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Social network analysis for optimal machining conditions in ultra-precision manufacturing

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Abstract

Ultra-precision machining (UPM) technology is extensively applied to manufacture top quality products with high precision level and complicated geometry. As complicated machining factors affect the surface quality of machined components in UPM, large numbers of experiments for understanding the influences from particular machining factors are needed, leading overestimate or underestimate of significance of machining factors at certain machining conditions and raising of experimental cost. For these reasons, a crucial approach is urged to adapt for providing a fast track to an optimal machining condition. In this study, social network analysis (SNA) is introduced firstly to develop UPM network, which the network shows the relationship between dominant machining factors in UPM. A complicated UPM network containing interdependencies between each machining factor is generated by SNA. The determinations of network metrics in the UPM network support the selection of optimal machining factors under various machining conditions. Furthermore, the constructed UPM network using SNA provides the complete framework of dependencies in UPM for well predicting the machining outcomes when particular machining factors are adjusted in practical situations. The study contributes to offering a detail guideline for constructing machining strategies or experimental plans to efficiently achieve desired machining outcomes

Keywords: Ultra-precision machining; Social network analysis (SNA); Manufacturing; Optimization; Machining factors

1. Introduction

An increase in the demand of high precision components with nanometric surface roughness and sub micrometric form is presented recently. Ultra-precision machining (UPM) technology is one of promising and efficient manufacturing technologies for fabricating the products which matches the increased demand. UPM has been extensively applied to fabricate high precise components such as optical lens, mould and medical elements etc. UPM denotes the reachable level of machined surface with form accuracy in the order of less than 0.2 μm and surface roughness in the order of less 10 nm. The resolution and repeatability of machined surface are less than 10 nm. Form accuracy and surface level are 1000 times larger in comparison to that of conventional machining. Although UPM has the superior capability of manufacturing great quality components with mirror surface finishing, the complicated cutting mechanism poses challenges in practical operations. The nano-surface generation is generally influenced by a large number of machining factors involved in UPM, only slight changes in the machining factors would possibility shift the optimal machining condition which the manufacturing process preserves originally.

In UPM, surface generation and surface topology are formed from the consequences of the transaction from the tool path to the workpiece surface, which they involved complicated mechanisms of material deformations and material separations, and they are manly determined by the combination effects of machining factors. The complicated effects from the factors affect each other and cannot be analysis based on one particular factor. Therefore, the relationship and influential flow between each factor should be recognized, for understanding the surface topography after the cutting process and the material removal mechanisms with the feature of the behaviors of material cutting. Up to now, there are lots of academic concerns about the investigation of the effect of machining factors on surface finishing and surface accuracy in UPM. The general machining factors in UPM involve machining parameters, cutting condition, tool geometry [1], material properties [2], tool wear [3], machining system vibration [4] and tool tip vibration [5]. Tool geometry significantly affects chip formation, heat generation, tool wear, surface roughness etc. Its effects have been a key topic for investigating cutting mechanisms [6]. Tool geometry consists of tool nose radius / tool profile, normally surface roughness theoretically decreases as tool nose radius increases. However, the influences of other factors actually integrated with the factor of tool geometry, which it makes fast considerations of this factor is impossible. Material property is another complicated factor in UPM. It imposes significant effects on surface generations in UPM because different materials have the unique characteristics affecting UPM processes, and it takes reversed effects in certain machining conditions to upstream machining factors. Tool tip vibration is a type of high frequency vibration to affect surface generation. It is reported as multi-mode vibrations and the involved theory is intricate which has been investigated by academia for long times. Actually, all the material factors do not solely provide its own influence on the surface generation. In UPM, they are integrated with other factor as the literature reported, therefore, a comprehensive network with all relationship between factors should be demonstrated in order to have the clear and solid concepts in implementing UPM.

The complexity of reaching to optimum machining condition increases with the number of machining factor increase and involves the choices of tolerance allocation in machining steps [7]. On the other hand, as high experiment costs and relatively unstable experimental environment exist in UPM, statistical, numerical and stochastic optimization techniques are seldom applied to determine the optimal machining condition in UPM. Conversely, theoretical modelling and computational simulation are commonly used to obtain the optimal machining factors and conditions in UPM. Cheung and Lee [8] developed a model-based simulation system with the consideration of tool geometry, machining parameters and tool-work vibration in order to determine the desired surface generation in ultra-precision diamond turning. Cheng et al. [9] proposed a theoretical model for an analysis of nano-surface generation in ultra-precision raster milling, which the model contributed to predict surface roughness of machined surface and obtain the optimal cutting condition under the consideration of different cutting strategies. Simulation modelling have been applied in UPM frequently because of high experimental costs involved in the statistical approaches. However, analytical models have been developed based on various assumptions which are normally available for the individual case, they should be modified once a slight change in the machining condition, which influences the prediction accuracy of these models. Numerical approaches have also been utilized under the elimination or simplification of several assumptions, although the model can be used to analysis more important parameters such as temperature distribution at tool/workpiece interface, material flow stress, the prediction outcome may underestimate the effects from some particular machining factors. Therefore, a structural network of UPM composed of main machining parameters and factors should be draw out in detail in order to provide the entire relationship map between each dependency, which it enables to deliver the instructions about how to adjust those dependencies before conducting the experiments, minimizing the machining costs and computational time in developing the physical based model.

Nowadays the optimization approaches for UPM are usually using orthogonal experimental design with gray relational analysis, and Taguchi method. For orthogonal experimental design and gray relational analysis, they are relied on the gray system theory which enable to observe different levels of development trends of factors involved in the analysis among various factors [10]. It is useful for employing at the conditions with several inputs, discrete data, and uncertainty in experimental design [11]. However, there is a particular limitation of this statistical method, which the computational method is solely relied in the numerical input. In UPM, several machining factors are normally displayed in qualitative and descriptive formats.

Especially chip formation and tool wear, they are commonly denoted as descriptive words to interpret the cutting mechanisms. These factors therefore are not able to analysis using the statistical approach like gray relational analysis. For Taguchi method, it uses of statistical methods concerning with the analysis of variance, and the factors in the experiments can be identified for the essential design factors causing to degradations of product performance. Taguchi method focuses on the importance of the parameter stage in the total design process. The parameters are therefore required to identify before conducting of Taguchi method, after that, a series of experiments which have the large influences on the performance and variation of the design are conducted. Therefore, the designer should identify the essential components of the processes which affect the desired machining outcome in advance. It means in UPM, the operators need to know the parameter setting for choosing the involved parameters at the beginning. In this case, the UPM network constructed by SNA can act as a guideline for operators to familiar with the process parameters before lots of experiments are conducted. Actually, traditional optimizations and SNA approach for UPM consist of their own strengths, this study provides the new insight of using SNA to assist the optimization processes. The future research is to integrate the traditional optimization with the SNA approach, providing the positive influences from both approaches for the optimization processes.

Apart from traditional optimization approaches, an artificial neural network, which is inspired by neurons in human brains and made use of information processing mechanisms. It obtains a great success in many areas such as classification, prediction, and control with reasonable accuracy [12]. However, it consists of drawbacks especially slow and difficult training issues. With these problems, a dendritic neuron model is applied in order to consider the nonlinearity of synapses, which offers an effective way for practical problems in reality. And, the learning algorithms in the dendritic neuron model include biogeography-based optimization, particle swarm optimization, genetic algorithm, ant colony optimization, evolutionary strategy, and population-based incremental learning for training data [13]. The results obtained from the dendritic neuron model are reported to be effective and promising. Researchers employ big bang-big crunch optimization algorithm and particle swarm optimization for minimizing the disadvantage of the large input of data, which this hybrid optimization approaches enables to transfer the overall algorithm into simple feed-forward data learning [14]. On the other hand, network-based analysis is frequently used in literatures to investigate and discuss the manufacturing processes and systems. Li et al. [15] developed the network for advanced manufacturing using literature review. They used updated scientific papers to identify the outstanding research gaps and applied them into the complex network of advanced manufacturing to demonstrate the opportunities of research opportunities of this area in the future. Chankov et al. [16] investigated the stability of synchronization of the network of manufacturing system based on the structure of the network. They firstly considered the synchronization-oriented design and control of manufacturing system in term of structural network properties. Lin and Chang [17] demonstrated the reliability evaluation of manufacturing processes with multiple production lines relying on the manufacturing network.. They employed a graphical methodology to convert the manufacturing system into a manufacturing network, and found out the general manufacturing paths and reworking paths in the manufacturing network. The academic attentions on network-based analysis is raised considerably.

Social network analysis (SNA), which it is a tool for examining social structures using network and graph theory, is becoming an essential tool for providing the fast track of optimization in advance recently. Actually, network analysis and theory has been applied into different areas successfully using its excellent analytical power, the application areas covers multi-disciplines such as medical [18,19], marketing [20], education [21], production lines [22], supply chain [23] and manufacturing system [24] Also, for the recent research directions in manufacturing, social manufacturing for high end appeal or some general industries [25,26] and Virtual Cellular Manufacturing Systems [27] which involve complicated factors in the procedures, can be potentially benefited from SNA approach. Actually, an analytical network process approach has been applied by scholars to support for choosing the optimal machining processes [28] and facility layout plan [29] by considering the interdependencies among the various requirements influencing the selections. SNA describes the networked structure using nodes, ties and edges. Caniato et al. [30] used SNA to survey a solid waste management system and collected a large number of information about the targeted system, they found out the satisfaction level of actors to the system according to the actors' characteristics using SNA. Gardy et al. [31] input the genomic data in the sequence order using SNA and constructed the social network by means of patient interviews, they used whole genome sequencing and SNA together to determine the outbreak conditions with entire guidance. Luo and Zhong [32] used SNA as a platform to investigate the communication characteristics of travel related to word of mouth among different tourists, observing their interactions and relationships to obtain the perspective information of influential decision making in tourism. Horvath and Dong [33] took the advantages of analytical capacity of SNA, proposing and reviewing the relationship among modules and module genes, which facilitated the application and development of system biologic methods. Although SNA has already been applied into different areas and achieved the comprehensive breakthrough, it has not been utilized into UPM area which is one of the networking theoretic concepts for minimizing the high experiment costs, instable experimental environment and complicated formulation in simulation-based model.

In this study, the network structural analysis using SNA technique has been firstly spread into UPM area. Actually, SNA provides network advantages which are rarely found on other traditional optimization algorithms. SNA draws attentions heavily on studies of the nature and characteristics of the factors within the network. It advantages of tracing forward and backward within the network as a proxy for the overall distribution of variable information of the particular factors within the networks. The UPM network containing of the machining factors states the accessibility and the level of the UPM process, the metrics of machining factors involve advantage contingents on the feature, characteristic, influential level and dynamics of network members, which they are the uniqueness of this study and are rarely found in the traditional optimization approaches. And the uniqueness of SNA has not been applied to UPM area to provide the outstanding and powerful analytical capability previously. Moreover, the UPM network enables to provide the overall concept of relationships between each machining factors, and operators can apply the network and search for their own situations to minimize the machining difficulties. All of the above by SNA enable to benefit to UPM and related industries exclusively.

By showing the UPM network visually, the conjunctions with associated numerical and descriptive data can be shown qualitatively. In this study, SNA approach for visualizing the UPM network provides opportunities for investigating the content behind the relationship along with the structural configurations in the network, which the meanings are attached into the ties and nodes of the networks qualitatively. From a related literature, it showed the network is processed qualitatively. A visual network investigation used a qualitative inquiry for investigating the topic of renewable energy in international development issue. Also, Lubbers et al. [61] also applied visual network survey qualitatively to investigate the migrant change in personal networks over time. For the case of UPM, the networking method reveals the relationship between each dependency and the level of influences from various machining factors to the machining outcomes, offering a wealth concepts for describing the connections among dependencies according to the reported literature and the data set of authors' laboratory. The UPM experts are able to use SNA approach in UPM. As several machining parameters in UPM involve deep knowledge in UPM, especially diamond tool wear, material swelling, chip formation and cutting temperature, which these machining factors are the unique characteristics in UPM and they become few of the ongoing researches nowadays. UPM experts enable to grasp the hints of these machining factors for uplifting UPM performance. SNA is a powerful analytical approach that copes with the actor interdependence, it provides objective descriptions to quantitative data involved in the UPM process with non-linear, iterative and interactive relations. In this article, the UPM network constructed by SNA and the main metrics of it are provided. The several case studies are further provided in order to demonstrate the effectiveness of the UPM network proposed in the article. The study provides a guideline for industries and academia for developing machining strategies to reach positive machining.

2. Theory

2.1 Social network analysis

SNA is a network construction approach which makes use of networking relationship composed of nodes and ties. In a social network, it measures the flow of relationship [34] and their changes between every node. Nodes could be interpreted as the actors based on what the targeted structure is aimed to investigate. Forward computing technology assists an evolution of SNA in supporting extremely complicated and graph-based structures [35] involving several nodes and ties. These networks are the clue and the start of procedure in problem solving, optimization and operation.

Network metrics could be determined in the aspect of two levels which are node level and network level. For the node level, it measures how the individual node is input in a network according to the individual node's view. For an application of SNA to UPM, several types of metrics in node-level are included: degree, closeness and betweenness centrality. For the network level, the considered metrics are network density and centralization.

2.1.1 Node level metrics

The determination and conceptualization of the key nodes are the main procedures to construct a network in SNA [36]. Centrality shows the relative significance of individual nodes within a network. Any node located at the center of network inputs remarkable impacts on itself and other nodes' properties. For the areas such as social behavior and society research, centrality is denoted as social status [37] and prestige [38].

Centrality metrics are much complicated in the node level. There are several types of centrality metrics which they interpret differently in various cases. Most common centrality applied into SNA is degree centrality, closeness centrality, and betweenness centrality [39], The nodes with higher degree centrality would be more dominant and visible in the network. Closeness centrality describes how closeness of an individual node is to other nodes within the same network, a node is treated as high closeness centrality if it can reach most of the other nodes, the nodes which have high closeness centrality take more chances to get resources over that of the other nodes. Betweenness centrality measures that the level of an individual node poses the shortest path between all the combinations of node pairs. Once the nodes with high betweenness centrality are disconnected, other dependent nodes would be blocked to communicate other nodes and the exchange of information is terminated. The nodes with higher betweenness centrality usually have the higher degree of control and level of influence over other nodes within the network.

2.1.2 Network level metrics

The information regarding to the entire network is also revealed by SNA, which is represented by network density and network centralization [40]. Network density considers the ratio of total number of ties to the number of potential ties within a network, it measures the level of connection of a network. Network centralization refers to the connection corresponding to a particular node in a network, it can be classified as the extended version of centrality in the node level [41]. A network has high centralized structure would have the characteristic that all connections between nodes pass through few central nodes, the classical structure which has the highest centralization is a star network, a single node in the star network is located at the center and it enables to connect to all other nodes. Network centralization is also depended on the network density [42].

3. Conceptual framework of ultra-precision machining using SNA

3.1 Node level analysis

An establishment of conceptual framework is an essential procedure in SNA, it provides the correct interpretation of the rule for nodes and the links between them. The key metrics of node-level of UPM network are discussed in detail in this section. In this study, the new framework is firstly constructed for UPM in order to provide the interpretation of metrics, Table 1 shows the overview of key metrics and the corresponding rules of different machining factors in UPM network. It is noted that UPM network is constructed using direction type because of the cause and effect relationship between machining factors in UPM.

Table 1. Node level metrics and their interpretations for the UPM network

Centrality metric	Interpretation	Conceptual definitions in UPM	Implications for central nodes in UPM*		
			Role	Description	Capabilities in UPM
In-degree	Machining factors be influenced	The degree of response in reacting incoming influences from the upstream machining factors	Influenced	To consider all of the machining factors involved in UPM process, transferring the integrated influences into downstream machining factors	Machine tool design; Material design; Machining component innovation
Out-degree	Machining factors influence others	The degree of response suffered from machining factors in dealing with incoming influences and how to transfer them to downstream machining factors	Influencer	To distribute its influences across other machining factors, aiming to control it in order to obtain desirable machining outcomes	Theoretical modelling; Optimization; Reduction of machining temperature/ friction at tool/workpiece

Betweenness	Machining factors lie between a pair of non-adjacent machining factors	The extent to the ability which a machining factor controls the impacts of final machining outcomes/ performances	Gatekeeper	To mediate the influences between network nodes (machining factors), aiming to balance the influences of machining factors with contradictive trend; providing the gateway to introduce the knowledge in interdisciplinary	Machining strategies for stabilization and alignment of upstream and downstream machining factors; Gateway for direct influences to the machining outcomes
Closeness	Machining factors enable to influence machining performances without relying on other machining factors	The extent to which a machining factor has the closest/ most immediate effects on the final machining outcomes/ performances	Facilitator	To easily access and explore the machining outcomes/ performances by controlling the nodes with high closeness	Machining strategies for stabilization upstream and downstream machining factors

*Implications given high centrality

3.1.1 Degree centrality

After providing the definitions and properties of metrics of UPM network in SNA, the calculation of each metric is discussed. Degree centrality is determined by the ratio of number of direct tie to a node. Degree centrality $C_D(n_i)$ is denoted as

$$C_D(n_i) = \sum_i x_{ij} \; = \; \sum_j x_{ji} \quad (1)$$

where x_{ij} is the positive number, it is equal to 1 if there exists a connection between n_i and n_j [43]. Degree centrality is commonly normalized as a percentage in the analysis process because the nodes are always directly proportional to their adjacent nodes. Degree centrality means the causes of the action in a network [44], it reveals the amount of related activities causing the nodes with high degree of visible. For the non-directional network, degree centrality means to the extent to which the actors influence other actors by their activities because the actors have more direct connections with others [45]. Conversely, the nodes with low degree centrality are treated as outlying within a network as the nodes are nearly separated without any connection with other nodes, which the nodes virtually place less influences in the network. Therefore, the machining factors which have more connecting edges in the network have the larger degree of influence on others, simultaneously, that machining factors normally are needed to fix in order to have alignments with other machining factors within the network. For directional UPM network, the problem would focus on the issue of cause initiated (out-degree) or cause received (in-degree). In-degree centrality and out-degree centrality refer to the size and amount of adjacent upstream nodes and downstream nodes respectively. In the management and marketing fields, in-degree or out degree centrality denote as the intensity of transaction of a firm. In UPM area, in-degree centrality of machining factors refers to the degree of difficulty experienced by the operators when they manage of that machining factors in the optimization process, this metric determines the complexity of influence flowed from the upstream machining factors. The machining factors with high in-degree centrality are treated as passive influencers which are responsible for gathering and organizing the direct or indirect effects from various machining factors to maintain the machining performances in UPM. The machining factors with high in-degree in the UPM network are essential signals for presenting the direction of machining condition change at the very beginning stage in UPM process. Out-degree centrality relates to the degree of difficulty encountered by adjusting the machining factors in order to match the downstream machining factors as well as final machining outcomes. The more links of the machining factors with the downstream machining factors, the more challenging is for adjusting or reallocating them to ensure the stabilization of optimal machining condition. The number of linked machining factors therefore positively associated with the complexity of achieving excellent machining performances. Therefore, the machining factors with high out-degree centrality are possibility got much attention, they should be given more resources and information through investigations as they gather the influences of upstream machining factors and flow the influences on the machining outcomes, they consist of high degree of influential ability.

3.1.2 Closeness centrality in UPM

The determination of closeness centrality is related to geodesic distance $d(n_i,n_j)$ between two nodes, which is defined as the shortest length of path between node n_i and node n_j[44,46]. In a directional network, the geodesic distance from node n_i to node n_j is high possibility not equal to the geodesic distance from node n_j to node n_i, there exists more than one geodesic distance between node n_i and node n_j. Therefore, the determination of the shortest path between two nodes is necessary as several paths from node n_j to node n_i are possible. The closeness centrality $C_c(n_i)$ is expressed as:

$$C_c(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1} \quad (2)$$

where $\sum_{j=1}^{g} d(n_i, n_j)$ is the total distance of node n_i connected with other nodes. The largest value of $C_c(n_i)$ appears when $C_c(n_i)$ is equal to $(g-1)^{-1}$. $C_c(n_i)$ would be equal to zero when the particular nodes are unreachable from other nodes at the same network. Closeness centrality is commonly normalized as percentage and falls in the range of 0-100.

Nodes with high closeness centrality do not require to rely on other nodes for acquiring information or initiating the activities [47]. In UPM, closeness centrality refers to the extent to the ability of machining factors able to influence the machining performances with more direct way; navigating the machining factors with high closeness centrality would cause significant influences on the machining outcomes. That particular machining factors with comparatively shorter path to other machining factors are the main focus to be accessed in order to get the optimal machining condition. Such accessibility increases the manufacturing capability to match contradictive machining targets such as obtaining high surface quality and high removal rate simultaneously, leading to less experiment costs and investigation time.

3.1.3. Betweenness centrality in UPM

Nodes can be located in between a pair of non-adjacent nodes within a network. The intermediary gives influences on the other nodes and their links. Between centrality $C_B(n_i)$ is measured as below under the assumption of linkage existence between nodes n_j and n_k:

$$C_B(n_i) = \sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}} \quad (3)$$

Where g_{jk} is the total number of geodesic link between two nodes, $g_{jk}(n_i)$ is the number of geodesic link involving node n_i. Betweenness centrality is then determined by summing up the probability of that particular nodes locating between other nodes. Betweenness centrality is usually expressed as the normalized form in SNA. Betweenness centrality can be treated as the capability of “gatekeeping” of particular nodes for the other nodes [37,48]. The function of gatekeeping is originated because the nodes with high betweenness centrality can control the flow from upstream machining factors to downstream machining factors as well as machining performances. The nodes with high betweenness centrality serve as hubs or pivots that transmit the influences along the UPM network. Once the nodes with high betweenness centrality are disconnected with machining factors, the flows of influence are blocked and cannot continuously flow to downstream machining factors. Betweenness centrality also refers to the extent of the machining factors affecting the downstream machining factors and the machining outcomes. On the other hand, if the nodes with high betweenness centrality are unable to control appropriately or not response to the changes induced by other nodes, in these cases, it would easily result to terminate the positive influences from the upstream machining factors and eventually lessen the effectiveness of the planned experimental approach. Similarly, the negative influences from the upstream nodes can spread within the UPM network through the nodes with high betweenness centrality, disturbing to achieve the optimal machining condition. On the other hand, considering the significance of betweenness metric as “bridge” function within a network, there is an advantage that the nodes with high betweenness centrality could be a hint to implement the novel approaches through interdisciplinary knowledge in order to improve the machinability of UPM. We could explore the possibility by using methods from other fields which have linkages with that nodes. The nodes with high betweenness centrality have chances to mediates many pathways between machining factors and thus enable to facilitate or disturb the linkage within the whole network. Academic literature explained that the node with high between centrality could enjoy the benefits of redundant influences and operators should try to control these nodes tightly over other nodes [49]. The nodes would be considered seriously to ensure consistent and harmony between each machining factor, guaranteeing the capability of cooperating with other approaches in the areas apart from machining.

3.2 Network level analysis

The network level metrics are discussed in this section in detail. Table 2 shows the theoretical interpretations and their implications in the UPM network using the definitions in SNA

3.2.1 Centralization in UPM network

Network centralization C_D is related to the maximum value $C_D(n_i^*)$ and defined as:

$$C_D = \frac{\sum_{i=1}^{g}[C_D(n^*) - C_D(n_i)]}{\max\sum_{i=1}^{g}[C_D(n^*) - C_D(n_i)]} \quad (4)$$

Provided that the number of node in the network is g, the denominator decreases to (g-1)(g-2). The value of C_D is equal to 1 when the nodes are linked with all other g-1 nodes, therefore, in this condition, other nodes could only contact with this particular node. The value of C_D is equal to 0 when all degree centrality of nodes in the network are equal. In UPM, centralization refers to the power or controllability that can be exercised by the core machining factors over other machining factors within the same network.

3.2.2 Density in UPM network

Network density refers to the number of node and degree of interdependency among other nodes within a network. In UPM, an increased number of nodes in the network means that more factors and instabilities are needed to handle in the machining process, therefore the optimization process is difficult to implement efficiently because of interruptive and interactive influences from other machining factors at the network level. Similarly, more connections in the network imply a higher possibility of obstruction in processing the nodes, resulting of more difficulty in coordinating between each node in the network. For example, for a machining factor with more than one upstream machining factors, that machining factor surely involves greater efforts in coordinating and aligning with the upstream machining factors in comparison with the nodes with only one upstream machining factor.

Table 2. Network level metrics and their interpretations for the UPM network

		Implications of overall network structure*	
Metric	Conceptual definitions in UPM	Characteristics in UPM	Performance implications in UPM

Centralization	The extent to machining factors to control and pose the impacts to the machining outcomes	Machining performances/ outcomes are influenced by few machining factors	High controllability in adjusting machining factors in order to reach the optimal machining condition, with a low level of optimization effectiveness because more efforts should be made to particular machining factors at the local level
Density	The number of nodes within a network that have already established a relationship with other nodes	More machining parameters are engaged in influencing the machining outcomes/performances	Low efficiency in adjusting machining factors in an optimization process at the network level because of huge amount of causes and noise involving from the upstream machining factors to the machining outcomes

*Implications given high metric value

4.Methodology

4.1 Data acquirement

The approach of Systematic literature review and data in the laboratory which the authors work currently are employed as the data source in this study. This approach makes use of relating scientific literatures and previous data for ensuring the transparency and integrity of data collection processes. Normally it involves few steps: 1. question formation, 2. locating studies, 3. study selection and determination, 4. analysis and synthesis and 5. reporting the results [50]. In this study, steps 4–5 are replaced by SNA, which SNA delivered the analysis and demonstrate the accurate results. For getting accurate data from systematic literature review, it is necessary to consider the rationales for the choice of literature detailly. In this study, the papers would be obtained by searching the designed strings in the electronic databases of several publishers focusing on scientific articles, which the electronic databases mainly in science direct of Elsevier. After that, the papers are filtered according to the knowledge of authors. And finally, certain papers are selected for constructing the SNA network in this study. The nodes defined in the network are machining factors in UPM including machining parameters and machining outcomes, which are shown in Table 3. The relationship between each node is linked according to the cause and effect relationship of each factor.

4.2 Data analysis

The machining factors are defined as nodes in UPM network in SNA, which are represented as the row in the matrix. The nodes are connected if they have relationship in UPM. UPM network in this study is asymmetric (i.e., directional) as the cause and effect relationship exists between each node. Once the whole structure is completed, it is imported into Nodexl Pro software which it enables to output the graphic network corresponding to the metric input in the network analysis format. NodeXL Pro is an open-source software for implementing network analysis and visualization announced by Microsoft cooperation, it includes the feature of accessing information or data from social media network. It is powerful software to conduct advanced network metric analysis, automation, and calculation.

5. Results and Discussion

The network of UPM constructed by SNA is shown graphically in Fig. 1, and the network metrics of both node and network level are shown in Fig. 2, Fig. 3, Fig. 4, Fig. 5, Fig. 6. The node “material” in Fig. 1 represents as materials of the workpiece, which is not linked to tool material. The tool material in UPM normally uses diamond. The diamond tool is commonly applied into UPM for generating high surface finishing with nanometric range [51]. As known in ultra-precision machining, the preferred and usual tool material is single-crystal diamond due to its superior properties, including high hardness, relatively strong resistance to wear and excellent chemical resistance [52]. Therefore, as the tool material for UPM is regularly diamond in academia and industries, so tool material is a stable factor and does not put as node in this study.

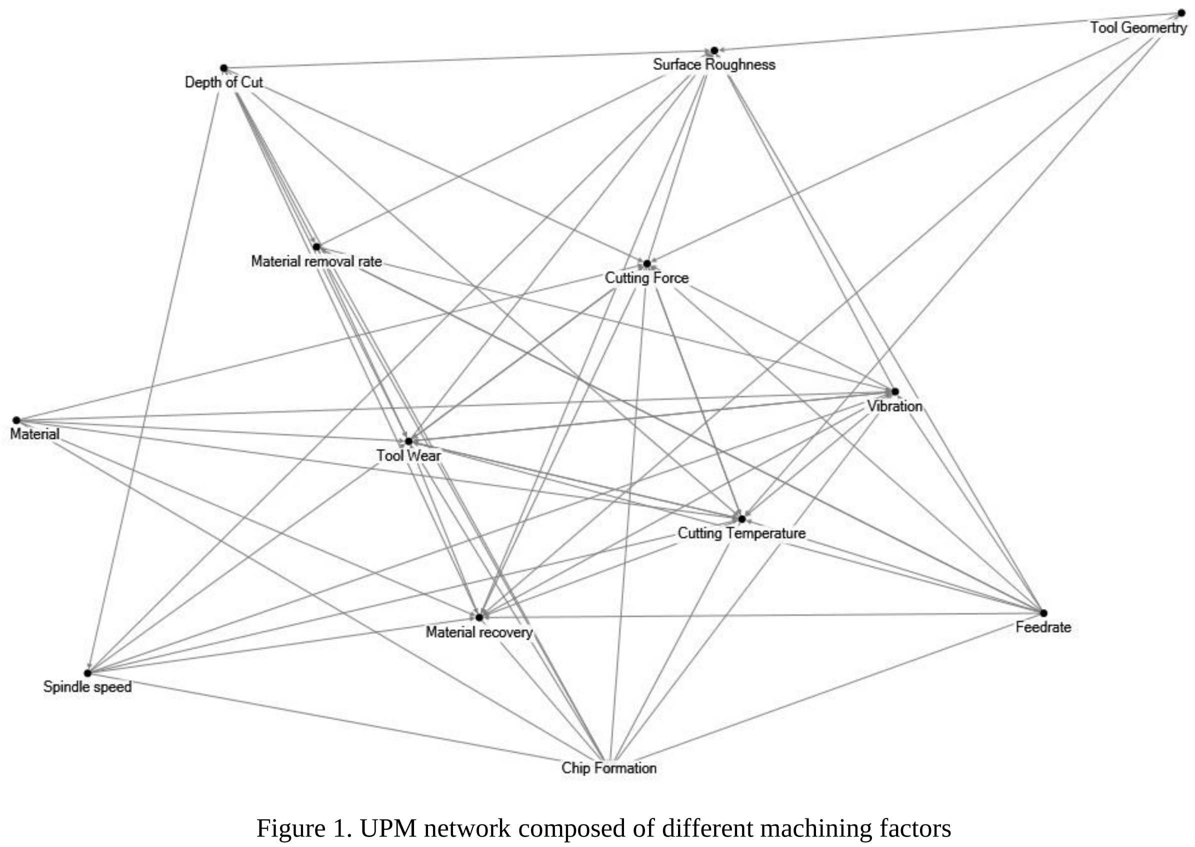

Figure 1. UPM network composed of different machining factors

5.1 Node level analysis

5.1.1 In-degree

According to Fig. 2, the nodes with relatively high in-degree are chip formation, tool wear and surface roughness, which in-degree are 10, 9 and 9 respectiveity. All of these are the machining factors that are influenced by most of of the other machining fators involved in the networks. The slight change in other machining factors individually in UPM process may affect them signifactcanly, therefore, they are served as an individual research topic for the optimization and improvement. Tool wear and surface roughness are the common goals to enhance in UPM which are the performance indicators/machining outcomes of the machined surface, consequencely they would be the nodes which receive the influences from other machining factors. Chip formation is one of the machining indicators that can reveal the correctness of machining parameter setting in UPM. Chip formation and its morphology are essential features in UPM [53], it gathers the information including noise in machining processes. Segmented chip formation implies high cutting force, tool wear, high surface roughness, high degree of material swelling and serious machining vibration etc. As surface roughness and tool wear are subsequence of change of chip shape, therefore the in-degree of chip formation is larger than that of them. Without the structural UPM network in SNA, the importance and observation of chip formation may be underestimated. The continuous and non-segmented chips generated in UPM process would be the signals gathering the influences from upstream machining factors including surface roughness and tool conditions.

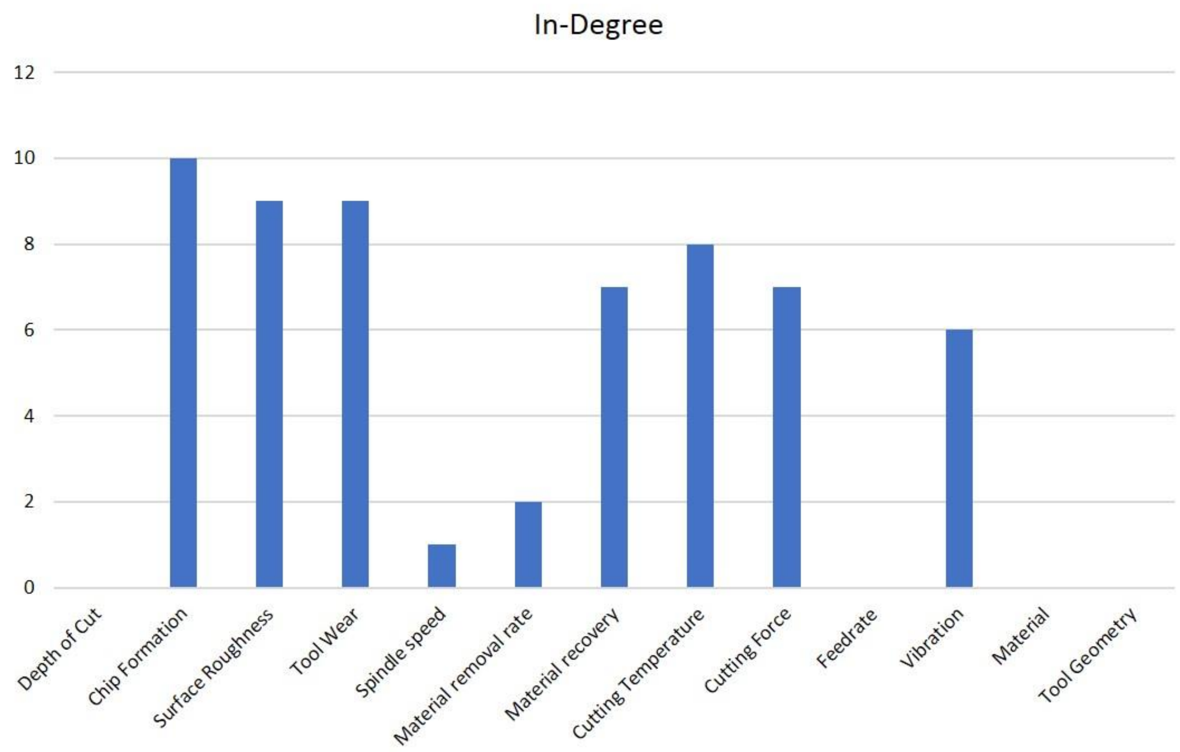

Figure 2. In-degree of the UPM network

5.1.2 Out-degree

The result of out-degree of the UPM network is shown in Fig. 3. The nodes with the highest out-degree are depth of cut and feedrate, which the values of their out degree are 8. They are treated as influencers that influence the other machining factors involved in the networks the most. The slight changes of them indiviudally cause large variations to other machining factors in UPM remarkablely. Therefore, they are always treated as dominant paramters in the theoretical modelling reported in literature for the optimization because of their large influencal powers. Depth of cut, feedrate and spindle speed are the machining parameters in UPM and they are adjusted depending on various machining factors such as worked materials, material removal rate and surface roughness etc. All of these three machining parameters (depth of cut, feedrate and spindle speed) are treated as equal importance because they are the same level in operating level of UPM machine, however, only two of these (depth of cut and feedrate) are determined as the highest out-degree value apart from spindle speed. Spindle speed may be considerated overly without the SNA network constructed. The metric values offer the operation guildline of the pirority of adjusting machining parameters in the experimental palnning step.

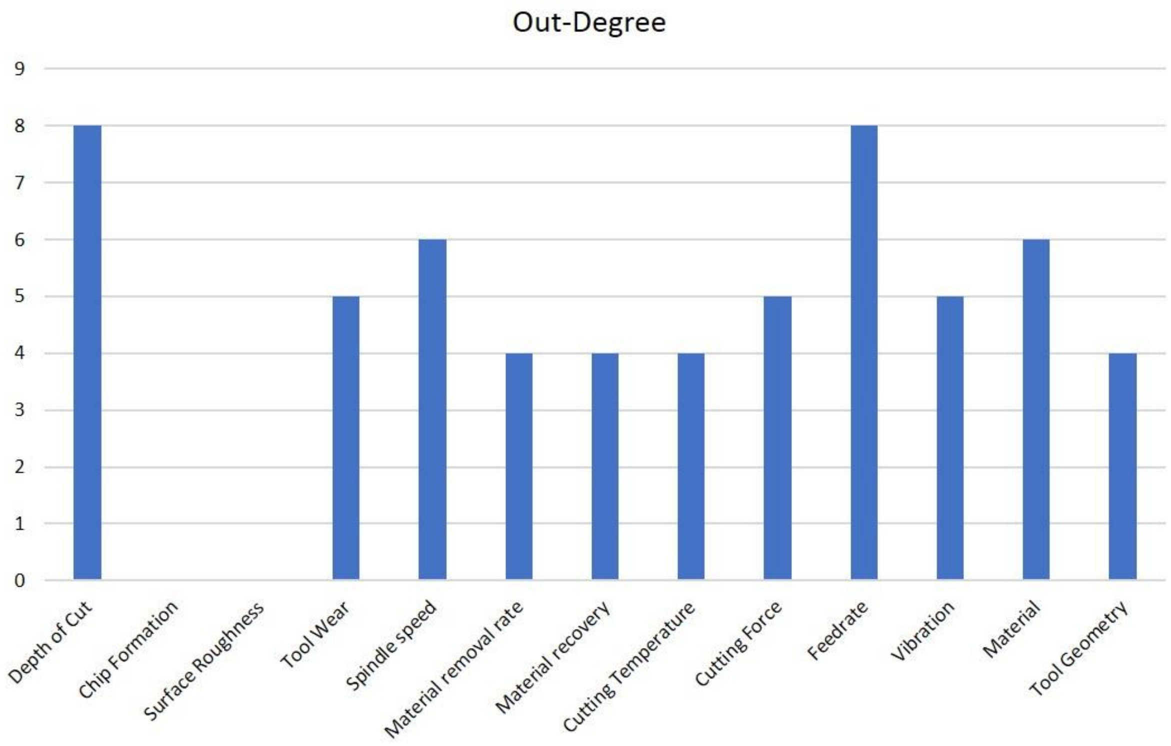

Figure 3. In-degree of the UPM network

5.1.3 Betweenness centrality

As shown in Fig. 4, the node with the highest value of betweenness centrality is material recovery. Nano-surface generation in UPM is a complicated procedure including the combination effects of plastic deformation and elastic recovery of machined surface. Dissimilar to the conventional machining, material factors are regonized as a great influence on the material removal process in UPM because depth of cut involved in UPM is always less than the grain size of machined materials [54]. When the cutting process is implemented under the extremely small depth of cut and feedrate, the machining mechanism automatically turns to single crystal nature [55]. Under cutting at the point shaped edge and small depth cut, the phenomenons of burnishing and material recovery esstensily happen. Therefore, material swelling and induced material recovery are the unique features and characteristic in UPM. The highest betweenness centriality of material recovery in SNA implies the uniquness of its nature in machining area, treating as a main gateway and direction to the machining outcomes – surface roughness, which it serves as the main and dominant control factor that could directly related the surface roughness. Most of the upstream machining factors should pass through this node (material recovery) in order to reach the node of surface roughness. If the linkage to the gatekeeper is broken, the updream machining factors do not enable to tranfer influences or resources to the downstream machining factors, the intermediate indicator of the machining performance is disrupted, as a result, there is no significant signal for the researchers to observe the influences induced from the alterations of upstream machining factors, the prelimarary prediction of the machining outcomes would become inaccessible. On the other hand, another important information inspried by the highest betweenness centrality is, the material factor which governs the level of material recovery of machined surface could be one of the mediator to faciliate the machining performances through interdisciplinary approaches. The uniqine feature of gatekeeper for the problemtic material recovery in UPM provides the oppunities to seek for the improvent from other areas of researches. No matter how the upstream machining factors are adjusted or enhanced, their effects must be brought to the main gatekeep (material recovery) in order to reach the final destination, which is the machining outcome. Therefore, the novel approcahes combining with outside knowledge could focus on the method of minimizing material recovery effect, therefore the positive influences enable to be effective in the most direct way, lessening the efforts of considerating the effects from other upstream mhcining factors. If the proposed approaches focus on other machining factors, the positive influences are averaged and scattered by other machining factors located at the upstream pathway, or, the adjustment of machining parameter is not able to control easily to the optimal range because there are serveral downstream machining fcators, and they are affected by the chain effects, causing many undesirable side effects and compensateing the benefits of novel approaches.

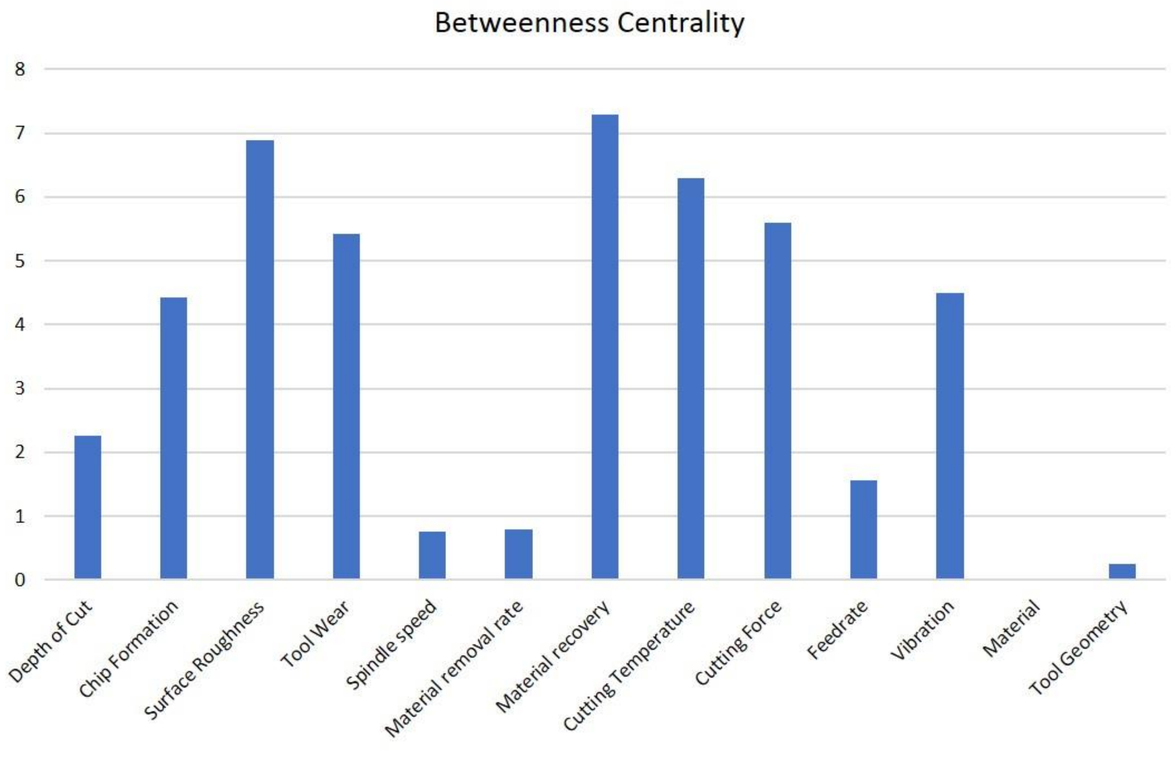

Figure 4. Betweenness centrality of the UPM network

5.1.4 Closeness centrality

According to Figure 5, there are two nodes with the highest closeness centrality, they are tool wear and material recovery which their closeness centrality are both 0.77. The highest closeness centrality in UPM implies these machining factors comprise the most direct influences to the machining outcomes as well as the shortest step to make their influences be effective to the machining outcomes. The highest value in closeness centrality of tool wear in UPM network reveals that it is the machining factor that takes the most immediate effect to surface integirty. Therefore, in order to generate fine surface finishing, the prioritized machining factor that researchers should consider is tool wear, which tool wear reduction is a popular research topic academically. The same logic is applied to material recovery which has the highest closeness centrality. Material recovery has the closest path to the machining outcome, it serves as the navigator to access and collect effects from various upstream mahining factors, offering the integral effects directly to the machining outcomes. Material recovery is the only machining factor having the highest values in both betweenness centrality and closeness centrality, which implies the worthiness of putting research efforts to investigate this factor causing poor machining outcomes.

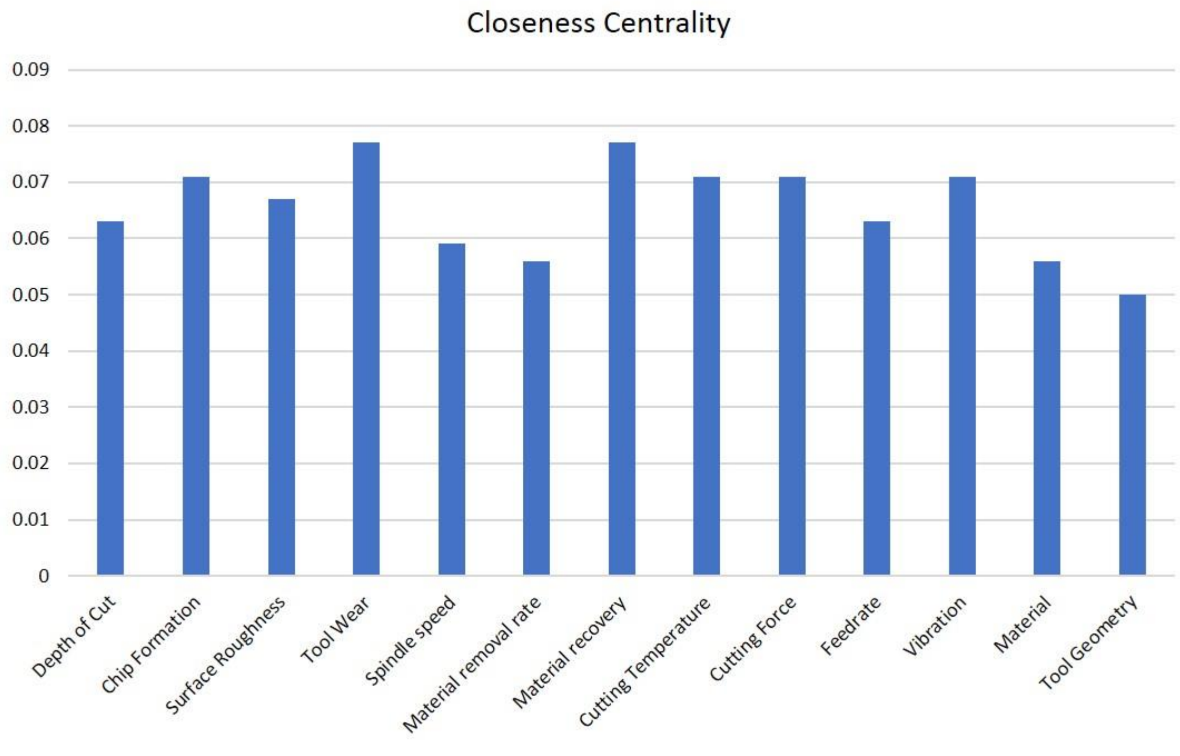

Figure 5. Closeness centrality of the UPM network

5.1.5 Other implications inspired by contructed UPM network

There are few main objectives which aim to achieve in UPM, they are enhancements of surface roughness, tool life and material removal rate, which should be shown as high value in in-degree metric and low value in out-degree metric. According to the metric results of SNA, however, material removal rate is the only machining factor among three (surface roughness, tool wear and material removal) obtaining low value in in-degree and moderately high value in out-degree, which the values are 2 and 4 respectively. The values in in-degree metric and out-degree of material removal rate imply that the position of material removal rate in SNA network is belonged to median-stream. It is hidden in the intermediate path within the network, which is not dominent as other two mahcining objectives like surface roughness and tool wear. This contradictive position of material removal rate in SNA network makes the influence of this machining factor be two way nature which is not easy to improve. The control of this node leads to affect the upstream and downstream machining factors simutanously, the balance between both upstream and downstream machining factors is always the challege in UPM, consequencly, rare successful acamedic work is done on uplifing of material removeal rate in UPM, the research gap relating to an increase in material removal rate still exists.

Actually, the constructed UPM network is not comparable with other machining technology networks. With the technology advancement nowadays, the comparisons of different machining technologies in order to retrieve the advantage each individual machining technology to another are one of the approaches for facilitating the technology. Therefore, in the situation of decision of implementations of machining technology, SNA approach may cause complexity as the decider needs to consider both networks with detail investigations. Also, the number of machining factor in UPM is increasing nowadays because of technology advancement. Therefore, once a machining factor is discovered and known, that factor is needed to add into the network. The entire network will need to reconstruct while the main metrics of the network redetermine. The interpretations of the metrics and contents would be consequently changed. Therefore, constant monitoring is needed for SNA approach in order to grasp the development of the SNA network and the establishment of related technology.

5.2 Network level analysis

5.2.1 Degree Centralization

In the network level, all of the metric values are considered entirely and they are observed all together. If any metric value is dominately high in comparision to other metric values, it means there is a particular machining factor dominant over other machining factors in the entire network. Machining outcomes are influenced by the machining factors intensively with relatively high degree centralization value. Accrding to Fig. 6, there is no machining factor with relatively high value in degree centrazation, it denotes the high degree of centralization structure for UPM network. The disadvantage of high centralization network is that the optimization effectiveness regarding to the network objects is low, it is because there is a high level of chain effect between each node, more efforts should be made in order to transfer the influences from upstream and downstream machining factors in UPM network. While the advantage of high centralization network is that the network poses a high stablity itself, it has high capability to shield against the instability form outside environment, the machining outcomes are low sensitivity to the noise from the environment.

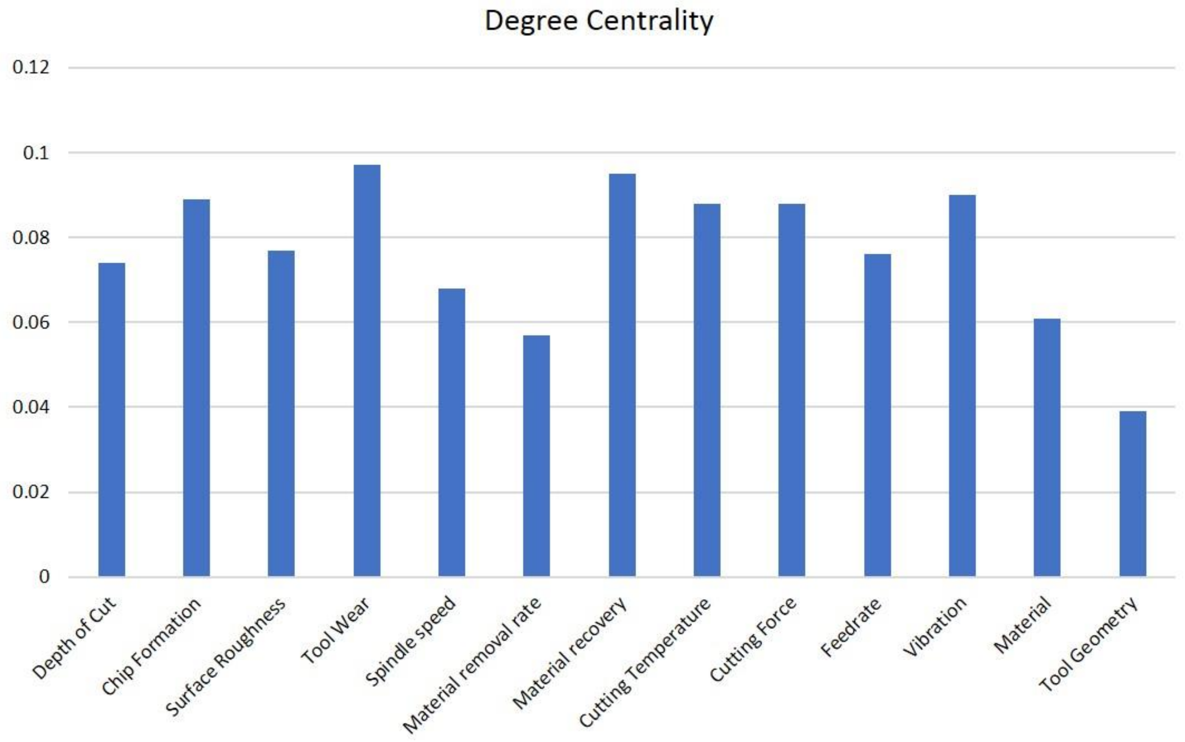

Figure 6. Degree centrality of the UPM network

5.2.2 Network density

As shown in Table 3, network desity of UPM network is 0.378. It means the amount of potential nodes that have already estblished a relationship with other nodes are only in the proportion of 0.378. Average Geodesic Distance in UPM network is 1.195. For UPM network with total 13 vertices, the number of edge of 1.195 per node is an acceptable value that each of machining factor could have sufficient path to flow its influences to downstream machining factors and machining outcomes. The network with overly high network density is not desiable in the practical situations as nodes would have too many paths reaching to the upstream or downstream actors, a change in a particuar node would cause an instablity in the network, even, it is difficult to trace back the source nodes which are originally altered. In the case of UPM network, the network density is in a moderate value and it implies the asseccable control of UPM process and the optimization process.

Table 3. The metric results in network level of the UPM network

Graph Metric in network level	Value

Graph Type	Directed
Vertices	13
Total Edges	60
Maximum Edges in a Connected Component	60
Average Geodesic Distance	1.195266
Network Density	0.378205

6. Case study

6.1 Tool condition influenced by feedrate

Abou-El-Hossein et al. [56] demonstrated the improvement of tool wear in fabricating of mould cavities made with aluminum alloys. As aluminum alloys feature coarse microstructures, leading negative effects to tool condition for mould shaping in UPM. In the authors' study, aluminum alloy (RSA905) surface was diamond turned under different feedrate. Although RSA 905 alloy is the modified alloy with higher strength, the machinability of it is still moderately high in UPM. The researchers discovered that tool wear in diamond turning process of RSA905 was significantly influenced by feedrate, which tool wear became serious and intensive at the middle value of feedrate. Feedrate is proven as the machining factor with the highest out-degree in UPM network. It proceeds the comparatively high influences on the downstream machining factors especially tool wear even the materials are not difficult to cut such as RSA905. Therefore, the work presented by Abou-El-Hossein et al. [56] demonstrated the considerable weight of feedrate in the machining outcome. If feedrate is not set into the proper operational range, the induced influences would deteriorate tool wear unexpectedly even for aluminum alloys. The optimization process should be originated by the problematic sources and the related factors should be recognized. The constructed UPM network provides the detail instructions of operation guideline for resolving the particular issues in UPM.

6.2 Material recovery reduction using an interdisciplinary approach

Material recovery is determined as the highest betweenness centrality among other machining factors within UPM network. As the highest betweenness centrality, material recovery is treated as a gatekeeper that most of influences from the upstream machining factors must flow across it in order to reach the machining outcomes. Therefore, researchers should take this advantage and focus on this machining factors to uplift the machining performances. The direction of resolving the problematic material recovery in UPM offers a chance and acts as a bridge to connect the knowledge from different fields to UPM area, contributing direct influences of integral knowledge on machining outcomes in UPM. Yip and To [57] demonstrated the consolidation of knowledge from physic into UPM area in order to resolve material recovery of titanium alloys, which they applied a magnetic field during the diamond cutting process.

Without altering the other machining factors in UPM, the experimental results showed that a successful suppression of material recovery of machined surface. The research focused on resolving the issue of material recovery and aimed to control this machining factor without adjusting other machining factors in UPM network, the experimental works from the authors apply the interdisciplinary knowledge which the theory of magnetic dipole alignment is categorized as physic area, delivering the excellent results of material recovery reduction and surface integrity enhancement. The work demonstrated the approach of using the advantage of gatekeeper in SNA, reducing the resources of controlling other machining factors in UPM.

6.3 Using UPM network for considering machining factors in advanced

Referring to the in-degree metric of SNA results, the nodes with relatively high values are tool wear and surface roughness. It interpretates that if we would like to enhance the machining outcomes from these machining factors, the upstream mahcining factors of these two factors in the UPM netwrok should be focused to optimize the mahcining processes. It is less effectiveness for solely improving tool wear and surface roughness without considerating the causal effect from the upstream mahcinig factors in manufacturing processes. Yip and To [58] conducted the study for improving the machinability of titanium alloys in UPM using intermittent cutting. The study showed that in order to achieve the final aim, which was to enhance surface quality and lower tool wear, the cutting temperature and material recovery effect in the diamond cutting process should be suppressed firstly. Although these machining factors showed less values in in-degree than that of tool wear and surface roughness, these factors still needs to be considered in advance. The above experimental results are consistant with the information shown in SNA metrics and UPM network. Actually, the causal effects for the entire network are required to observe and it can be done by using UPM network and related metrics of SNA. With the support of the UPM network, researchers could have the better prepartion before the machining processes starts.

6.4 Design the cutting strategies in UPM

Referring to the metric results of SNA, it is worth to notice that tool geometry gets zero value in in-degree. This implies that tool geometry is not sensitive to be changed and adjusted for UPM processes, as this machining factor does not receive or accumulate the influence from upstream machining parameters. Moreover, the value of out-degree of it is 4, which is the moderate value among all the other factors, showing this factor will impose limited influences on downstream factors in the UPM network. Therefore, because of the characteristics of insensible to upstream factors and limited influence power to downstream factors, cutting tool is suggested to be adjust or modified based on the technology trend and the purposes of machining. Literatures reported the practical effectiveness of modifying and redesigning of diamond tool for uplifting of machining performance in UPM [59]. Kawasegi et al. [60], fabricated a diamond tool with depth of 43 nm and width of 1.8 μm using a focused ion beam and heat treatment. The experimental results showed that by using the new design tool, cutting force and surface quality of aluminum alloys were highly reduced under different cutting environments. In this study, researchers focus on how to design and fabricate the textured diamond tool, which they are not affected by the previous procedure or other machining parameters involving. They successfully showed the individual status of the redesign of diamond tool in machining outcomes. The results are consistent with the findings in SNA metric, the machining factor, which gets zero value in in-degree, is highly individual and enable to develop it with less outer noises.

7. Conclusion

Ultra-precision machining (UPM) technology is a promising machining technology to fabricate products with high precision level and complicated geometry. A large number of machining factors with complicated interrelationship are involved in UPM process, thus elaborated of the optimization process. For the cases of high equipment costs in machining such as diamond tool and single crystal sample, they inevitably cause high experimental costs for concluding the influences of machining factors and the integral effects of upstream and downstream machining factors. On the other hand, high tool wear rate leads difficult experimental controls in UPM. Therefore, the entire figure of UPM composing of detail relationship of main machining factors is needed to construct, it provides the guideline for the researchers to implement the step of optimization or develop the theoretical model for uplifting machining performances, contributing to reducing resources such as machining costs, experimental costs and investigation time in UPM. In this study, SNA is firstly introduced into UPM to construct the structural network, the detail analysis is provided based on the network metrics relating to an entire set of machining factors. A complete view of the cause and effect relationship of UPM is explicated, and the machining strategies focusing on the unique features with supporting by case studies are demonstrated. Some important notes from this study are listed below:

1. The machining factors in UPM with the highest in-degree and out-degree are distinguished through SNA, they are chip formation, tool wear and surface roughness. On the other hand, the nodes with the highest out-degree are depth of cut and feedrate. They can be treated as the factors which receive the most influence from other machining parameters within the network (in-degree) and the factors which output the influences most to the various machining factors (out-degree).

2. Material recovery is the machining factor which has the highest betweenness centrality. Therefore, it serves as the important information for researchers to reach the excellent machining outcomes. Because of the highest betweenness centrality, Material recovery is

a gatekeeper to gather all the influences from the upstream machining factors and is observable prior to show experimental results. On the other hand, it can act as a bridge to connect the information outside the UPM network, enhancing the interdisciplinary researches and transferring the outside knowledge to UPM area.

3. Material recovery is the machining factor with the highest closeness centrality. Therefore, there are strong consequential connections of this machining factor that should entitle particular attentions, as they can serve as the shortest link to the final machining outcomes. Decision-makers are suggested to focus on studying this machining factor in order to enjoy the greatest and fastest influences on the machining outcome arising from the characteristics of material recovery, which can save the resources and shorten investigating time to upgrade other machining factors.
4. Network density and centralization in the network level analysis of SNA provide the overall image of UPM structural network. There is no machining factor with relatively high value in centralization, it means that no dominate machining factor puts significantly high influences on the other machining factors and machining outcomes. The density value of UPM network reveals the moderately high effectiveness of optimization process, as the chain effect in the network is not dominant in UPM network.

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