

# A Network based Approach for Reducing Variant Diversity in Production Planning and Control

Shailesh Tripathi, Sonja Strasser and Herbert Jodlbauer

*University of Applied Sciences Upper Austria, Austria*

**Keywords:** Discrete Event Simulation, Network Analysis, Bipartite Graph, Community Detection, Production Planning and Control, Data Mining.

**Abstract:** This paper presents a network-based procedure for selecting representative materials using routings of materials as features and applies this procedure to a sheet metal processing case study which is used for parameterizing discrete event simulation models for PPC control. The discrete event simulation model (*simgen*) is a generic and scalable model that is commonly used to deal with optimization problems in production planning and control, such as manufacturing resource planning. The preparatory steps of discrete event simulations for production planning and control are data preprocessing, parameterization, and experimental design. Given the complexity of the manufacturing environment, discrete event simulation models must incorporate appropriate model details for parameterization and a practical approach to experimental design to ensure efficient execution of simulation models in a reasonable time. The parameterization for discrete event simulation is not trivial; it requires optimizing parameter settings for different materials dependent on routing, bill of materials complexity, and other production process-related features. For a suitable parameterization that completes the execution of discrete event simulation in an expected time, we must reduce variant diversity to an optimized level that removes redundant materials and reflects the validity of the overall production scenario. We employ a network based approach by constructing a bipartite graph and Jaccard-index measure with an overlap threshold to group similar materials using routing features and identify representative materials and manufacturing subnetworks, thus reducing the complexity of products and manufacturing routes.

## 1 INTRODUCTION

A competitive and changeable market scenario, customized-, personalized-, large volume-production, and complexity of the production environment present various challenges for production systems' efficiency, performance, and customer satisfaction. Therefore, a production company must formulate a production plan, optimize orders, and deliver in a planned way to the expected time frame, maintaining the quality and cost. In this regard, production planning and control (PPC) activities play an important role in managing production-related problems due to the production complexities driven by changing market scenarios, and allows manufacturers to monitor and control the whole process efficiently. PPC strategies ensure that materials, assembly parts, and other resources for different production phases are provided in the right quantity, at the correct time and location. Therefore such strategies optimize resource availability at a reasonable cost in

accordance with production requirements. In such scenarios, the main objectives of PPC are to minimize idle time for machines and other resources, minimize bottlenecks in routing, optimize run times and set up times, minimize inventory cost, keeping inventory levels low, and maximize customer satisfaction by ensuring to meet production-related commitments regarding product quality, quantity, and well-timed delivery. The major challenges in PPC are to reduce work in progress, minimize shop floor throughput times and lead times, lower stockholding costs, improve responsiveness to changes in demand, and improve delivery date adherence (Stevenson\* et al., 2005; Tseng and Radke, 2011).

PPC activities should be investigated systematically, and for this purpose various modeling methods are used; the main methods are conceptual models, analytical models, AI models, and simulation models. Among these methods, simulation models are considered the most suitable for PPC because they can be practically implemented, can consider uncertainties,

and can be adapted to complex manufacturing scenarios. Three common simulation methods for PPC are discrete event simulation (DES), system dynamics simulation, and agent-based simulation.

DES is applicable to a wide range of PPC problems (Jeon and Kim, 2016), and one example of a discrete-event simulation model is *simgen*, a generic and scalable simulation model that is commonly used to deal with optimization problems in PPC (Altendorfer et al., 2016; Hübl et al., 2011; Kronberger et al., 2006). *Simgen* can be used for any production structure and uses a hierarchical production planning concept divided into the following three levels:

- Long-term. Capacity investment decisions, resource planning, and aggregate production planning.
- Medium-term. Includes shift model, overtime, PPC methods such as material requirement planning (MRP) and constant work in progress (CONWIP), and production system structures such as flow shop and job shop.
- Short-term. Includes various day-to-day operational planning details such as dispatching rules.

An advantage of the *simgen* model is its practical application due to its input parameters. The input parameters selected from Enterprise Resource Planning (ERP) system data are processed and stored in a database. These sets of parameters are known as master data parameters. The main master data parameters are the bill of materials (BOM), routing sequence of materials, qualification matrix, production planning parameters for each item, shift calendars, skill groups, total available employees, production program, expected forecasts of the final items, the customer's demand in terms of order size, and the customer's expected lead time. The combined BOM and material routing table (named as WS Master) contains three attribute types:

- Parent. Parents can have one or more child items. End products are always parents, and product sub-assemblies can be a parent or child.
- Child. These are material variants and product sub-assemblies required to build a parent item.
- Machine/workstation group. The machines (assigned machine IDs) or groups of employees working at the workstations (assigned workstation IDs) where items are assembled or produced.

In *simgen*, transaction data are employed for another set of parameters that characterize probability distributions and the corresponding parameter estimations. The estimated distributions' parameters are used to

randomly initialize processing, setup, sales data variables, repair time, delivery time, and production planning variables. The parameter selections and experimental design are then applied to discrete event simulations for various PPC scenarios.

The PPC simulation parameterization follows three steps:

- Creation of a production structure from master data;
- Generation of various random variables for processing time, set-up-time, mean time to repair, mean time between failures, customer demand, sales details, and lead time (customer required, replenishment, delivery), performed by characterizing probability distributions and their parameters based on transaction data;
- Experimental design, by varying different combinations of parameters to match the optimization problem's objectives.

The discrete event simulation results are compared and validated with previous years' real-world business results, for example, previous years' real-world inventory, work in progress, and service level data for a manufacturing company. Further, the results are evaluated by business experts for managerial insights related to various production scenarios.

One of the challenges in discrete event simulation using *simgen* is the computational time complexity, because there may be a large number of product variants, but similar characteristics, if modeled in combination with heuristic optimization methods, can lead to long execution times without generating useful results.

In realistic production scenarios, a large number of variants with similar features (BOM, routing) may add inappropriate model details and cause a simulation model to take a long time to optimize PPC tasks. Therefore, we must reduce the numbers of materials and resources to reasonable numbers of groups, which is done by finding representative materials and resources for various similar or redundant routing sequences from the routing data obtained from the ERP database. The preliminary steps are thus data and parameter selection. These preparatory steps for master data and transaction data for various parameter settings used by *simgen* are not trivial tasks; expert insight is required for data preprocessing and selecting BOM data, representative materials, other relevant parameters, and experimental designs. The most straightforward approach to selecting representative materials in order to reduce high variant diversity is to apply unsupervised learning to group materials with similar features. We apply a graph-based community

detection and path-overlap approach by creating a bipartite graph representing material and routing relationships to group materials with similar features.

This study applies a data-mining approach entailing graph-based community detection by constructing a bipartite graph and Jaccard index measure with an overlap threshold to group similar materials together using routing features that identify the unique routing of materials, identifying representative material and manufacturing subnetworks, thus reducing the complexity of products and manufacturing routes.

The remainder of this paper is organized as follows. In Section 2, related work on unsupervised learning methods for grouping product processes in industrial manufacturing is discussed. Section 3 discusses a framework for detecting representative materials with the construction of a bipartite graph, routing features, and community detection algorithms. Section 4 presents a case study using sheet metal processing data. The final section concludes the paper.

## 2 RELATED WORK

Clustering or grouping methods applied in industrial scenarios seek to manage complexities by grouping many entities with similar features into smaller subsets, thus reducing complexity and enabling several production and planning-related decisions to be made with higher competence. Various types of similarity and distance-based methods can be applied, according to the features of products, customer segmentation, tools, parts, and operations, in order to cluster them for purposes of production planning, resource sharing, tooling, anomaly detection, customer service support, and operation management. (Jiao\* et al., 2005) proposes a method to develop a product-process variety grid by integrating BOM data and routing information. The product-process variety grid allows configuration of product design in terms of BOM and production process for a customer order. The integration of product and process information also allows the grouping of similar variants for various purposes in industrial manufacturing (Choudhary et al., 2009; Lin et al., 2017; Dogan and Birant, 2020; Li et al., 2019).

References (Macchiaroli and Riemma, 1996; Macchiaroli and Riemma, 1994) discuss clustering methods to group operations that are shared by different parts on different machines. In a flexible manufacturing process, each part requires a set of tools for performing operations that are shared by other distinct parts. For a part to be processed on the same machine, tool exchange should be minimized, which lowers

the tools' unavailability for parts. Clustering aims to identify the group of part programs that require the same tools. A clustering that identifies the same set of operations allows effective production planning and reduces manufacturing cost and time. Shabaka and ElMaraghy (Shabaka and ElMaraghy, 2007) perform clustering to group operation sequences that are to be executed on the same set of machines. Hochdörffer et al. (Hochdörffer et al., 2017) propose clustering methods for product variety management to reduce planning complexity when designing production networks. References (Romanowski and Nagi, 2005; Chowdhury and Nayak, 2013) use a network-based approach to estimate a symmetric difference metric between unordered BOM trees where for the same components and parts, the structure for different BOM trees differs. The distance between BOM trees is used to calculate a distance measure for clustering similar BOM trees.

(Chowdhury and Nayak, 2014) uses an augmented adjacency matrix of BOM data to compute a cosine similarity measure for grouping similar products. Strasser et al. (Strasser and Peirleitner, 2017) use cosine similarity for clustering materials into different groups in order to identify representative materials. However, the approach does not consider routing paths and assumes that the workstation orders are the same. Several studies (Bianchesi et al., 2019; Aksoy et al., 2017; Dao et al., 2020) evaluate various clustering, complex-network, and bipartite-network community evaluation methods, using benchmark data that provide a general understanding to enable different clustering and community detection algorithms to be applied effectively. The present study applies a network-based approach to determine the representative materials and set of workstation networks used for routing different groups of materials. The graph-based approach has some advantages over standard similarity measures and clustering. First, our data are sparse in nature because the data contain  $< 0.02\%$  non-zero entries of a  $m \times n$  data matrix where  $m$  and  $n$  represent materials and routing features respectively. Thus, a graph provides a simplified way of processing the data for visualization, exploration, and non-euclidean domain analysis. Additionally, the representation by graph allows us to analyze various complex characteristics of the networks such as neighbors, paths, communities, node importance (page rank), and various local and global measures. Various community detection algorithms are also used to reduce the computational complexity when applying community detection methods. Various network-based studies have proven such algorithms' usefulness for optimizing maintenance schedules, work-in-progress

buffer extensions, flow controls, process planning, and resource allocation in workstation/manufacturing/production system networks (Yang et al., 2010; Becker et al., 2011; Becker et al., 2014; Chen et al., 2018). The objective of the analysis is to reduce many materials into different groups that follow significantly different routings and identify subcommunities used to obtain a reduced number of materials that represent a manageable variant diversity for simulation modeling. Additionally, we wish to develop an approach that can be used as a quick and efficient means of identifying communities in data represented in various networks for visual exploration and analysis by domain experts.

### 3 METHODS

Before discussing community detection and group selection for representative materials, we define the workstation network and bipartite network.

**Workstation Network:** For the workstation network, we first construct a directed path graph,  $G_{m_p} = (V_{m_p}, E_{m_p})$ , of the routing sequence of each material. The vertex set of each material  $m_p$  is a set of workstations,  $V_{m_p} = \{v_1, \dots, v_n\}$ , and edges,  $E_{m_p} = \{e_1, \dots, e_{n-1}\}$  show routing, where  $e_k = (v_k, v_{k+1})$  for every  $1 \leq i \leq (n-1)$ . The final network is constructed as follows:  $G_{ws} = G_{m_1} \cup G_{m_2} \dots \cup G_{m_p}$ .

**Routing Features:** We use the edges of workstation network,  $W'_{ftr} = E(G_{ws})$ , as routing features to construct bi-partite graph given below.

**Construction of Bipartite-graph:** Suppose we have a set of work stations,  $V = \{v_1, v_2, v_3, \dots, v_n\}$ , and material-set,  $M = \{m_1, m_2, \dots, m_k\}$  of  $|M|$  materials. Let  $G_{m_p} = (V_{m_p}, E_{m_p})$ , a directed path graph of the routing sequence of material  $m_p$ .  $E_{m_p}$  is the edge-set, where,  $E_{m_p} = \{e_1, \dots, e_n\}$  and  $e_k = (v_k, v_{k+1})$ . We use  $W'_{ftr}$  as a routing feature set, and construct a bipartite-graph,  $G = (M, W'_{ftr}, E_{m,w})$ ; an edge,  $e_a \in E_{m,w}$ , is drawn between  $m_p \in M$  and  $w'_q \in W'_{ftr}$  if  $w'_q \in E(G_{m_p})$ , where  $G_{m_p}$  is the path graph for material  $m_p$ . To avoid confusion we use  $W'_{ftr}$  as a vertex set which uniquely labels edges of graph  $G_{ws}$  as a routing feature.

#### 3.1 Community Detection

In graphs, communities are subsets of nodes of a graph that are connected strongly (high edge density) compared to the other nodes of the graph. Various algorithms including graph clustering algorithms

are used to detect communities in various types of network (Pesántez-Cabrera and Kalyanaraman, 2017; Tripathi et al., 2016; Zhang et al., 2019; Han et al., 2017). Community detection algorithms identify communities by partitioning vertices in a manner that maximizes the modularity of the network. Modularity measures for bipartite graphs include Newman's (Newman, 2006), Barbers' (Barber, 2007), and Muratas' modularity (Murata, 2009). Our analysis uses three community detection algorithms: LP-BRIM, LPAwb+, and biLouvain community detection algorithms, applied for weighted, unweighted, and bipartite graphs. The main purpose of selecting three algorithms is that these algorithms are applicable for community detection in large bipartite graphs (Pesántez-Cabrera and Kalyanaraman, 2017) efficiently. The second purpose is to compare the communities that each algorithm identifies and the time complexity of detecting communities in the networks. The third purpose is to select an algorithm that can perform faster for large bipartite graphs for interactive visual exploration of bipartite graphs. Below we provide brief overviews of the selected algorithms.

##### 3.1.1 LP-BRIM

LP-BRIM (Liu and Murata, 2010) is a combination of the label propagation (LP) algorithm and BRIM (bipartite recursively induced modules) algorithm for large bipartite graphs. In the first step, the LP algorithm provides an initial partition of the bipartite graph, and in the second step, the partition is refined by the BRIM algorithm using Barber's modularity.

LP is divided into following steps:

1. Let  $G = (U, V, E)$  be a bipartite graph.
2. Assign unique labels to nodes in  $U$ .
3. Propagate labels from  $U$  to  $V$  and vice versa, until modularity increases.
4. Label each node with the label with highest number in its neighbourhood.
5. Divide  $U$  and  $V$  into,  $C = \{C_1, C_2, \dots, C_k\}$ ,  $k$ , communities.

BRIM is divided into following steps:

1. Let  $S = [R_{|U| \times |C|}, T_{|V| \times |C|}]^T$ , where  $S$  is an index matrix which denotes the values of  $U$  and  $V$  belonging to particular partitions of  $C$ . Let  $N$  denote total iterations.
2. Calculate Barber's modularity using partition matrix  $S$  acquired from LP.
3. Use the partition of  $R$  vertices and induce a new partition of  $T$ .

4. Calculate Barber's modularity with the new partition and compare with step 2; if the modularity is higher, update the partition  $C$ .
5. Repeat until  $N$  iterations.

**Barber's Modularity** is calculated as follows: The adjacency matrix for the bipartite graph of block-off diagonal is defined as:

$$A = \begin{bmatrix} \mathbf{0}_{|U| \times |U|} & \tilde{A}_{|U| \times |V|} \\ \tilde{A}_{|V| \times |U|}^T & \mathbf{0}_{|V| \times |V|} \end{bmatrix}.$$

Let  $P$  define the probability matrix of randomly connected vertices  $U$  and  $V$ .

$$P = \begin{bmatrix} \mathbf{0}_{|U| \times |U|} & \tilde{P}_{|U| \times |V|} \\ \tilde{P}_{|V| \times |U|}^T & \mathbf{0}_{|V| \times |V|} \end{bmatrix},$$

where  $\tilde{P}_{ij} = \frac{k_i \sum_{j \in V} k_j}{|E|}$ ,  $k_i$  is the degree of the  $i^{th}$  node.

Barbers' modularity for a bipartite graph is:

$$Q = \frac{1}{|E|} \sum_{i=1}^{|U|} \sum_{j=1}^{|V|} \tilde{B}_{ij} \delta(c_i, c_j),$$

where  $\tilde{B} = \tilde{A} - \tilde{P}$ ,  $C_i, C_j$  are the communities of  $i^{th}$  and  $j^{th}$  nodes where  $i \in U$  and  $j \in V$ .

### 3.1.2 LPAwb+

The LPAwb+ algorithm (Beckett, 2016) follows two steps to perform community detection. The first step is the bottom-up approach using the LP method by asynchronous updating of labels that maximize modularity locally of the bipartite graph, as described in Section 3.1.1.

The second step is the top-down approach where two communities  $C_a$  and  $C_b$ , both of which consist of  $U$  and  $V$  labels, are merged if the Barbers' modularity statistic is highest when comparing  $C_a$  and  $C_b$  with all other communities. This merging step is repeated between all communities if the resulting modularity is improved.

### 3.1.3 BiLouvain

This algorithm provides a faster implementation of community detection for bipartite graphs (Pesántez-Cabrera and Kalyanaraman, 2017) using the following steps:

1. Let  $G = (U, V, E, w)$  be a bipartite graph, assign nodes in  $U$  and  $V$  with  $n_1$  and  $n_2$  community labels, i.e.,  $n_1 = |U|$  and  $n_2 = |V|$ , and calculate initial modularity.
2. For each  $u_i \in U$  and  $v_j \in V$ , for each node  $(U \cup V)$ , find candidate communities for which merging the node into that community would result in a modularity gain.
3. From the candidate communities, select a community that maximizes the modularity gain and exceeds a defined threshold.
4. Perform a graph compaction, i.e., generate a new graph,  $G' = (U', V', E', w')$ , where  $U', V'$  are vertices that are created by collapsing vertices in the same community, and edges  $E'$  between communities are generated by collapsing edges connecting two communities  $c_i(U)$  and  $c_j(V)$ . Edge weight  $w'$  is the sum of total edges between communities  $c_i(U)$  and  $c_j(V)$ .
5. Repeat from step 1 for  $G'$ .

## 3.2 Jaccard Index

The shared routing features of material  $m_a$  and  $m_b$ , using a Jaccard index (Jaccard, 1901), are calculated as follows:

$$J(m_a, m_b) = \frac{|W'(m_a) \cap W'(m_b)|}{|W'(m_a) \cup W'(m_b)|}.$$

Here,  $W'(m_a), W'(m_b) \subset W'$ , provide a set of routing features of materials  $m_a$  and  $m_b$  from the directed path-graphs,  $G_{m_a}$  and  $G_{m_b}$ .

## 3.3 Representative Material Selection

The idea of using representative materials is to reduce a large set of materials into a smaller subset of representative materials with similar production characteristics and reflecting the overall routing of workstation networks similar to the complete workstation network  $G_{ws}$ . A simple approach to representative material selection is to apply unsupervised learning or community detection algorithms, using routing as features to group similar materials. The representative material selection approach is divided into five main steps.

The first step is to construct workstation networks and use edges of the workstation networks as routing features. The second step is to construct a bipartite graph that connects each material  $m_i$  to the routing features ( $e_j$ ) if the material  $m_i$  is processed between the workstations represented as an edge feature,  $e_j$ . The third step is to identify communities in bipartite graphs that provide different groups of materials and workstation subnetworks. Each subnetwork and the related materials in the group describe a load of materials in different subnetworks. The identified communities also allow us to identify different end-items and their allocation in different subnetworks; the communities of subnetworks can be utilized to restructure the workstation routing for different materials. The fourth step is to identify path-overlaps of materials within

the groups identified by community detection algorithms and further identify subgroups with path overlaps larger than the defined threshold ( $\alpha$ ). The different subgroups can be optimized based on the selection of  $\alpha$ , which identifies overlaps between routing of two materials of a group. The fifth step is to map groups of materials used for manufacturing end items and select a representative material from each group. A schematic diagram is shown in Figure 1. The algorithmic implementation of the approach is shown in Algorithm 1. The advantage of this approach is that it explores materials, workstation subnetworks, and path-overlap faster than the traditional approach of clustering. The approach can produce representative materials based on the routing of the materials and can generate several simulation scenarios for workstation subnetworks. Additionally, routing in the workstation-subnetworks can be rearranged and re-assigned to different materials for efficient processing for future manufacturing and can be used for discrete event simulation purposes.

With this approach, a domain expert can utilize network-based approaches to visualize and explore the workstation network for routing various materials and can select individual materials as representative materials with other relevant details useful for PPC optimization.

## 4 CASE STUDY

### 4.1 Data

Our analysis uses real-world manufacturing data from a sheet metal processing operation. First, we export data from the ERP system relating to BOM, routing data with processing time at each workstation, and other production planning parameters required for the discrete event simulation. The BOM data contain material IDs (unique), sub-assembly IDs, and the end products and lot size policy for each material. Lot size policies can be fixed order period (FOP), fixed order quantity (FOQ), or consumption-based (CB).

The routing data contain material IDs, workstation IDs (unique), expected time spent at the corresponding workstation, and operation sequence numbers defined by integer values. Individual material IDs have multiple rows in the routing data with different sequence numbers, representing the complete routing sequence of the material.

The BOM data and routing sequence data are integrated by joining both tables using the material ID as the primary key. The joined table is called a master table; an example master table is shown in Table 1.

---

Algorithm 1: Algorithm for communities and material grouping.

---

Preprocess the data,  $D$ , by integrating BOM data and routing data.

Construct a workstation network  $G_{ws} = (V_{ws}, E_{ws})$ , where  $e_i = (v_i, v_j) | e_i \in E_{ws}$  is an ordered set of vertices.

Construct a bipartite graph,  $G = (M, W'_{fir}, E_{m,w})$  from  $D$ .

Perform the community detection algorithm on  $G$ . Let there be  $C = \{C_1, C_2, \dots, C_k\}$ ,  $k$  non-overlapping communities of materials and routing features identified.

$L = \{\}$  ▷ empty list

**for**  $i = 1$  to  $k$  **do**

Let set  $M_i$  contain materials of community  $C_i$

**for**  $j = 1$  to  $|M_i| - 1$  **do**

$e_a = W'_{fir}(m_j)$

**for**  $l = (j+1)$  to  $|M_i|$  **do**

$e_b = W'_{fir}(m_l)$

$ji = jaccard(e_a, e_b)$

**if**  $ji \geq \alpha$

$L = \text{append}(L, \{m_j, m_l\})$

**end for**

**end for**

**end for**

Use  $L$  as an edge list and construct graph  $G_m(L)$ .

$Cmp = \text{BFS}(G_m(L))$  and obtain a set of disconnected components of  $G_m(L)$ . ▷ BFS (breadth first search) returns the set of disconnected components as subgraphs from  $G_m(L)$

Total groups of material are  $|Cmp|$ .

Let  $I = I_1, I_2, \dots, I_p$  end items; each end item is a set of materials grouped in different communities.

Let  $Cmp(I_p) \subset Cmp$  be a subset of subgraphs where materials for end item  $I_p$  are grouped

Select the highest degree material from each  $Cmp(I_p)$ , where  $p = \{1, 2, \dots, |I|\}$ , as representative material.

---

This preparation step yielded 387,367 items of data, which comprise 127 vertices (workstations) and 657 edges (routing features).

In the master data set, the workstation network is constructed using data from the *Workstation* column and corresponding process IDs to decide the directionality (routing) of each item. The bipartite network,  $G$ , is constructed using data from the *Material ID* column and the routing features of the workstation network, obtained by ordered pairs of process IDs for each material and shown as edges in the workstation network. The BOM network,  $G_{BOM}$ , is constructed by combining the *End item*, *Subassembly ID*, and *Material ID* columns. Examples are shown in Figure 2.

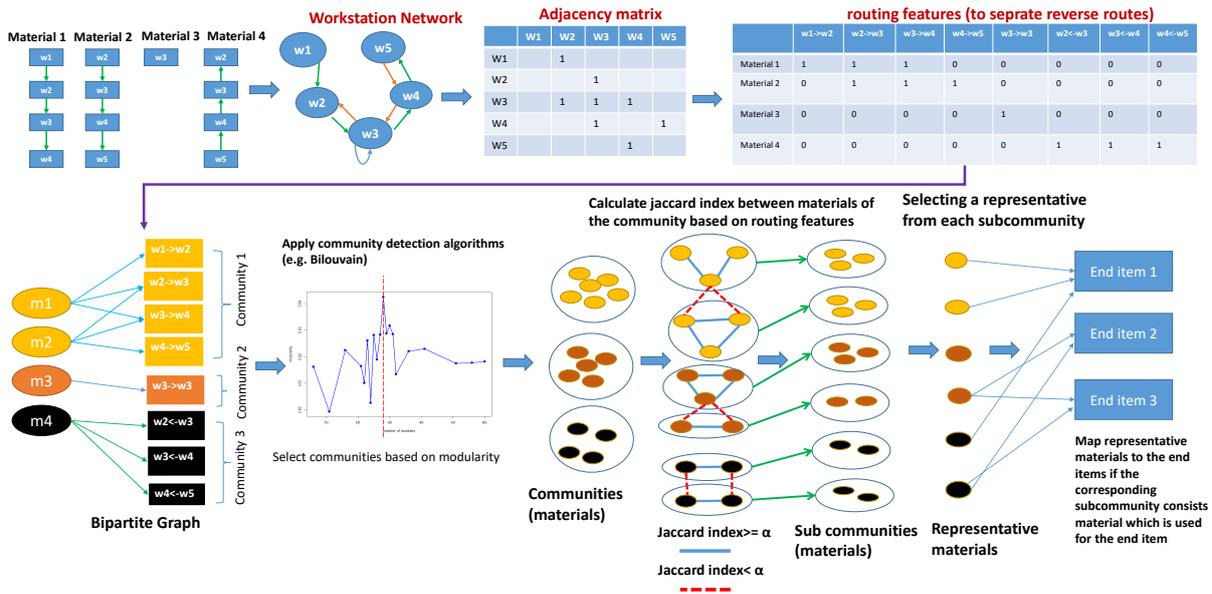


Figure 1: Schematic diagram of representative material analysis from ERP data.

Table 1: Example master table joining BOM data and routing sequence data.

End item	Subassembly ID	Material ID	Workstation	Process ID	Lot size policy	Standard time
A	SA1	M00001	W1	1	FOP1	0.20
A	SA1	M00001	W2	2	FOP1	0.25
A	SA1	M00001	W3	3	FOP1	0.25
A	SA1	M00002	W1	1	FOP2	0.15
A	SA1	M00002	W4	2	FOP2	0.20

For representative material selection, different groups of materials are mapped to corresponding end items where the material of the end item resides and the prominent material is selected as the representative material for each end item.

### 4.2 Results

After the data preprocessing steps, we constructed a workstation network and bipartite network. The workstation network  $G_{ws}$  contains 127 vertices and 657 edges shown in Figure 3 (A). Thus we have 657 routing features for constructing the bipartite graph  $G$ , which has vertices based on  $|M| = 29,612$  (materials) and  $|W'_{ftr}| = 657$  (routing) features. The three bipartite graph algorithms were applied for obtaining modules in the bipartite network. The results are shown in Table 2. The high modularities estimated by all three algorithms show the presence of communities, which do not overlap significantly with each other, implying that we can divide groups of materials and workstation features into relatively independent sets (communities). One example is shown in Figure 3(B). The figure show subnetworks of three communities which are obtained from the routing features in three differ-

ent communities from total of 76 communities identified by the biLouvain algorithm. The communities are highlighted in different colors, denoting different subnetworks of workstations constructed by selecting routing features grouped in three different communities of the bipartite graph. The total number of materials processed in each of the three communities are 2,219, 135, and 10 materials. Among the three algorithms used, the biLouvain algorithm performs best; its execution is faster and achieves higher modularity than the other two algorithms. We next computed the normalized mutual information (NMI) (Danon et al., 2005) between communities obtained by the three bipartite algorithms, to examine the differences in the sets of communities obtained. We compute NMI for both types of vertices ( $M$  (materials) and  $W'_{ftr}$  (routing features)) of the bipartite graph. The results are shown in Table 3. The high NMI values between all algorithms show that the detected communities exhibit significant similarity for both types of vertices; however, they are not entirely the same because the number of detected communities and modularity measures are not equal. This method may yield different results for subcommunity analysis. However, given the performance information for the community detection

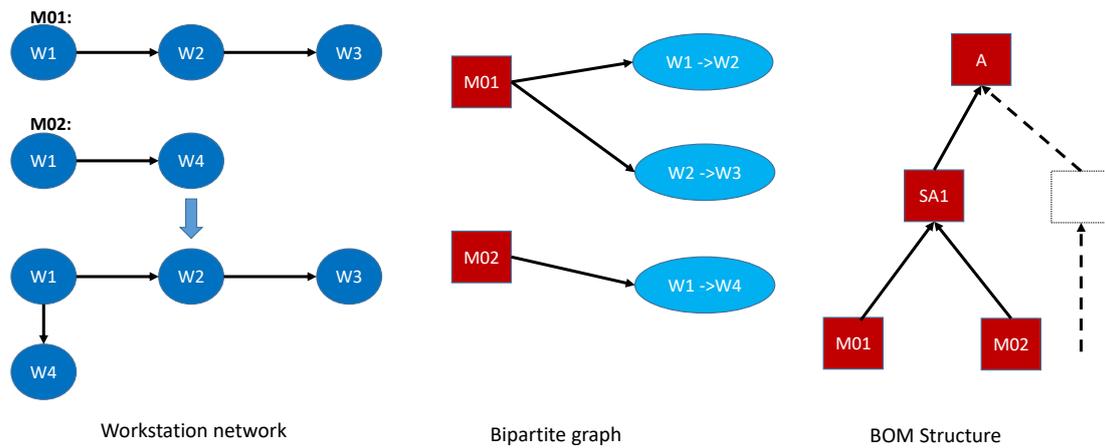


Figure 2: Different types of networks created from the master data shown in Table 1.

algorithms, the biLouvain algorithm performs better and faster than the other two; therefore, it can be applied for identifying communities of bipartite graphs constructed from materials and routing features of the large ERP data.

In the next step, after obtaining the communities, we applied the Jaccard index to detect sub-communities in each community based on routing path overlap. We use path overlap  $\alpha = 0.8$ , i.e., if two materials show an overlap in terms of Jaccard index  $\alpha \geq 0.80$ , they both belong to the same sub-community. We identified 1,077, 1,162, and 1,154 sub-communities using LP-BRIM, LPAwb+, and biLouvain algorithms, respectively. We select a single material from each sub-community for representative material selection, selecting that with the maximum average path-overlap value (Jaccard index). However, one could adopt another method for selecting the representative material from each sub-community based on the material’s prominence or other relevant features chosen based on domain understanding. The number of reduced materials is between 1,000 and 1,200, which is suitable for discrete event simulation with *simgen* for representative materials. The other advantage of this approach is that we can select each community, routing the community’s subnetwork and the corresponding end-items existing in the community for representative materials selection only from the community, using path overlap. We can generate required parameters from master data for each community for discrete event simulation and reduce the parameter space. The discrete event simulation for independent communities can be applied for simulation by selecting representative materials from a single community.

In the next step, we provide a comparative analysis by calculating graph edit distance (GED) (Bunke

et al., 2007), we applied GED only for insertions and deletions of vertices and edges, between workstation network ( $G_{ws}$ ) and workstation subnetwork of  $M_r$  representative materials  $G_{ws}(M_r)|_{G_{ws}(M_r)} \subset G_{ws}$  from the subcommunities obtained from the communities identified by different community detection algorithms and randomly selected materials ( $M_{random}$ ) from the data. In this approach we first select a set of representative materials,  $M_r = \{m_1, m_2, \dots, m_n\}$ , by randomly selecting a single material from each sub-community and the corresponding routing features to create subnetworks,  $G_{ws}(M_r)$ , of workstations as discussed in Section 3. Similarly we select materials randomly from the data and construct subnetworks,  $G_{ws}(M_{random})$ , where  $|M_r| = |M_{random}|$ . We compute GED between  $G_{ws}$  and  $G_{ws}(M_r)$  and between  $G_{ws}$  and  $G_{ws}(M_{random})$ ; the results are shown in Figure 4. The idea of representative material selection is to select representative materials from a large number of variants that follow similar production features (routing) and reflect an overall routing of the workstation network that is similar to the complete workstation network  $G_{ws}$ , when  $GED(G_{ws}, G_{ws}(M_r)) \sim 0$ . The representative materials should be selected when  $arg \min_{|M_r|} GED(G_{ws}, G_{M_r})$ . From the analysis, we see that the random selection does not converge to  $GED \sim 0$  and is significantly higher than when the same number of materials are selected based on the three community detection algorithms.

## 5 CONCLUSIONS

In this paper, we applied a network-based approach to identify groups of similar materials, considering routing of materials as features of a manufacturing company. The paper’s main aim is to design an ef-

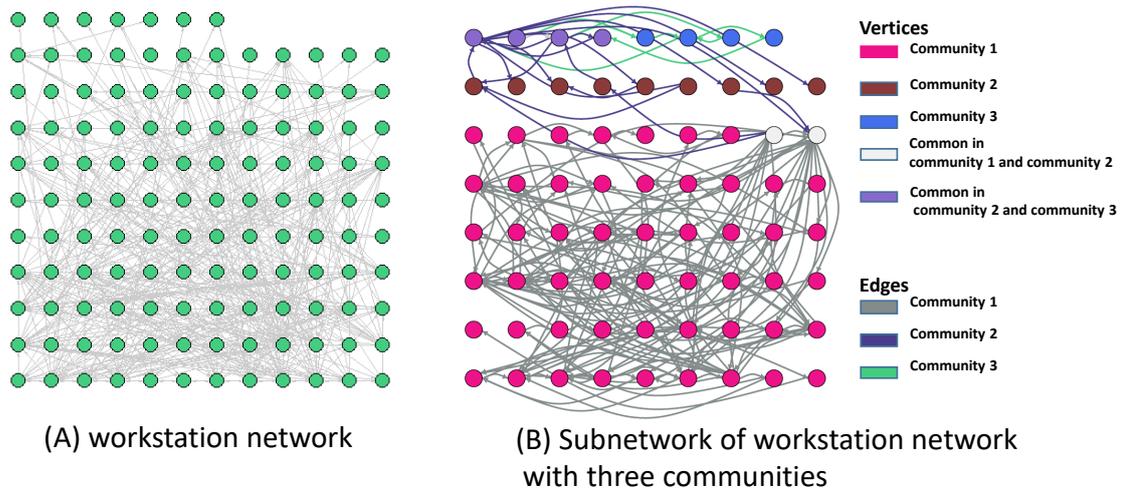


Figure 3: Visualization of (A) the workstation network and (B) the routing of three communities of materials identified by the biLouvain community detection algorithm.

Table 2: Total communities, maximum size community, modularity, and execution time of different bi-partite graph algorithms.

Algorithm	LP-BRIM	LPAbw+	BiLouvain
Total communities	89	329	76
Total subcommunities	1077	1162	1154
Maximum size community	11235	8317	12081
Modularity	0.67	0.61	0.68
Time (minutes)	~ 40	~ 4320	< 2

Table 3: Comparison of module detection algorithms between different algorithms, we measure NMI of communities for both set of vertices ( $M, W'_{fir}$ ) between two algorithms for the bipartite graph.

Algorithms	NMI of materials in modules ( $M$ )	NMI of workstation features in modules ( $W'_{fir}$ )
LP-BRIM, LPAbw+	0.810	0.708
LP-BRIM, BiLouvain	0.790	0.709
LPAbw+, BiLouvain	0.697	0.662

efficient approach to identifying a set of representative materials for discrete event simulation using *simgen*. The detected communities and subcommunities within each community are used to identify a set of representative materials that perform better than a random selection of materials. The community detection algorithms identify groups of materials according to their routings, and the subcommunities identify materials with similar routing based on a threshold selected by a user. The selection of this optimizing threshold for path overlap requires domain insight. We compare the performance of three algorithms and conclude that the biLouvain community detection algorithm allows users to obtain the superior results faster than other methods. The community identification approach can also be used for ERP data exploration for similar products and independent workstation sub-networks by domain experts. Similarly, vi-

sual exploration can help identify loads in workstation networks and allow re-routing of various materials.

Given the complexity of the real-world manufacturing environments, a discrete event simulation method must consider various product features, variant diversity, BOM structures, and routing to estimate efficient PPC results. The network-based approach provides a useful and efficient solution for the modeling of real-world manufacturing problems.

In our future research, the proposed approach will be applied to different real-world manufacturing scenarios and will be compared to other heuristic approaches for representative material selection for larger datasets. We will also compare the results of discrete event simulations using representative materials of each community independently, and will further evaluate how discrete event simulation (*simgen*) performs using representative materials selected us-

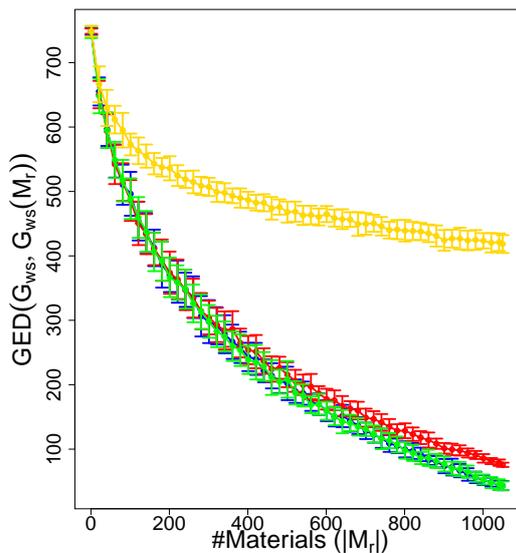


Figure 4: Comparison of graph edit distance between  $G_{ws}$  and  $G_{ws}(M_r)$ , when we select  $M_r$  materials from sub-communities of communities, biLouvain (blue), LP-BRIM (red), LPAwb+ (green), and randomly from the data (yellow).

ing routing information. We will also apply network-based approaches for ERP data exploration, representative material selection, and visual modeling using the interactive platform for discrete event simulation by using multilayer networks that integrate BOM structure complexity (BOM network) and work station network (routing) for selection of materials, routes, and resource allocation to understand the complexity of PPC challenges and prepare parameters efficiently with the collaborative effort of business experts from different industrial-production domains within a company.

## ACKNOWLEDGEMENTS

This paper is a part of X-pro project. The project is financed by research subsidies granted by the government of Upper Austria.

## REFERENCES

- Aksoy, S. G., Kolda, T. G., and Pinar, A. (2017). Measuring and modeling bipartite graphs with community structure. *Journal of Complex Networks*, 5(4):581–603.
- Altendorfer, K., Felberbauer, T., and Jodlbauer, H. (2016). Effects of forecast errors on optimal utilisation in aggregate production planning with stochastic customer demand. *International Journal of Production Research*, 54(12):3718–3735.

- Barber, M. J. (2007). Modularity and community detection in bipartite networks. *Physical Review E*, 76(6):066102.
- Becker, T., Beber, M., Windt, K., and Hütt, M. (2011). Flow control in production logistic networks. In *Proceedings of the 44th CIRP International Conference on Manufacturing Systems*.
- Becker, T., Meyer, M., and Windt, K. (2014). A manufacturing systems network model for the evaluation of complex manufacturing systems. *International Journal of Productivity and Performance Management*.
- Beckett, S. J. (2016). Improved community detection in weighted bipartite networks. *Royal Society open science*, 3(1):140536.
- Bianchesi, N. M. P., Romao, E. L., Lopes, M. F. B., Balestrassi, P. P., and De Paiva, A. P. (2019). A design of experiments comparative study on clustering methods. *IEEE Access*, 7:167726–167738.
- Bunke, H., Dickinson, P. J., Kraetzl, M., and Wallis, W. D. (2007). *A graph-theoretic approach to enterprise network dynamics*, volume 24. Springer Science & Business Media.
- Chen, N., Yin, Y., and Liu, Q. (2018). Research on complex network modeling of cellular manufacturing system. In *2018 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS)*, pages 528–531. IEEE.
- Choudhary, A. K., Harding, J. A., and Tiwari, M. K. (2009). Data mining in manufacturing: a review based on the kind of knowledge. *Journal of Intelligent Manufacturing*, 20(5):501–521.
- Chowdhury, I. J. and Nayak, R. (2013). A novel method for finding similarities between unordered trees using matrix data model. In *International Conference on Web Information Systems Engineering*, pages 421–430. Springer.
- Chowdhury, I. J. and Nayak, R. (2014). Identifying product families using data mining techniques in manufacturing paradigm. In *AusDM*, pages 113–120.
- Danon, L., Diaz-Guilera, A., Duch, J., and Arenas, A. (2005). Comparing community structure identification. *Journal of statistical mechanics: Theory and experiment*, 2005(09):P09008.
- Dao, V. L., Bothorel, C., and Lenca, P. (2020). Community structure: A comparative evaluation of community detection methods. *Network Science*, 8(1):1–41.
- Dogan, A. and Birant, D. (2020). Machine learning and data mining in manufacturing. *Expert Systems with Applications*, page 114060.
- Han, X., Cao, S., Shen, Z., Zhang, B., Wang, W.-X., Cressman, R., and Stanley, H. E. (2017). Emergence of communities and diversity in social networks. *Proceedings of the National Academy of Sciences*, 114(11):2887–2891.
- Hochdörffer, J., Laule, C., and Lanza, G. (2017). Product variety management using data-mining methods—reducing planning complexity by applying clustering analysis on product portfolios. In *2017 IEEE International Conference on Industrial Engineering*

- and *Engineering Management (IEEM)*, pages 593–597. IEEE.
- Hübl, A., Altendorfer, K., Jodlbauer, H., Gansterer, M., and Hartl, R. F. (2011). Flexible model for analyzing production systems with discrete event simulation. In *Proceedings of the 2011 Winter Simulation Conference (WSC)*, pages 1554–1565. IEEE.
- Jaccard, P. (1901). Distribution de la flore alpine dans le bassin des dranses et dans quelques régions voisines. *Bull Soc Vaudoise Sci Nat*, 37:241–272.
- Jeon, S. M. and Kim, G. (2016). A survey of simulation modeling techniques in production planning and control (ppc). *Production Planning & Control*, 27(5):360–377.
- Jiao\*, J., Zhang, L., and Pokharel, S. (2005). Coordinating product and process variety for mass customized order fulfilment. *Production Planning & Control*, 16(6):608–620.
- Kronberger, G., Weidenhiller, A., Kerschbaumer, B., and Jodlbauer, H. (2006). Automated simulation model generation for scheduler-benchmarking in manufacturing. In *Proceedings of the International Mediterranean Modelling Multiconference (I3M 2006)*, pages 45–50.
- Li, Y., Wang, Z., Zhong, X., and Zou, F. (2019). Identification of influential function modules within complex products and systems based on weighted and directed complex networks. *Journal of Intelligent Manufacturing*, 30(6):2375–2390.
- Lin, Y., Zhang, R., Li, C., Yang, L., and Hanzo, L. (2017). Graph-based joint user-centric overlapped clustering and resource allocation in ultradense networks. *IEEE Transactions on Vehicular Technology*, 67(5):4440–4453.
- Liu, X. and Murata, T. (2010). Community detection in large-scale bipartite networks. *Transactions of the Japanese Society for Artificial Intelligence*, 25(1):16–24.
- Macchiaroli, R. and Riemma, S. (1994). Clustering methods for production planning and scheduling in a flexible manufacturing system. In *Proceedings of the 1994 IEEE International Conference on Robotics and Automation*, pages 3155–3160. IEEE.
- Macchiaroli, R. and Riemma, S. (1996). Clustering algorithms to optimize the tool handling system management in an fms. *International journal of flexible manufacturing systems*, 8(2):183–201.
- Murata, T. (2009). Detecting communities from bipartite networks based on bipartite modularities. In *2009 International Conference on Computational Science and Engineering*, volume 4, pages 50–57. IEEE.
- Newman, M. E. (2006). Modularity and community structure in networks. *Proceedings of the national academy of sciences*, 103(23):8577–8582.
- Pesántez-Cabrera, P. and Kalyanaraman, A. (2017). Efficient detection of communities in biological bipartite networks. *IEEE/ACM transactions on computational biology and bioinformatics*, 16(1):258–271.
- Romanowski, C. J. and Nagi, R. (2005). On comparing bills of materials: a similarity/distance measure for unordered trees. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 35(2):249–260.
- Shabaka, A. and ElMaraghy, H. A. (2007). Generation of machine configurations based on product features. *International Journal of Computer Integrated Manufacturing*, 20(4):355–369.
- Stevenson\*, M., Hendry, L. C., and Kingsman, B. G. (2005). A review of production planning and control: the applicability of key concepts to the make-to-order industry. *International journal of production research*, 43(5):869–898.
- Strasser, S. and Peirleitner, A. (2017). Reducing variant diversity by clustering. In *Proceedings of the 6th International Conference on Data Science, Technology and Applications*, pages 141–148. SCITEPRESS-Science and Technology Publications, Lda.
- Tripathi, S., Moutari, S., Dehmer, M., and Emmert-Streib, F. (2016). Comparison of module detection algorithms in protein networks and investigation of the biological meaning of predicted modules. *BMC bioinformatics*, 17(1):129.
- Tseng, M. M. and Radke, A. M. (2011). Production planning and control for mass customization—a review of enabling technologies. In *Mass Customization*, pages 195–218. Springer.
- Yang, T., Zhang, D., Chen, B., and Li, S. (2010). Analysis of mixed production line based on complex weighted network. In *2010 International Conference on Intelligent Computation Technology and Automation*, volume 1, pages 667–670.
- Zhang, N., Yang, Y., Zheng, Y., and Su, J. (2019). Module partition of complex mechanical products based on weighted complex networks. *Journal of Intelligent Manufacturing*, 30(4):1973–1998.