UPM parameter has extremely high impacts on the other UPM parameters and denominates UPM performance.

Chapter 5. Conclusion and further study

5.1. Conclusion

As mentioned in section 1, the influencing relationships of the sustainable parameters on each other have not been investigated, which may lead to difficulties to reach the target of sustainable manufacturing. Similarly, the process of UPM has a complicated mechanism of surface generation, which causes the optimal condition hard to achieve. In previous work, it still lacks the investigation on the sustainable manufacturing and UPM parameters focusing on the influencing relationships among them to evaluate their role and importance.

To fill these research gaps, this project established a method by combining social network analysis and unsupervised learning approaches to evaluate the relationships among sustainable manufacturing and UPM parameters. Firstly, the parameters and their interactive relationships were identified from previous studies and considered as the nodes and edges to construct the SNA network. Then, some SNA technologies, including centrality metrics and link prediction metrics, were utilized to do node-level analysis, edge-level analysis, as well as network-level analysis. After that, the unsupervised learning method can be used based on the metrics calculation results to classify the parameters to provide the overall picture of the distribution of centralities. By utilizing this approach, two case studies have been conducted.

For the first case study, a total of 16 sustainable manufacturing parameters and their interactive connections were identified and analyzed. Then, there were three main findings discovered from the results in this case study. Firstly, cutting quality need to be considered as the key factor for the overall sustainable level in the manufacturing system as it has the highest centrality index. Secondly, the relationship between environmental regulations and production rate should be investigated in future studies based on the link prediction metrics. And sustainable manufacturing parameters can be classified into four clusters by using the k-means method according to the similarity of centralities. So the parameters in the two clusters with high centralities, such as cutting quality and product cost, should be considered first when designing a new manufacturing system.

For the case study of optimal conditions in UPM, a total of 13 UPM parameters were identified and evaluated by using the node-level analysis and network-level analysis. Based on that, there were several findings of the optimal machining setting. For example, the UPM parameters in the machining process with the highest in-degree were identified through SNA, which are chip formation, tool wear, and surface roughness. It means that they are the parameters that can gather the most influences from other UPM factors. For the network-level analysis, no UPM parameter has a relevantly high score in centralization, which means that no UPM parameter denominates UPM performances.

All in all, there are three main contributions from the study. It is the first time to introduce the SNA method in the research areas of sustainable manufacturing and UPM. And the unsupervised learning approach was also applied firstly to classify the centrality metrics results to shows the distribution of the factors based on their importance. Finally, the roles and importance of sustainable manufacturing and UPM parameters have been evaluated to support companies to achieve optimal settings in operations.

5.2. Research and managerial implications

Based on the analysis results, the below research and managerial implications are suggested:

1. Based on case study 1, it was found that environmental regulations and production rate has the highest link prediction index. Currently, the relationships between environmental regulations and agricultural production have been investigated by some economists (de Waroux et al., 2019). Therefore, it is suggested that more economists can develop more research projects to study the impact of environmental regulations on the manufacturing production rate to understand the economic aspects of sustainable manufacturing.

2. Cutting quality and process management are the top two sustainable manufacturing factors with the highest centrality values. According to the research of (Rodriguez-Zurrunero, Utrilla, Rozas, & Araujo, 2019), new technology like IoT can improve the efficiency of process management. Thus, the manufacturing companies may establish a real-time tracking process management system based on the IoT method.
3. This work is the application of unsupervised learning in sustainable manufacturing and the UPM area. As pointed by Tayal, Solanki, and Singh (2020), machine learning in the field of sustainable manufacturing is in the initial stages and remains in the theoretical aspect. Therefore, discovering more application scenarios of machine learning and big data in SM research is a new research direction with high potential value.

5.3. Limitation and Further study

Besides the contributions, there are also several limitations in this project. Firstly, text mining technology is not applied to achieve an automatic selection of the parameters or keywords from a scale of literature. Besides, in this study, the node-level analysis was focused while the edge-level analysis played the role of assistant.

Therefore, a new study can be conducted to investigate the relationships among the parameters by using the link prediction metrics. For example, the topic discovery model based on machine learning and SNA has been applied in multiple disciplines studies like geographical topics (Yin, Cao, Han, Zhai, & Huang, 2011), which has not been used in the sustainable manufacturing field. Therefore, the link prediction metrics can be applied to uncover the hidden value and patterns of the undiscussed relationships of two-parameter topics in the future. What's more, a text mining model can also be developed by utilizing natural language processing (NLP) technology like the Latent Dirichlet allocation (LDA) to evaluate the relevant literature and discover the hidden topics in the research area of sustainable manufacturing. Is a statistical model to discovering the latent "topics" distribution that occurs in a collection of documents (Cho, 2019). By using this method to evaluate the literature in different periods, the main themes and developing trends can be discovered.

Appendix: Python code for case study 1

Part 1: Node level analysis

```
# Import package
import numpy as np
import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt
```

```
# create direct network
edges_df=pd.read_excel(r"C:\Mphil Study\confirmation\Dataset.xlsx",header=None)
edges=edges_df.as_matrix()
G=nx.DiGraph()
G.add_edges_from(edges)
```

Figure 27 Create the sustainable manufacturing direct graph

```
# check network info
print(nx.info(G))
```

```
Name:
Type: DiGraph
Number of nodes: 16
Number of edges: 91
Average in degree:   5.6875
Average out degree:   5.6875
```

Figure 28 Check graph information

```
# Network visulation
nx.draw(G,nx.circular_layout(G),with_labels=True, node_size=800)
plt.show()
nx.write_graphml(G,r"C:\Research\thesis\images\network.png")
```

```
C:\Users\ezhou\AppData\Local\Continuum\anaconda3\lib\site-packages
The iterable function was deprecated in Matplotlib 3.1 and will be
  if not cb.iterable(width):
C:\Users\ezhou\AppData\Local\Continuum\anaconda3\lib\site-packages
The iterable function was deprecated in Matplotlib 3.1 and will be
  if cb.iterable(node_size):  # many node sizes
```

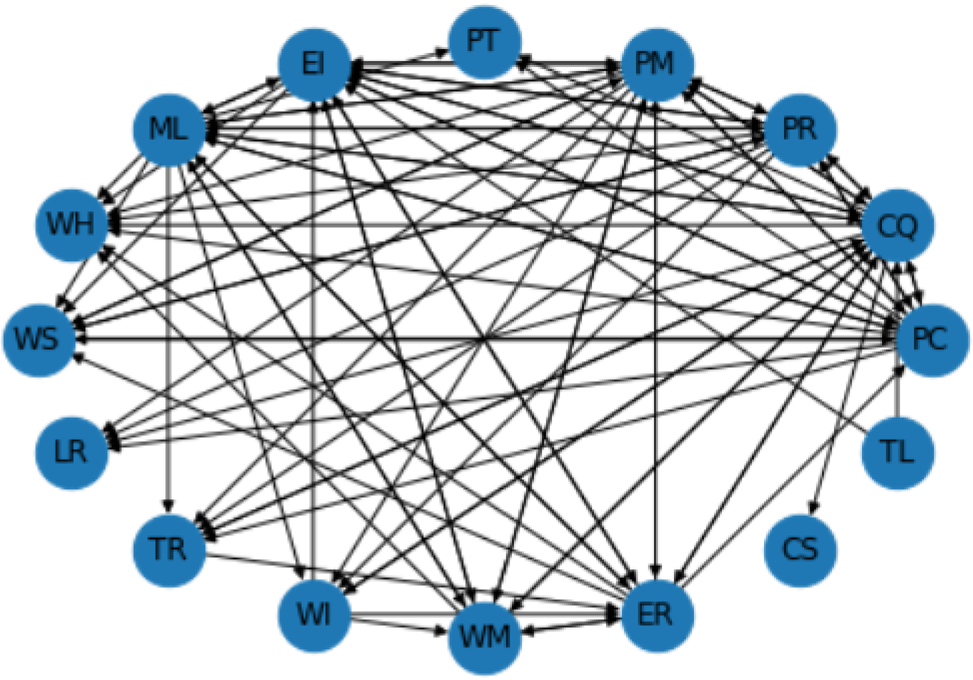

Figure 29 Visualisation of the graph

```python
# calculate in degree centrality
indeg=nx.in_degree_centrality(G)
indeg=pd.Series(indeg)
indeg=indeg.to_frame()
indeg.tail()
```

	0
WI	0.266667
WM	0.400000
ER	0.466667
CS	0.066667
TL	0.000000

```python
# calculate out degree centrality
outdeg=nx.out_degree_centrality(G)
outdeg=pd.Series(outdeg)
outdeg=outdeg.to_frame()
outdeg.tail()
```

	0
WI	0.266667
WM	0.400000
ER	0.533333
CS	0.000000
TL	0.133333

Figure 30 Calculation of the in-degree centrality and out-degree centrality

```
# calculate betweenness centrality
btw=nx.betweenness_centrality(G)
btw=pd.Series(btw)
btw=btw.to_frame()
btw.tail()
```

	0
WI	0.001746
WM	0.003571
ER	0.029524
CS	0.000000
TL	0.000000

```
# calculate closeness centrality
cls=nx.closeness_centrality(G)
cls=pd.Series(cls)
cls=cls.to_frame()
cls.tail()
```

	0
WI	0.448148
WM	0.504167
ER	0.537778
CS	0.400000
TL	0.000000

Figure 31 Calculation of the betweenness and closeness centrality

```python
# calculate eigenvector centrality
eig=nx.eigenvector_centrality(G,max_iter=10000)
eig=pd.Series(eig)
eig=eig.to_frame()
eig.tail()
```

	0
WI	1.742145e-01
WM	2.459338e-01
ER	2.729432e-01
CS	4.884850e-02
TL	1.635634e-08

```python
# aggreagte five metrics result
centrality=pd.DataFrame()
centrality = pd.concat([indeg,outdeg,btw,cls,eig], axis=1, sort=False)
centrality.columns = ["indeg", "outdeg","btw","cls","eig"]
centrality.tail()
```

	indeg	outdeg	btw	cls	eig
WI	0.266667	0.266667	0.001746	0.448148	1.742145e-01
WM	0.400000	0.400000	0.003571	0.504167	2.459338e-01
ER	0.466667	0.533333	0.029524	0.537778	2.729432e-01
CS	0.066667	0.000000	0.000000	0.400000	4.884850e-02
TL	0.000000	0.133333	0.000000	0.000000	1.635634e-08

```python
# export centrality result
centrality.to_excel(r"C:\Research\thesis\images\node level result.xlsx")
```

Figure 32 Calculation of eigenvector centrality and save the metrics results in one data frame

```
array_centrality=centrality.copy()
array_centrality=array_centrality.values
array_centrality
```

```
array([[4.66666667e-01, 6.66666667e-01, 2.99206349e-02, 5.37777778e-01,
        2.94052968e-01],
       [6.66666667e-01, 8.66666667e-01, 1.74444444e-01, 6.72222222e-01,
        3.42155876e-01],
       [4.00000000e-01, 6.66666667e-01, 2.00000000e-02, 5.04166667e-01,
        2.59953898e-01],
       [5.33333333e-01, 8.00000000e-01, 4.74603175e-02, 5.76190476e-01,
        3.24777857e-01],
       [2.00000000e-01, 0.00000000e+00, 0.00000000e+00, 4.57142857e-01,
        1.32715008e-01],
       [6.00000000e-01, 6.00000000e-01, 4.01587302e-02, 6.20512821e-01,
        3.15146493e-01],
       [4.66666667e-01, 8.00000000e-01, 2.68253968e-02, 5.37777778e-01,
        2.93381721e-01],
       [5.33333333e-01, 0.00000000e+00, 0.00000000e+00, 6.00000000e-01,
        3.35267241e-01],
       [4.00000000e-01, 2.00000000e-01, 7.93650794e-04, 5.04166667e-01,
        2.51307121e-01],
       [2.66666667e-01, 0.00000000e+00, 0.00000000e+00, 4.80000000e-01,
        1.74309959e-01],
       [3.33333333e-01, 1.33333333e-01, 1.74603175e-03, 4.74509804e-01,
        2.16195479e-01],
       [2.66666667e-01, 2.66666667e-01, 1.74603175e-03, 4.48148148e-01,
        1.74214487e-01],
       [4.00000000e-01, 4.00000000e-01, 3.57142857e-03, 5.04166667e-01,
        2.45933786e-01],
       [4.66666667e-01, 5.33333333e-01, 2.95238095e-02, 5.37777778e-01,
        2.72943169e-01],
       [6.66666667e-02, 0.00000000e+00, 0.00000000e+00, 4.00000000e-01,
        4.88484951e-02],
       [0.00000000e+00, 1.33333333e-01, 0.00000000e+00, 0.00000000e+00,
        1.63563371e-08]])
```

Figure 33 Transfrom dataframe to array

```python
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0, 1))
scaled_centrality=scaler.fit_transform(array_centrality)
scaled_centrality
```

```
array([[0.7       , 0.76923077, 0.17151956, 0.8       , 0.85941229],
       [1.        , 1.        , 1.        , 1.        , 1.        ],
       [0.6       , 0.76923077, 0.11464968, 0.75      , 0.75975283],
       [0.8       , 0.92307692, 0.27206551, 0.85714286, 0.94921022],
       [0.3       , 0.        , 0.        , 0.68004723, 0.38787876],
       [0.9       , 0.69230769, 0.23020928, 0.92307692, 0.92106117],
       [0.7       , 0.92307692, 0.15377616, 0.8       , 0.85745047],
       [0.8       , 0.        , 0.        , 0.89256198, 0.97986697],
       [0.6       , 0.23076923, 0.00454959, 0.75      , 0.73448137],
       [0.4       , 0.        , 0.        , 0.71404959, 0.50944602],
       [0.5       , 0.15384615, 0.0100091 , 0.70588235, 0.63186252],
       [0.4       , 0.30769231, 0.0100091 , 0.66666667, 0.50916699],
       [0.6       , 0.46153846, 0.02047316, 0.75      , 0.71877702],
       [0.7       , 0.61538462, 0.16924477, 0.8       , 0.79771585],
       [0.1       , 0.        , 0.        , 0.59504132, 0.14276675],
       [0.        , 0.15384615, 0.        , 0.        , 0.        ]])
```

Figure 34 Normalization of centrality metrics

```python
# calculate Centrality Index
centrality_df_scaled = pd.DataFrame(scaled_centrality,index=centrality.index)
centrality_df_scaled.columns = ["indeg", "outdeg","btw","cls","eig"]
CI=centrality_df_scaled.sum(axis=1)
CI
```

```
PC    3.300163
CQ    5.000000
PR    2.993633
PM    3.801496
PT    1.367926
EI    3.666655
ML    3.434304
WH    2.672429
WS    2.319800
LR    1.623496
TR    2.001600
WI    1.893535
WM    2.550789
ER    3.082345
CS    0.837808
TL    0.153846
dtype: float64
```

```python
centrality_ci=centrality.copy()
centrality_ci['CenIndex']=CI
centrality_ci.tail()
```

	indeg	outdeg	btw	cls	eig	CenIndex
WI	0.266667	0.266667	0.001746	0.448148	1.742145e-01	1.893535
WM	0.400000	0.400000	0.003571	0.504167	2.459338e-01	2.550789
ER	0.466667	0.533333	0.029524	0.537778	2.729432e-01	3.082345
CS	0.066667	0.000000	0.000000	0.400000	4.884850e-02	0.837808
TL	0.000000	0.133333	0.000000	0.000000	1.635634e-08	0.153846

Figure 35 Calculation of centrality index

```python
# Ranking
centrality_ci2=centrality_ci.copy()
centrality_ci2['Rank']=centrality_ci2['CenIndex'].rank(ascending=False)
centrality_ci2=centrality_ci2.sort_values('Rank')
centrality_ci2
```

	indeg	outdeg	btw	cls	eig	CenIndex	Rank
CQ	0.666667	0.866667	0.174444	0.672222	3.421559e-01	5.000000	1.0
PM	0.533333	0.800000	0.047460	0.576190	3.247779e-01	3.801496	2.0
EI	0.600000	0.600000	0.040159	0.620513	3.151465e-01	3.666655	3.0
ML	0.466667	0.800000	0.026825	0.537778	2.933817e-01	3.434304	4.0
PC	0.466667	0.666667	0.029921	0.537778	2.940530e-01	3.300163	5.0
ER	0.466667	0.533333	0.029524	0.537778	2.729432e-01	3.082345	6.0
PR	0.400000	0.666667	0.020000	0.504167	2.599539e-01	2.993633	7.0
WH	0.533333	0.000000	0.000000	0.600000	3.352672e-01	2.672429	8.0
WM	0.400000	0.400000	0.003571	0.504167	2.459338e-01	2.550789	9.0
WS	0.400000	0.200000	0.000794	0.504167	2.513071e-01	2.319800	10.0
TR	0.333333	0.133333	0.001746	0.474510	2.161955e-01	2.001600	11.0
WI	0.266667	0.266667	0.001746	0.448148	1.742145e-01	1.893535	12.0
LR	0.266667	0.000000	0.000000	0.480000	1.743100e-01	1.623496	13.0
PT	0.200000	0.000000	0.000000	0.457143	1.327150e-01	1.367926	14.0
CS	0.066667	0.000000	0.000000	0.400000	4.884850e-02	0.837808	15.0
TL	0.000000	0.133333	0.000000	0.000000	1.635634e-08	0.153846	16.0

```python
# export final centrality result
centrality_ci2.to_excel(r"C:\Research\thesis\images\node_final_result.xlsx")
nx.write_graphml(G, r'C:\Research\thesis\images\sn2.graphml')
```

Figure 36 Rank the parameters based on the centrality index and save results

Part 2: Edge level analysis

```python
G2=nx.Graph()
G2.add_edges_from(edges)
```

```python
# assign communities
c1=['PC','CQ','PR','PM','PT']
for x in c1:
    G2.node[x]['community']=0

c2=['WI','EI','ML','WM','ER','TL']
for x in c2:
    G2.node[x]['community']=1

c3=['WH','WS','LR','TR','CS']
for x in c3:
    G2.node[x]['community']=2
```

Figure 37 Create the non-directional graph and assign communities of TBL

```python
print(nx.info(G2))
nx.draw(G2,nx.circular_layout(G2),with_labels=True, node_size=300)
plt.show()
```

```
Name:
Type: Graph
Number of nodes: 16
Number of edges: 62
Average degree:   7.7500
```

```
C:\Users\ezhou\AppData\Local\Continuum\anaconda3\lib\site-packages\r
The iterable function was deprecated in Matplotlib 3.1 and will be r
  if not cb.iterable(width):
```

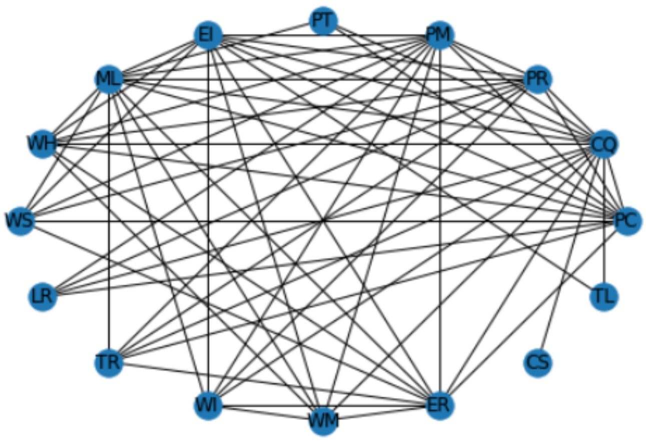

Figure 38 Check the graph information and visualization

```python
# measurement 1 common_neigh
common_neigh=[(e[0],e[1],len(list(nx.common_neighbors(G2,e[0],e[1])))) for e in nx.non_edges(G2)]

# measurement 2 jaccard_coefficient
jaccard_coefficient=list(nx.jaccard_coefficient(G2))

# measurement 3 resource_allocation
resource_allocation=list(nx.resource_allocation_index(G2))

# measurement 4 adamic_adar_index
adamic_adar_index=list(nx.adamic_adar_index(G2))

# measurement 5 preferential_attachment
preferential_attachment=list(nx.preferential_attachment(G2))

# measurement 6 cn_soundarajan_hopcroft
cn_soundarajan_hopcroft=list(nx.cn_soundarajan_hopcroft(G2))

# measurement 7 ra_index_soundarajan_hopcroft
ra_index_soundarajan_hopcroft=list(nx.ra_index_soundarajan_hopcroft(G2))
```

```python
df = pd.DataFrame(index=[(x[0], x[1]) for x in common_neigh])
df['common neighbors'] = [x[2] for x in common_neigh]
df['jaccard coefficient'] = [x[2] for x in jaccard_coefficient]
df['resource allocation'] = [x[2] for x in resource_allocation]
df['adamic adar index'] = [x[2] for x in adamic_adar_index]
df['preferential attachment'] = [x[2] for x in preferential_attachment]

df['community common neighbors'] = [x[2] for x in cn_soundarajan_hopcroft]
df['community resource allocation'] = [x[2] for x in ra_index_soundarajan_hopcroft]
```

Figure 39 Calculation of link prediction metrics

```python
#Normalization
array_df=df.copy()
array_df=array_df.values

scaler=MinMaxScaler(feature_range=(0, 1))
scaled_metrics=scaler.fit_transform(array_df)

df_scaled = pd.DataFrame(scaled_metrics,index=df.index)
df_scaled.columns = ["metric 1", "metric 2","metric 3","metric 4","metric 5","metric 6","metric 7"]
LPI=df_scaled.sum(axis=1)

df_lpi=df.copy()
df_lpi['LP Index']=LPI
df_lpi
```

	common neighbors	jaccard coefficient	resource allocation	adamic adar index	preferential attachment	community common neighbors	community resource allocation	LP Index
(PM, PT)	3	0.250000	0.245671	1.198385	36	5	0.162338	3.052381
(PM, TL)	2	0.166667	0.162338	0.795956	24	2	0.000000	1.211171
(PM, CS)	1	0.083333	0.071429	0.378923	12	1	0.000000	0.581228
(TL, WI)	2	0.285714	0.162338	0.795956	14	3	0.090909	1.916296
(TL, LR)	1	0.200000	0.071429	0.378923	8	1	0.000000	0.673745
(TL, PC)	2	0.181818	0.162338	0.795956	22	2	0.000000	1.208079
(TL, TR)	1	0.142857	0.071429	0.378923	12	1	0.000000	0.649255
(TL, WM)	2	0.285714	0.162338	0.795956	14	3	0.090909	1.916296

Figure 40 Normalize the metrics results

```
# LP Index Ranking
df_lpi2=df_lpi.copy()

df_lpi2['Rank']=df_lpi2['LP Index'].rank(method='max',ascending=False)
df_lpi2=df_lpi2.sort_values('Rank')
df_lpi2
```

	common neighbors	jaccard coefficient	resource allocation	adamic adar index	preferential attachment	community common neighbors	community resource allocation	LP Index	Rank
(PR, ER)	9	0.818182	1.021104	4.128865	100	9	0.000000	5.935065	1.0
(WH, WI)	7	0.875000	0.671861	2.983302	56	7	0.000000	4.487099	2.0
(WM, PR)	6	0.545455	0.596861	2.595611	70	6	0.000000	3.863763	3.0
(PC, WM)	6	0.500000	0.554004	2.516008	77	6	0.000000	3.821993	4.0
(WH, WS)	6	0.750000	0.548485	2.507513	48	6	0.000000	3.804326	6.0
(CQ, WS)	6	0.428571	0.548485	2.507513	84	6	0.000000	3.804326	6.0
(PC, WI)	6	0.500000	0.529004	2.469404	77	6	0.000000	3.786222	7.0
(TR,	6	0.750000	0.529004	2.469404	48	6	0.000000	3.776018	8.0

```
# export final centrality result
df_lpi2.to_excel(r"C:\Research\thesis\images\edge_final_result.xlsx")
```

Figure 41 Rank the edges according to the Link Prediction index

Part 3: k-means

```
import seaborn as sns
from sklearn.decomposition import PCA
```

```
centrality_scaled = pd.DataFrame(scaled_centrality,columns = ["indeg", "outdeg","btw","cls","eig"],index=centrality.index)
```

Figure 42 Transform the array to the data frame

```
# Correlation analysis among attributes
centrality_scaled1=centrality_scaled.copy()
corr = centrality_scaled1.corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
with sns.axes_style("white"):
    f, ax = plt.subplots(figsize=(8,8))
    ax = sns.heatmap(corr,annot=True, mask=mask)

corr_fig= ax.get_figure()
corr_fig.savefig(r'C:\Research\thesis\images\corr_heatmap.png',dpi=800)
```

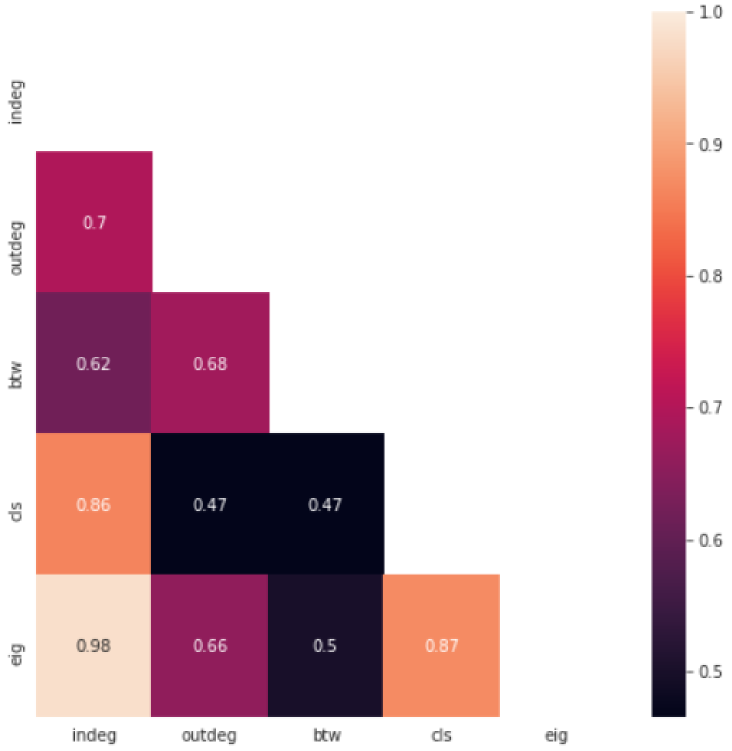

Figure 43 Check the correlation matrix

```python
from sklearn.cluster import MiniBatchKMeans, KMeans
from sklearn.metrics import silhouette_score
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

```python
SSE = []  # save sum of the squared errors
for k in range(1,9):
    estimator = KMeans(n_clusters=k)
    estimator.fit(scaled_centrality)
    SSE.append(estimator.inertia_)

sns.set_style("whitegrid")
X = range(1,9)
plt.xlabel('k')
plt.ylabel('SSE')
plt.plot(X,SSE,'o-')
plt.show()
```

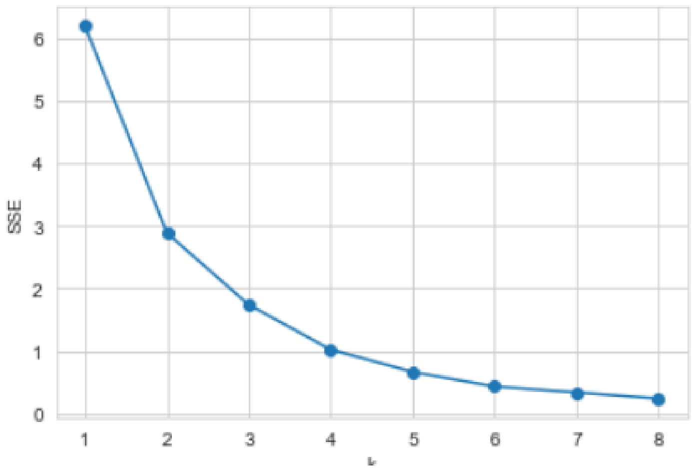

Figure 44 Calculation of the SSE

```
Scores = []  # Silhouette Coefficient
for k in range(2,9):
    estimator = KMeans(n_clusters=k)
    estimator.fit(scaled_centrality)
    Scores.append(silhouette_score(scaled_centrality,estimator.labels_,metric='euclidean'))

sns.set_style("whitegrid")
X = range(2,9)
plt.xlabel('k')
plt.ylabel('Silhouette Coefficient')
plt.plot(X,Scores,'o-')
plt.show()
```

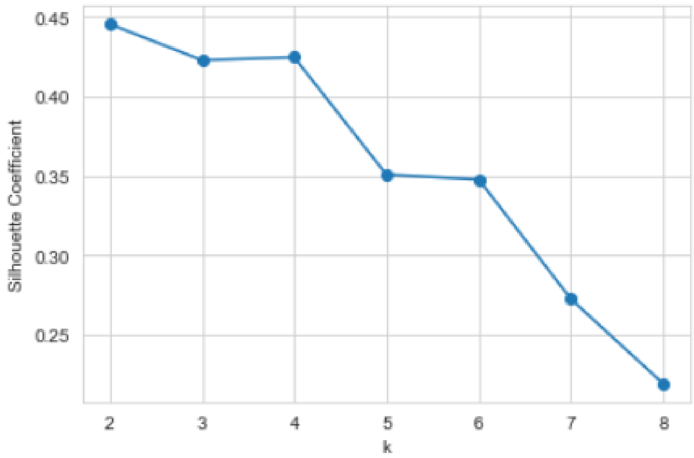

Figure 45 Calculation of the Silhouette Coefficient

```
# SSE and Silhouette Coefficient
sns.set_style("whitegrid")

fig = plt.figure(figsize = (6, 6))

X1 = range(1,9)
X2 = range(2,9)

ax1 = fig.add_subplot(211)
ax1.plot(X1, SSE,'o-', label="SSE")
#ax1.set_xlabel("k")
ax1.set_ylabel("SSE")
plt.legend()

ax2 = fig.add_subplot(212)
ax2.plot(X2, Scores,'oy-', label="Silhouette Coefficient")
ax2.set_xlabel("k")
ax2.set_ylabel("Silhouette Coefficient")
plt.legend()

plt.savefig(r"C:\Research\thesis\images\SSE & Silhouette Coefficient.png",dpi=800)
plt.show()
```

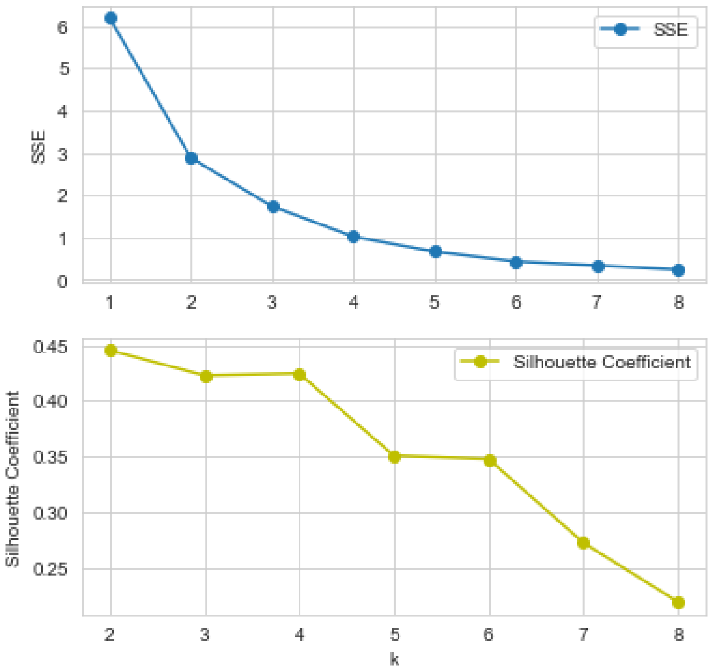

Figure 46 Combine the SSE and Silhouette Coefficient

```
# set k=4
kmeans = KMeans(n_clusters=4).fit(scaled_centrality)
```

Figure 47 Set k value be 4 and run k-means

Part 4: Dimension reduction and plot

```
# PCA with 2 components
pca = PCA(n_components=2)
pas = pca.fit_transform(scaled_centrality)
pa_df = pd.DataFrame(data = pas,columns = ['PC1', 'PC2'])
pa_df['label']=kmeans.labels_
pca.explained_variance_ratio_
```

```
array([0.75811014, 0.15560134])
```

Figure 48 Run PCA to reduce the dimensions of centrality metrics results

```
df2=pa_df.copy()
sns.set_style("ticks")
fig = plt.figure(figsize = (8,8))
ax1 = fig.add_subplot(211)
ax1.plot(df2['PC1'],df2['PC2'],'.')
ax1.title.set_text('(a). Unclassified sustainable manufacturing')

ax2 = fig.add_subplot(212)
d1 = df2[df2['label'] == 0]
ax2.plot(d1['PC1'], d1['PC2'], 'ro', label="C1")
d2 = df2.loc[df2['label'] == 1]
ax2.plot(d2['PC1'], d2['PC2'], 'gv',label="C2")
d3 = df2.loc[df2['label'] == 2]
ax2.plot(d3['PC1'], d3['PC2'], 'b*', label="C3")
d4 = df2.loc[df2['label'] == 3]
ax2.plot(d4['PC1'], d4['PC2'], 'y.', label="C4")

ax2.title.set_text('(b). Classified sustainable manufacturing')
plt.gcf().savefig(r'C:\Research\thesis\images\clustering.png',dpi=800)
plt.show()
```

Figure 49 Plot the classification result in 2D figure

```python
# save and export data
df3=centrality_ci.copy()
df3['label']=kmeans.labels_
df3['Rank']=df3['CenIndex'].rank(method='max',ascending=False)
df3=df3.sort_values('Rank')
df3.to_excel(r"C:\Research\thesis\images\Centrality Index.xlsx")
```

Figure 50 Save the figure and calculation results

References

Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley interdisciplinary reviews: computational statistics, 2*(4), 433-459.

Abdul-Rashid, S. H., Sakundarini, N., Ghazilla, R. A. R., & Thurasamy, R. (2017). The impact of sustainable manufacturing practices on sustainability performance. *International Journal of Operations and Production Management*.

Adamic, L. A., & Adar, E. (2003). Friends and neighbors on the web. *Social networks, 25*(3), 211-230.

Afolabi, R. O., Dadlani, A., & Kim, K. (2012). Multicast scheduling and resource allocation algorithms for OFDMA-based systems: A survey. *IEEE Communications Surveys and Tutorials, 15*(1), 240-254.

Alsayat, A., & El-Sayed, H. (2016). *Social media analysis using optimized K-Means clustering.* Paper presented at the 2016 IEEE 14th International Conference on Software Engineering Research, Management and Applications (SERA).

Alsyouf, I. (2007). The role of maintenance in improving companies' productivity and profitability. *International Journal of production economics, 105*(1), 70-78.

Alting, D. L., & Jøgensen, D. J. (1993). The life cycle concept as a basis for sustainable industrial production. *CIRP annals, 42*(1), 163-167.

Amui, L. B. L., Jabbour, C. J. C., de Sousa Jabbour, A. B. L., & Kannan, D. (2017). Sustainability as a dynamic organizational capability: a systematic review and a future agenda toward a sustainable transition. *Journal of Cleaner Production, 142*, 308-322.

Armenti, K. R., Moure-Eraso, R., Slatin, C., & Geiser, K. (2011). Primary prevention for worker health and safety: cleaner production and toxics use reduction in Massachusetts. *Journal of Cleaner Production, 19*(5), 488-497.

Azulay, H. (2014). *A Design Methodology for Reconfigurable Milling Machine Tools and An Implementation.*

Barbour, M. T., Graves, C. G., Plafkin, J. L., Wisseman, R. W., & Bradley, B. (1992). Evaluation of EPA's rapid bioassessment benthic metrics: metric redundancy and variability among reference stream sites. *Environmental Toxicology and Chemistry: An International Journal, 11*(4), 437-449.

Bhanot, N., Rao, P. V., & Deshmukh, S. (2015). Sustainable manufacturing: an interaction analysis for machining parameters using graph theory. *Procedia-Social and Behavioral Sciences, 189*, 57-63.

Bhanot, N., Rao, P. V., & Deshmukh, S. (2016). Identifying the perspectives for sustainability enhancement. *Journal of Advances in Management Research*.

Bhattacharya, A., Das, S., Majumder, P., & Batish, A. (2009). Estimating the effect of cutting parameters on surface finish and power consumption during high speed machining of AISI 1045 steel using Taguchi design and ANOVA. *Production Engineering, 3*(1), 31-40.

Bliss, C. A., Frank, M. R., Danforth, C. M., & Dodds, P. S. (2014). An evolutionary algorithm approach to link prediction in dynamic social networks. *Journal of Computational Science, 5*(5), 750-764.

Buccafurri, F., Fotia, L., Lax, G., & Saraswat, V. (2016). Analysis-preserving protection of user privacy against information leakage of social-network Likes. *Information Sciences, 328*, 340-358.

Camargo, M., Dumas, M., & González-Rojas, O. (2020). Automated discovery of business process simulation models from event logs. *Decision Support Systems, 134*, 113284.

Chan, K., & Liebowitz, J. (2006). The synergy of social network analysis and knowledge mapping: a case study. *International journal of management and decision making, 7*(1), 19-35.

Chankov, S., Hütt, M.-T., & Bendul, J. (2018). Understanding synchronizability of manufacturing networks: A multi-method study on structural network properties. *Journal of Manufacturing Systems, 46*, 127-136.

Cheng, M., Cheung, C., Lee, W., To, S., & Kong, L. (2008). Theoretical and experimental analysis of nano-surface generation in ultra-precision raster milling. *International Journal of machine tools and manufacture, 48*(10), 1090-1102.

Cheong, F., & Cheong, C. (2011). Social Media Data Mining: A Social Network Analysis Of Tweets During The 2010-2011 Australian Floods. *PACIS, 11*, 46-46.

Cheung, C., & Lee, W. (2000). Study of factors affecting the surface quality in ultra-precision diamond turning. *Materials and Manufacturing Processes, 15*(4), 481-502.

Cheung, C. F., & Lee, W. B. (2000). A multi-spectrum analysis of surface roughness formation in ultra-precision machining. *Precision Engineering, 24*(1), 77-87.

Cho, H.-W. (2019). Topic Modeling. *Osong public health and research perspectives, 10*(3), 115.

Choudhury, A. K. R. (2017). Sustainable chemical technologies for textile production. In *Sustainable Fibres and Textiles* (pp. 267-322): Elsevier.

Clemente, F. M., Martins, F. M. L., Wong, P. D., Kalamaras, D., & Mendes, R. S. (2015). Midfielder as the prominent participant in the building attack: A network analysis of national teams in FIFA World Cup 2014. *International Journal of Performance Analysis in Sport, 15*(2), 704-722.

Correa, M., Bielza, C., & Pamies-Teixeira. (2009). Comparison of Bayesian networks and artificial neural networks for quality detection in a machining process. *Expert Systems with Applications, 36*(3), 7270-7279.

de Waroux, Y. l. P., Garrett, R. D., Graesser, J., Nolte, C., White, C., & Lambin, E. F. (2019). The restructuring of South American soy and beef production and trade under changing environmental regulations. *World Development, 121*, 188-202.

Debnath, S., Reddy, M. M., & Yi, Q. S. (2016). Influence of cutting fluid conditions and cutting parameters on surface roughness and tool wear in turning process using Taguchi method. *Measurement, 78*, 111-119.

Dekker, A. (2002). Applying social network analysis concepts to military C4ISR architectures. *Connections, 24*(3), 93-103.

Dogra, M., Sharma, V., & Dureja, J. (2011). Effect of tool geometry variation on finish turning-A Review. *ournal of Engineering Science and Technology Review, 4*(1).

du Preez, A., & Oosthuizen, G. A. (2019). Machine learning in cutting processes as enabler for smart sustainable manufacturing. *Procedia Manufacturing, 33*, 810-817.

Fečiková, I. (2004). An index method for measurement of customer satisfaction. *The TQM magazine*.

Filleti, R. A. P., Silva, D. A. L., da Silva, E. J., & Ometto, A. R. (2017). Productive and environmental performance indicators analysis by a combined LCA hybrid model and real-time manufacturing process monitoring: A grinding unit process application. *Journal of Cleaner Production, 161*, 510-523.

Friedman, S. R., Neaigus, A., Jose, B., Curtis, R., & Des Jarlais, D. (1998). Networks and HIV risk: an introduction to social network analysis for harm reductionists. *International Journal of Drug Policy, 9*(6), 461-469.

Furukawa, Y., & Moronuki, N. (1988). Effect of material properties on ultra precise cutting processes. *CIRP annals, 37*(1), 113-116.

Gao, S., Zhou, M., Wang, Y., Cheng, J., Yachi, H., & Wang, J. (2018). Dendritic neuron model with effective learning algorithms for classification, approximation, and prediction. *IEEE transactions on neural networks and learning systems*, *30*(2), 601-614.

Garetti, M., & Taisch, M. (2012). Sustainable manufacturing: trends and research challenges. *Production planning and control, 23*(2-3), 83-104.

Gutowski, T. G. (2007). *The carbon and energy intensity of manufacturing.* Paper presented at the 40th Seminar of CIRP, Keynote Address, Liverpool University, Liverpool, UK.

Han, Y., Caldwell, N. D., & Ghadge, A. (2020). Social network analysis in operations and supply chain management: a review and revised research agenda. *International Journal of Operations and Production Management*.

Harberger, A. C. (1995). Monopoly and resource allocation. In *Essential readings in economics* (pp. 77-90): Springer.

Hromic, H., Le Phuoc, D., Serrano, M., Antonić, A., Žarko, I. P., Hayes, C., & Decker, S. (2015). *Real time analysis of sensor data for the internet of things by means of clustering and event processing.* Paper presented at the 2015 IEEE International conference on communications (ICC).

Huang, A., & Badurdeen, F. (2018). Metrics-based approach to evaluate sustainable manufacturing performance at the production line and plant levels. *Journal of Cleaner Production, 192*, 462-476.

Jiang, Q., Liu, Z., Liu, W., Li, T., Cong, W., Zhang, H., & Shi, J. (2018). A principal component analysis based three-dimensional sustainability assessment model to evaluate corporate sustainable performance. *Journal of Cleaner Production, 187*, 625-637.

Jollands, N., Lermit, J., & Patterson, M. (2004). Aggregate eco-efficiency indices for New Zealand—a principal components analysis. *Journal of environmental management, 73*(4), 293-305.

Kim, K.-j., & Ahn, H. (2008). A recommender system using GA K-means clustering in an online shopping market. *Expert Systems with Applications, 34*(2), 1200-1209.

Kim, Y., Choi, T. Y., Yan, T., & Dooley, K. (2011). Structural investigation of supply networks: A social network analysis approach. *Journal of Operations Management, 29*(3), 194-211.

Kotsiantis, S., & Pintelas, P. (2004). Recent advances in clustering: A brief survey. *WSEAS Transactions on Information Science and Applications, 1*(1), 73-81.

Krzysik, A. J. (1979). Resource allocation, coexistence, and the niche structure of a streambank salamander community. *Ecological Monographs, 49*(2), 173-194.

Kucukoglu, I., Atici-Ulusu, H., Gunduz, T., & Tokcalar, O. (2018). Application of the artificial neural network method to detect defective assembling processes by using a wearable technology. *Journal of Manufacturing Systems, 49*, 163-171.

Kumar, A., & Goyal, P. (2013). Forecasting of air quality index in Delhi using neural network based on principal component analysis. *Pure and Applied Geophysics, 170*(4), 711-722.

Kumar, D., Rai, C., & Kumar, S. (2010). Analysis of unsupervised learning techniques for face recognition. *International Journal of Imaging Systems and Technology, 20*(3), 261-267.

Kusuma, G. P., & Chua, C.-S. (2011). PCA-based image recombination for multimodal 2D+ 3D face recognition. *Image and Vision Computing, 29*(5), 306-316.

LaGrega, M. D., Buckingham, P. L., & Evans, J. C. (2010). *Hazardous waste management*: Waveland Press.

Lee, S., Geum, Y., Lee, H., & Park, Y. (2012). Dynamic and multidimensional measurement of product-service system (PSS) sustainability: a triple bottom line (TBL)-based system dynamics approach. *Journal of Cleaner Production, 32*, 173-182.

Lee, W., & Zhou, M. (1993). A theoretical analysis of the effect of crystallographic orientation on chip formation in micromachining. *International Journal of machine tools and manufacture, 33*(3), 439-447.

Li, T., Zhang, H., Yuan, C., Liu, Z., & Fan, C. (2012). A PCA-based method for construction of composite sustainability indicators. *The International Journal of Life Cycle Assessment, 17*(5), 593-603.

Li, Y., Tao, F., Cheng, Y., Zhang, X., & Nee, A. (2017). Complex networks in advanced manufacturing systems. *Journal of Manufacturing Systems, 43*, 409-421.

Lieber, D., Stolpe, M., Konrad, B., Deuse, J., & Morik, K. (2013). Quality prediction in interlinked manufacturing processes based on supervised & unsupervised machine learning. *Procedia Cirp, 7*, 193-198.

Lin, J., & Lin, C. (2002). The use of the orthogonal array with grey relational analysis to optimize the electrical discharge machining process with multiple performance characteristics. *International Journal of machine tools and manufacture, 42*(2), 237-244.

Lin, Q., Liu, H., Zhu, C., Chen, D., & Zhou, S. (2020). Effects of different shot peening parameters on residual stress, surface roughness and cell size. *Surface and Coatings Technology, 398*, 126054.

Lin, Y.-K., & Chang, P.-C. (2013). Reliability-based performance indicator for a manufacturing network with multiple production lines in parallel. *Journal of Manufacturing Systems, 32*(1), 147-153.

Liu, G., Yang, J., Hao, Y., & Zhang, Y. (2018). Big data-informed energy efficiency assessment of China industry sectors based on K-means clustering. *Journal of Cleaner Production, 183*, 304-314.

Liu, S., Ji, X., Liu, C., & Bai, Y. (2017). Extended resource allocation index for link prediction of complex network. *Physica A: Statistical Mechanics and its Applications, 479*, 174-183.

Lu, H., Chang, C., Hwang, N., & Chung, C. (2009). Grey relational analysis coupled with principal component analysis for optimization design of the cutting parameters in high-speed end milling. *Journal of materials processing technology, 209*(8), 3808-3817.

Lü, L., Jin, C.-H., & Zhou, T. (2009). Similarity index based on local paths for link prediction of complex networks. *Physical Review E, 80*(4), 046122.

Lusher, D., Koskinen, J., & Robins, G. (2013). *Exponential random graph models for social networks: Theory, methods, and applications*: Cambridge University Press.

Manufuture, N. (2004). A vision for 2020, assuring the future of manufacturing in Europe. *Report of the High-level Group, European Commission*.

Maurino, D. E., Reason, J., Johnston, N., & Lee, R. B. (2017). *Beyond aviation human factors: Safety in high technology systems*: Routledge.

McCulloh, I., Armstrong, H., & Johnson, A. (2013). *Social network analysis with applications*: John Wiley & Sons.

McIllwain, J. S. (1999). Organized crime: A social network approach. *Crime, law and social change, 32*(4), 301-323.

Metsalu, T., & Vilo, J. (2015). ClustVis: a web tool for visualizing clustering of multivariate data using Principal Component Analysis and heatmap. *Nucleic acids research, 43*(W1), W566-W570.

Murray, P. W., Agard, B., & Barajas, M. A. (2015). Forecasting supply chain demand by clustering customers. *IFAC-PapersOnLine, 48*(3), 1834-1839.

Newman, M. E. (2001). Clustering and preferential attachment in growing networks. *Physical Review E, 64*(2), 025102.

Newman, M. E. (2005). A measure of betweenness centrality based on random walks. *Social networks, 27*(1), 39-54.

Niwattanakul, S., Singthongchai, J., Naenudorn, E., & Wanapu, S. (2013). *Using of Jaccard coefficient for keywords similarity*. Paper presented at the Proceedings of the international multiconference of engineers and computer scientists.

Nunes, M., & Abreu, A. (2020). Applying social network analysis to identify project critical success factors. *Sustainability, 12*(4), 1503.

Olawale, F., & Garwe, D. (2010). Obstacles to the growth of new SMEs in South Africa: A principal component analysis approach. *African journal of Business management, 4*(5), 729-738.

Oliveira, M., & Gama, J. (2012). An overview of social network analysis. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 2*(2), 99-115.

Onat, N. C., Kucukvar, M., & Afshar, S. (2019). Eco-efficiency of electric vehicles in the United States: A life cycle assessment based principal component analysis. *Journal of Cleaner Production, 212*, 515-526.

Panda, S., Sahu, S., Jena, P., & Chattopadhyay, S. (2012). Comparing fuzzy-C means and K-means clustering techniques: a comprehensive study. In *Advances in computer science, engineering & applications* (pp. 451-460): Springer.

Paramati, S. R., Sinha, A., & Dogan, E. (2017). The significance of renewable energy use for economic output and environmental protection: evidence from the Next 11 developing economies. *Environmental Science and Pollution Research, 24*(15), 13546-13560.

Park, Y. S., Egilmez, G., & Kucukvar, M. (2015). A novel life cycle-based principal component analysis framework for eco-efficiency analysis: case of the United States manufacturing and transportation nexus. *Journal of Cleaner Production, 92,* 327-342.

Pavlopoulos, G. A., Secrier, M., Moschopoulos, C. N., Soldatos, T. G., Kossida, S., Aerts, J., . . . Bagos, P. G. (2011). Using graph theory to analyze biological networks. *BioData mining, 4*(1), 10.

Peng, T., Kellens, K., Tang, R., Chen, C., & Chen, G. (2018). Sustainability of additive manufacturing: An overview on its energy demand and environmental impact. *Additive Manufacturing, 21*, 694-704.

Perra, N., & Fortunato, S. (2008). Spectral centrality measures in complex networks. *Physical Review E, 78*(3), 036107.

Petroni, A., & Braglia, M. (2000). Vendor selection using principal component analysis. *Journal of supply chain management, 36*(1), 63-69.

Proietti, P., Calisti, R., Gigliotti, G., Nasini, L., Regni, L., & Marchini, A. (2016). Composting optimization: Integrating cost analysis with the physical-chemical properties of materials to be composted. *Journal of Cleaner Production, 137*, 1086-1099.

Rajemi, M., Mativenga, P., & Aramcharoen, A. (2010). Sustainable machining: selection of optimum turning conditions based on minimum energy considerations. *Journal of Cleaner Production, 18*(10-11), 1059-1065.

Rashid, A., Asif, F. M., Krajnik, P., & Nicolescu, C. M. (2013). Resource conservative manufacturing: An essential change in business and technology paradigm for sustainable manufacturing. *Journal of Cleaner Production, 57*, 166-177.

Reid, R. D., & Sanders, N. R. (2019). *Operations management: an integrated approach*: John Wiley & Sons.

Richardson, J., & Henriques, A. (2013). *The triple bottom line: does it all add up?* : Routledge.

Rodriguez-Zurrunero, R., Utrilla, R., Rozas, A., & Araujo, A. (2019). Process management in IoT operating systems: cross-influence between processing and communication tasks in end-devices. *Sensors, 19*(4), 805.

Rosen, M. A., & Kishawy, H. A. (2012). Sustainable manufacturing and design: Concepts, practices and needs. *Sustainability, 4*(2), 154-174.

Roweis, S. T. (1998). *EM algorithms for PCA and SPCA.* Paper presented at the Advances in neural information processing systems.

Ruhnau, B. (2000). Eigenvector-centrality—a node-centrality? *Social networks, 22*(4), 357-365.

Ryberg, T., & Christiansen, E. (2008). Community and social network sites as technology enhanced learning environments. *Technology, Pedagogy and Education, 17*(3), 207-219.

Sahin, Y. (2009). Comparison of tool life between ceramic and cubic boron nitride (CBN) cutting tools when machining hardened steels. *Journal of materials processing technology, 209*(7), 3478-3489.

Sanders, K. T., & Webber, M. E. (2012). Evaluating the energy consumed for water use in the United States. *Environmental Research Letters, 7*(3), 034034.

Scheren, P., Zanting, H., & Lemmens, A. (2000). Estimation of water pollution sources in Lake Victoria, East Africa: application and elaboration of the rapid assessment methodology. *Journal of environmental management, 58*(4), 235-248.

Schneider, F., Das, J., Kirsch, B., Linke, B., & Aurich, J. C. (2019). Sustainability in ultra precision and micro machining: a review. *International Journal of Precision Engineering and Manufacturing-Green Technology*, 1-10.

Shaw, M. E. (1954). Group structure and the behavior of individuals in small groups. *The Journal of psychology, 38*(1), 139-149.

shen How, B., & Lam, H. L. (2018). Sustainability evaluation for biomass supply chain synthesis: novel principal component analysis (PCA) aided optimisation approach. *Journal of Cleaner Production, 189*, 941-961.

Soni, K. G., & Patel, A. (2017). Comparative Analysis of K-means and K-medoids Algorithm on IRIS Data. *International Journal of Computational Intelligence Research*, *13*(5), 899-906.

Stern, N. (2006). Stern review on the economics of climate change, 2006. *London: Government of the United Kingdom*.

Streeck, W. (1987). The uncertainties of management in the management of uncertainty: Employers, labor relations and industrial adjustment in the 1980s. *Work, employment and Society*, *1*(3), 281-308.

Su, Y., Jia, Z., Niu, B., & Bi, G. (2017). Size effect of depth of cut on chip formation mechanism in machining of CFRP. *Composite Structures, 164*, 316-327.

Suominen, A., & Toivanen, H. (2016). Map of science with topic modeling: Comparison of unsupervised learning and human-assigned subject classification. *Journal of the Association for Information Science and Technology*, *67*(10), 2464-2476.

Takasu, S., Masuda, M., Nishiguchi, T., & Kobayashi, A. (1985). Influence of study vibration with small amplitude upon surface roughness in diamond machining. *CIRP annals, 34*(1), 463-467.

Tan, F., Xia, Y., & Zhu, B. (2014). Link prediction in complex networks: a mutual information perspective. *PloS one, 9*(9), e107056.

Tan, P., Liu, M., Shao, Z., & Ni, M. (2017). Recent advances in perovskite oxides as electrode materials for nonaqueous lithium–oxygen batteries. *Advanced Energy Materials, 7*(13), 1602674.

Tayal, A., Solanki, A., & Singh, S. P. (2020). Integrated frame work for identifying sustainable manufacturing layouts based on big data, machine learning, meta-heuristic and data envelopment analysis. *Sustainable Cities and Society, 62*, 102383.

Tipping, M. E., & Bishop, C. M. (1999). Probabilistic principal component analysis. *Journal of the Royal Statistical Society: Series B, 61*(3), 611-622.

Vinodh, S., Ramesh, K., & Arun, C. (2016). Application of interpretive structural modelling for analysing the factors influencing integrated lean sustainable system. *Clean Technologies and Environmental Policy, 18*(2), 413-428.

Vinodh, S., Ruben, R. B., & Asokan, P. (2016). Life cycle assessment integrated value stream mapping framework to ensure sustainable manufacturing: a case study. *Clean Technologies and Environmental Policy, 18*(1), 279-295.

Wada, R., Kodama, H., Nakamura, K., Mizutani, Y., Shimura, Y., & Takenaka, N. (1980). Wear characteristics of single crystal diamond tool. *CIRP annals, 29*(1), 47-52.

Wang, H., To, S., Chan, C., Cheung, C., & Lee, W. (2010a). A study of regularly spaced shear bands and morphology of serrated chip formation in microcutting process. *Scripta Materialia, 63*(2), 227-230.

Wang, H., To, S., Chan, C., Cheung, C., & Lee, W. (2010b). A theoretical and experimental investigation of the tool-tip vibration and its influence upon surface generation in single-point diamond turning. *International Journal of machine tools and manufacture, 50*(3), 241-252.

Wang, J., & Kumbasar, T. (2019). Parameter optimization of interval Type-2 fuzzy neural networks based on PSO and BBBC methods. *IEEE/CAA Journal of Automatica Sinica, 6*(1), 247-257.

Wang, S., To, S., & Cheung, C. (2012). Effect of workpiece material on surface roughness in ultraprecision raster milling. *Materials and Manufacturing Processes, 27*(10), 1022-1028.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8): Cambridge university press.

Westkämper, E., Alting, L., & Arndt, G. (2001). Life cycle management and assessment: approaches and visions towards sustainable manufacturing. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 215*(5), 599-626.

Wichmann, B. K., & Kaufmann, L. (2016). Social network analysis in supply chain management research. *International Journal of Physical Distribution and Logistics Management*.

Willis, R. M., Stewart, R. A., Panuwatwanich, K., Williams, P. R., & Hollingsworth, A. L. (2011). Quantifying the influence of environmental and water conservation attitudes on household end use water consumption. *Journal of environmental management, 92*(8), 1996-2009.

Xu, W., Shao, L., Yao, B., Zhou, Z., & Pham, D. T. (2016). Perception data-driven optimization of manufacturing equipment service scheduling in sustainable manufacturing. *Journal of Manufacturing Systems, 41*, 86-101.

Yang, Z., Hu, R., & Zhang, R. (2016). *An improved link prediction algorithm based on common neighbors index with community membership information.* Paper presented at the 2016 7th IEEE International Conference on Software Engineering and Service Science (ICSESS).

Yie, K.-Y., Chien, T.-W., Yeh, Y.-T., Chou, W., & Su, S.-B. (2021). Using Social Network Analysis to Identify Spatiotemporal Spread Patterns of COVID-19 around the World:

Online Dashboard Development. *International Journal of Environmental Research and Public Health, 18*(5), 2461.

Yin, Z., Cao, L., Han, J., Zhai, C., & Huang, T. (2011). *Geographical topic discovery and comparison*. Paper presented at the Proceedings of the 20th international conference on World wide web.

Yip, W., & To, S. (2017). Reduction of material swelling and recovery of titanium alloys in diamond cutting by magnetic field assistance. *Journal of Alloys and Compounds, 722*, 525-531.

Yip, W., & To, S. (2018). Sustainable manufacturing of ultra-precision machining of titanium alloys using a magnetic field and its sustainability assessment. *Sustainable Materials and Technologies, 16*, 38-46.

Yip, W., To, S., & Zhou, H. (2020). Social network analysis for optimal machining conditions in ultra-precision manufacturing. *Journal of Manufacturing Systems, 56*, 93-103.

Yiu, N. S., Sze, N., & Chan, D. W. (2018). Implementation of safety management systems in Hong Kong construction industry–A safety practitioner's perspective. *Journal of safety research, 64*, 1-9.

Yu, T., Zhang, T., Yu, X., Yang, X., & Sun, J. (2019). Study on optimization of ultrasonic-vibration-assisted polishing process parameters. *Measurement, 135*, 651-660.

Yuan, B., Ren, S., & Chen, X. (2017). Can environmental regulation promote the coordinated development of economy and environment in China's manufacturing industry?–A panel data analysis of 28 sub-sectors. *Journal of Cleaner Production, 149*, 11-24.

Yuan, C., Zhai, Q., & Dornfeld, D. (2012). A three dimensional system approach for environmentally sustainable manufacturing. *CIRP annals, 61*(1), 39-42.

Zeng, S. (2016). Link prediction based on local information considering preferential attachment. *Physica A: Statistical Mechanics and its Applications, 443*, 537-542.

Zhang, S., Guo, P., Xiong, Z., & To, S. (2020). Cyclic shear angle for lamellar chip formation in ultra-precision machining. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 0954406220908890.

Zhang, S., To, S., Wang, S., & Zhu, Z. (2015). A review of surface roughness generation in ultra-precision machining. *International Journal of machine tools and manufacture, 91*, 76-95.

Zhang, S., To, S., Zhu, Z., & Zhang, G. (2016). A review of fly cutting applied to surface generation in ultra-precision machining. *International Journal of machine tools and manufacture, 103,* 13-27.

Zhang, X., Wang, H., Chen, S., & Huang, Q. (2018). A novel two-stage optimization approach to machining process selection using error equivalence method. *Journal of Manufacturing Systems, 49,* 36-45.

Zhao, J., Lui, J. C., Towsley, D., & Guan, X. (2014). *Measuring and maximizing group closeness centrality over disk-resident graphs.* Paper presented at the Proceedings of the 23rd International Conference on World Wide Web.

Zheng, P., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., Mubarok, K., . . . Xu, X. (2018). Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. *Frontiers of Mechanical Engineering, 13*(2), 137-150.

Zhong, S., Geng, Y., Liu, W., Gao, C., & Chen, W. (2016). A bibliometric review on natural resource accounting during 1995–2014. *Journal of Cleaner Production, 139,* 122-132.

Zhou, H., Yip, W. S., Ren, J., & To, S. (2020). An Interaction Investigation of the Contributing Factors of the Bullwhip Effect Using a Bi-Level Social Network Analysis Approach. *IEEE Access, 8*, 208737-208752.

Zong, W., Li, Z., Sun, T., Cheng, K., Li, D., & Dong, S. (2010). The basic issues in design and fabrication of diamond-cutting tools for ultra-precision and nanometric machining. *International Journal of machine tools and manufacture*, *50*(4), 411-419.