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A network analysis of decision strategies of human experts in steel manufacturing

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ABSTRACT

Steel production scheduling is typically accomplished by human expert planners. Hence, instead of fully automated scheduling systems, steel manufacturers prefer auxiliary recommendation algorithms. Through the suggestion of suitable orders, these algorithms assist human expert planners who are tasked with the selection and scheduling of customer orders. However, it is hard to estimate, what degree of complexity these algorithms should have as steel campaign planning generally lacks precise rule-based procedures; in fact, it requires far-reaching domain knowledge as well as intuition that can only be acquired by years of business experience. Here, contrary to developing new algorithms or improving older ones, we introduce a shuffling-aided network method to assess the complexity of the selection patterns established by a human expert. This technique allows us to formalize and represent the tacit knowledge that enters the campaign planning. As a result of the network analysis, we have discovered that the choice of appropriate customer orders for immediate production is primarily determined by the orders' carbon content (to be precise: the carbon equivalent). Surprisingly, trace elements like manganese, silicon, and titanium have a lesser impact on the selection decision than assumed by the pertinent literature. Our approach can serve as an input to a range of automated decision-support systems, whenever an expert needs to create groups of orders ('production campaigns') that fulfill certain implicit selection criteria.

1. Introduction

Steel is an exceptionally versatile material. Its malleability, durability, and yield strength are crucial in the construction of buildings, cars, and machines. As modern steel factories try to meet the global steel demand, they started to directly couple steelmaking, continuous casting (CC), and hot rolling to increase their economic output (Tang, Liu, Rong, & Yang, 2001). Properly planning these manufacturing steps and steadily operating the necessary equipment is imperative for the profitability of a steel enterprise because any disruptions could reduce the product quality or, even worse, force the plant to be shut down for lengthy and costly maintenance activities. In order to ensure a steady and seamless production, an extensive number of planning constraints must be abided by (Cowling, 2003; Cowling, Ouelhadj, & Petrovic, 2004; Lee, Murthy, Haider, & Morse, 1996; Mattik, Amorim, & Günther, 2014; Park, Hong, & Chang, 2002). For instance, an important constraint (and simultaneously the focal point of this study) refers to the chemical compatibility of consecutively processed steel customer orders (Tang, Wang, & Chen, 2014). The chemical compatibility of two orders is basically governed by their hardness or carbon content / carbon equivalent. Expectedly, the steel hardness belongs to the most frequently discussed planning parameters (Jia, Yi, Yang, Du, & Zhu, 2013; Vanhoucke & Debels, 2009; Kosiba, Wright, & Cobbs, 1992) and is acknowledged by virtually every hot rolling planning method (Özgür, Uygun, & Hütt, 2020). Nevertheless, it is not entirely clear how steel production constraints are prioritized by practitioners and to what detail the chemical compatibility is taken into account.

In the light of the numerous advantages of Industry 4.0 technologies (Branca, et al., 2020; Miśkiewicz & Wolniak, 2020; Tolettini & Lehmann, 2020) it is interesting to see that steel production planning and scheduling are still heavily influenced by humans (Crawford & Wiers, 2001; Cowling, 2003; Cowling, 2001). Obviously, the steel sector appears to be skeptical towards automation or digitization (Özgür, Uygun, & Hütt, 2020), although scheduling tools and software theoretically guarantee lower labor costs, improved machine utilization, increased work rates, and enhanced product quality (Co, Patuwo, & Hu, 1998). For example, the selection of customer orders for immediate production is carried out manually by human expert planners in a lot of cases. Based

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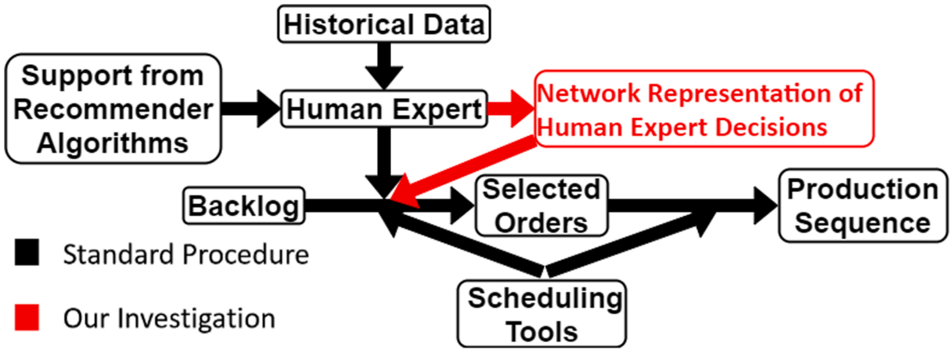

Fig. 1. Flow chart illustrating how the steel planning process could profit from our network method.

on their understanding of operational and commercial aspects these human expert planners pick a subset from a larger pool of customer orders and group them in production campaigns. However, some of these constraints constitute tacit knowledge because they derive from the long-term professional experience of expert planners who usually disseminate their thoughts through word-of-mouth only. This lack of documentation puts the steel plant's productivity at risk if the expert planner is absent and substituted by a less experienced worker (Turban, Aronson, & Liang, 2005; Chergui, Zidat, & Marir, 2020). To the detriment of steel enterprises, planning staff shortages happen more often than not, as these expert planners are employed during normal office working hours, whereas the steel production strides ahead continuously (Cowling, 2001). Beyond that, steel manufacturers are regularly faced with situations where generating a feasible schedule seems inconceivable which compels them to ignore certain unessential constraints. Unfortunately, there is no straightforward and universally valid algorithmic solution to this problem since the exact relevance of the planning constraints commonly depends on a variety of distinct factors (e.g. product mix, type of equipment, customer requirements) and is often not documented in a structured way. As it is shown in Chapter 2 ("Related Work"), many academic articles covering order suggestion algorithms remain extremely vague regarding the exploitation of such tacit knowledge (e.g. regarding the appropriate choice of selection rules and constraints) – especially when it comes to the chemical compatibility of different steel grades / customer orders. The existence of this research gap might further consolidate the steel industry's suspicion against automation and digitization.

In our opinion, this lack of trust can only be overcome if decision support systems comply with actual business practices in a stricter fashion. In other words, support systems need to comprehend which rules are deemed indispensable by steel decision-makers and, conversely, which constraints may be relaxed. Here, instead of devising a new algorithm or testing older ones, we concentrate on an explorative analysis of historical production data that discloses both the prioritization of the planning parameters as well as the level of complexity inherent in the decision process. To this end, we obtained association rules (with particular emphasis on chemical features) from the selection records of a human expert planner; then, we mapped these rules into a network similar to the interval graph in Lee et al. (2004). Association rules learning is a routinely used data mining method (Hahsler & Karpienko, 2017) as it represents an immensely helpful approach to discover which kinds of customer orders (i.e. which steel grades) are preferably combined in production campaigns. Now, looking at association rules from a network / graph perspective and detecting areas of tightly connected nodes (i.e. network communities; Girvan & and Newman, 2002) allows us to identify steel grade groups that are considered linkable in the mind of the expert planner. Afterward, we compare our steel grade network to suitable randomized graphs by deploying a powerful shuffling-based network method found in Enders et al. (2018) that capitalizes on popular network concepts such as the clustering coefficient (Watts & Strogatz, 1998), and the betweenness centrality (Freeman, 1977). These methods enable the formal extraction of "first principles" that drive the selection procedure as we ascertain which steel grades are just connected by chance and what external order attributes (e.g. chemical composition) dictate the grade togetherness.

Consequently, our experiments reveal that the human planner operates with a small set of simplistic selection rules that solely focuses on the steel's carbon content while trace elements like manganese or silicon do not play a significant role. At last, through simulations, we contextualize the shape of our steel grade network and the carbon equivalent (C.E.) formula which is a weighted sum of the steel composition that quantifies the hardness and, thus, the compatibility of different grades (Kasuya & Yurioka, 1993; Talaş, 2010). As a result of this investigation, it is shown how already a few planning practices can give rise to complex campaign selection patterns. Apart from less experienced human planners, also some previously proposed decision support systems (e.g. Tang, Meng, Chen, & Liu, 2016) could benefit from our work by incorporating these practices as seen in Fig. 1. The remainder of this article is divided into 2. Related Work, 3. Background Information and Theory, 4. Methods, 5. Results and Discussion, 6. Conclusion.

2. Related work

The following literature review is split into six sub-sections that each shed light on knowledge-based systems, knowledge elicitation, automation bias, association rule mining, complex networks, and order selection algorithms. Throughout the review, we aim at clarifying current research gaps and explaining how our article advances the state of knowledge. This will be complemented by an in-depth report on the theory / history of both association rules mining and complex networks in the third chapter ("3. Background Information and Theory").

2.1. Knowledge-based systems

Knowledge-based systems (KBS) are thoroughly reviewed in (Zhang, Chen, Lu, & Zhang, 2017). KB systems formalize, store, and harness knowledge to solve a variety of problems (Hendriks & Vriens, 1999; Akerkar & Sajja, 2009). Their benefits include better decision-making as well as expertise availability, and reduced knowledge erosion (Hendriks & Vriens, 1999; Akerkar & Sajja, 2009). Typical examples of KBS are presented by so-called expert systems (ES) which offer decision support by subjecting human expert knowledge to artificial intelligence (AI) technologies (Ruggles III, 1997; Liao, 2003; Turban, Aronson, & Liang, 2005). Even though acquiring knowledge is described to be a vital step for the development of expert systems or other automated devices (Madni, 1988; Ruggles III, 1997; Barthélemy, Bisdorff, & Coppin, 2002; Kohout, Anderson, & Bandler, 2019), many authors have studied KBS from a rather technological angle (Hendriks & Vriens, 1999; Cobo, Martínez, Gutiérrez-Salcedo, Fujita, & Herrera-Viedma, 2015; Ahmed, et al., 2019). So, in this article, we focus on eliciting and validifying the knowledge hidden in the steel production planning process as opposed to exploring e.g. the AI component of a certain KB system.

2.2. Knowledge elicitation

Knowledge elicitation or similar activities are integral parts of a company's knowledge management (KM) process (Nonaka & Takeuchi, 1995; Ruggles III, 1997; Rowley, 1999; Akerkar & Sajja, 2009; Fred, Dietz, Liu, & Filipe, 2017; Zaim, Muhammed, & Tarim, 2019; Ansari, 2019; Bettiol, Di Maria, & Micelli, 2020). Through this process, expert knowledge becomes more accessible such that it can reach less informed company staff (Turban, Aronson, & Liang, 2005) which in turn leads to competitive / strategic advantages (Akerkar & Sajja, 2009; Fred, Dietz, Liu, & Filipe, 2017) and enhanced productivity (Ruggles III, 1997) or organizational performance (Curado & Bontis, 2011; Zaim, Muhammed, & Tarim, 2019; Schniederjans, Curado, & Khalajhedayati, 2020). Recently, KM has profited from the introduction of Industry 4.0 and digitization technologies (Ustundag & Cevikcan, 2017; Ediz, 2018; Abubakar, Elrehail, Alatailat, & Elçi, 2019; Ansari, 2019; Bettiol, Di Maria, & Micelli, 2020; Kolyasnikov & Kelchevskaya, 2020; Schniederjans, Curado, & Khalajhedayati, 2020) as well as from, inter alia, the implementation of data mining (DM) approaches (Nemati & Barko, 2001; Shaw, Subramaniam, Tan, & Welge, 2001; Liao, 2003; Turban, Aronson, & Liang, 2005; Fred, Dietz, Liu, & Filipe, 2017; Abubakar, Elrehail, Alatailat, & Elçi, 2019; Ansari, 2019; Kolyasnikov & Kelchevskaya, 2020). Out of the plethora of DM concepts used in knowledge management, we primarily rely on data visualization (Keim & Kriegel, 1996; Shaw, Subramaniam, Tan, & Welge, 2001; Fred, Dietz, Liu, & Filipe, 2017) and statistical methods (Shaw, Subramaniam, Tan, & Welge, 2001; Liao, 2003; Grobelnik & Mladenić, 2005; Fred, Dietz, Liu, & Filipe, 2017) in this paper.

Unfortunately, statistical methods like association rules analysis alone (see Sub-sections 2.4 and 3.1) are often not sufficient to capture knowledge adequately (Meski, Belkadi, Laroche, Ladj, & Furet, 2019) especially when it comes to tacit knowledge. Unlike its explicit counterpart, tacit knowledge eludes elicitation (Polanyi, 1966; Nonaka, 1994; Nonaka & Takeuchi, 1995; Howells, 1996; Hendriks & Vriens, 1998; Noh, Lee, Kim, Lee, & Kim, 2000; Kikoski & Kikoski, 2004; Turban, Aronson, & Liang, 2005; Collins, 2010; Arling & Chun, 2011; Hadjimichael & Tsoukas, 2019; Chergui, Zidat, & Marir, 2020; Schniederjans, Curado, & Khalajhedayati, 2020) since it is intertwined in the know-how, experience, actions, ideas, beliefs, values, emotions, etc. of the corresponding knowledge holder(s) (Polanyi, 1958; Hendriks & Vriens, 1998; Madhavan & Grover, 1998; Nonaka, Toyama, & Konno, 2000; Turban, Aronson, & Liang, 2005; Akerkar & Sajja, 2009; Arling & Chun, 2011; Chergui, Zidat, & Marir, 2020; Schniederjans, Curado, & Khalajhedayati, 2020). In order to effectively elicit such knowledge, ontologies (Chen Y. J., 2010; Mezghani, Exposito, & Drira, 2016; Fred, Dietz, Liu, & Filipe, 2017; Ansari, Khobreh, Seidenberg, & Sihn, 2018; Ansari, 2019; Meski, Belkadi, Laroche, Ladj, & Furet, 2019; Chergui, Zidat, & Marir, 2020) and semantic networks (Turban, Aronson, & Liang, 2005; Sowa, 2014) could embed the knowledge of interest into its operational context (Meski, Belkadi, Laroche, Ladj, & Furet, 2019). However, there are not a lot of ontological models for tacit knowledge yet (Chergui, Zidat, & Marir, 2020) – partly because the means of creating these models (e.g. expert interviews, queries, or questionnaires) are prone to human errors (Madni, 1988) and, therefore, unsuitable for tacit knowledge (Sajja & Akerkar, 2010).

Instead of elicitation protocols (Hemming, Burgman, Hanea, McBride, & Wintle, 2018; O'Hagan, 2019), expert interviews or similar techniques (Ferrari, Spoletini, & Gnesi, 2016; Kerrigan, Hullman, & Bertini, 2021), we intend to derive best practices (Turban, Aronson, & Liang, 2005) or universal rules (Turban, Aronson, & Liang, 2005; Meski, Belkadi, Laroche, Ladj, & Furet, 2019) by capitalizing not only on statistical methodds but also on complex network techniques (see Sub-sections 2.4–2.5 and 3.1–3.2, Chapter 4). On top of that, these rules or practices are verified and explicated through and network simulations that base on canalizing functions (see Chapter 4: Carbon equivalent simulations (Step 7)). Still, we are not only dependent on the elicited knowledge to be correct but the knowledge also needs to be interpretable by humans (Madni, 1988; Turban, Aronson, & Liang, 2005) or else adverse phenomena like automation bias may arise.

2.3. Automation bias

Automated decision support systems (DSS) have been introduced to raise the production planning quality (Turban, Aronson, & Liang, 2005; Cummings, 2017) as they consistenly perform better than human experts (Skitka, Mosier, & Burdick, 1999). Having said this, automated decision support systems might fail to give appropriate advice under some circumstances (Madhavan, Wiegmann, & Lacson, 2006; Wickens, Clegg, Vieane, & Sebok, 2015). In such a case, human experts tend to adhere to the decision advice even if it contradicts their own conviction, presumptions or training (Wickens, Clegg, Vieane, & Sebok, 2015; Cummings, 2017).

As a remedy to this sort of automation bias, authors have suggested for decision support systems to disclose their reasoning (Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003; Goddard, Roudsari, & Wyatt, 2012) or to articulate their level of confidence (McGuirl & Sarter, 2006; Goddard, Roudsari, & Wyatt, 2012; Wickens, Clegg, Vieane, & Sebok, 2015). The methods proposed further below (see Chapters 3 and 4) can effectively promote both the comprehensible explication of DSS results and the expression of confidence levels: (i) Once the support system has formulated a decision advice it could highlight the set of extracted planning rules or best practices that led to this advice and (ii) a mixture of different association rules interest measures (see Sub-section 3.1) can be employed to demonstrate how confident the DSS is concerning its advice.

2.4. Association rules

Association rules have been a vital tool to learn from historical data in manufacturing (Choudhary, Harding, & Tiwari, 2009; Harding, Shahbaz, & Kusiak, 2006) and other industries such as retail sales (Julander, 1992; Ünvan, 2021). For instance, an association rules system that facilitates production planning by mapping the relationships between products and processes was designed by Jiao et al. (2008). In addition to retail customer analysis and manufacturing in general, association rules were also adopted in steel production. Martínez-de-Pisón et al. (2012) and Verma et al. (2014) mined association rules to evaluate the sources of poor corrosion protection on steel strips and the emergence of occupational accidents in a steel factory, respectively. Yet, association rules have never been exploited to map the chemical compatibility of steel customer orders into networks.

2.5. Complex networks

Note that in the subsequent chapters, we will use the terms "network" and "graph" synonymously. Li et al. (2017) have thoroughly reviewed complex networks / graphs in manufacturing. Rao (2007) illustrates how network theory concepts can enhance decision-making in miscellaneous manufacturing settings. A network-based framework to assess the complexity and affinity of products in a job shop environment is created by Jenab and Liu (2010). On top of that, a few precedent articles deal with steel scheduling by incorporating approaches from network theory (Lee, Chang, & Hong, 2004; Pacciarelli & Pranzo, 2004). Nevertheless, as far as we are aware, there is no single piece of research that merges shuffling network techniques (Enders, Hütt, & Jeschke, 2018) and data mining with the goal of exposing the implicit knowledge entrenched in the steel planning process.

Table 1
Sample snapshot of the steel production data explored in this article; the entire dataset comprises >100 thousand row entries; the elemental contributions are given in mass percentages.

Production Campaign	Steel Grade	Width [mm]	Thickness [mm]	Carbon Content	Manganese Content	Silicon Content
A	1	1800	55	0.010	0.030	0.005
A	2	1750	65	0.010	0.040	0.015
B	3	1800	65	0.020	0.040	0.010
B	4	1750	70	0.020	0.030	0.025

Table 2
Sample snapshot of the synthetic steel grade data; the elemental contributions are given in mass percentages.

Steel Grade	Carbon	Manga-nese	Copper	Nickel	Chromium	Molyb-denum	Vana-dium
1	0.010	0.030	0.174	0.026	0.040	0.015	0.003
2	0.010	0.040	0.104	0.029	0.032	0.007	0.004
3	0.020	0.040	0.144	0.030	0.064	0.009	0.003
4	0.020	0.030	0.063	0.041	0.033	0.018	0.000

Table 3
Distribution parameters of the synthetic steel grade data; the carbon values stem from a bimodal normal distribution, while the other elements are unimidally distributed.

Distribution Parameter	Carbon	Manga-nese	Copper	Nickel	Chromium	Molyb-denum	Vana-dium
Mean(s)	0.060; 0.240	0.675	0.125	0.045	0.050	0.013	0.002
Standard Deviation(s)	0.020; 0.030	0.163	0.038	0.013	0.013	0.004	0.001
Minimum Value(s)	0.020; 0.200	0.250	0.050	0.020	0.025	0.005	0.000
Maximum Value(s)	0.100; 0.300	1.000	0.200	0.070	0.075	0.020	0.005

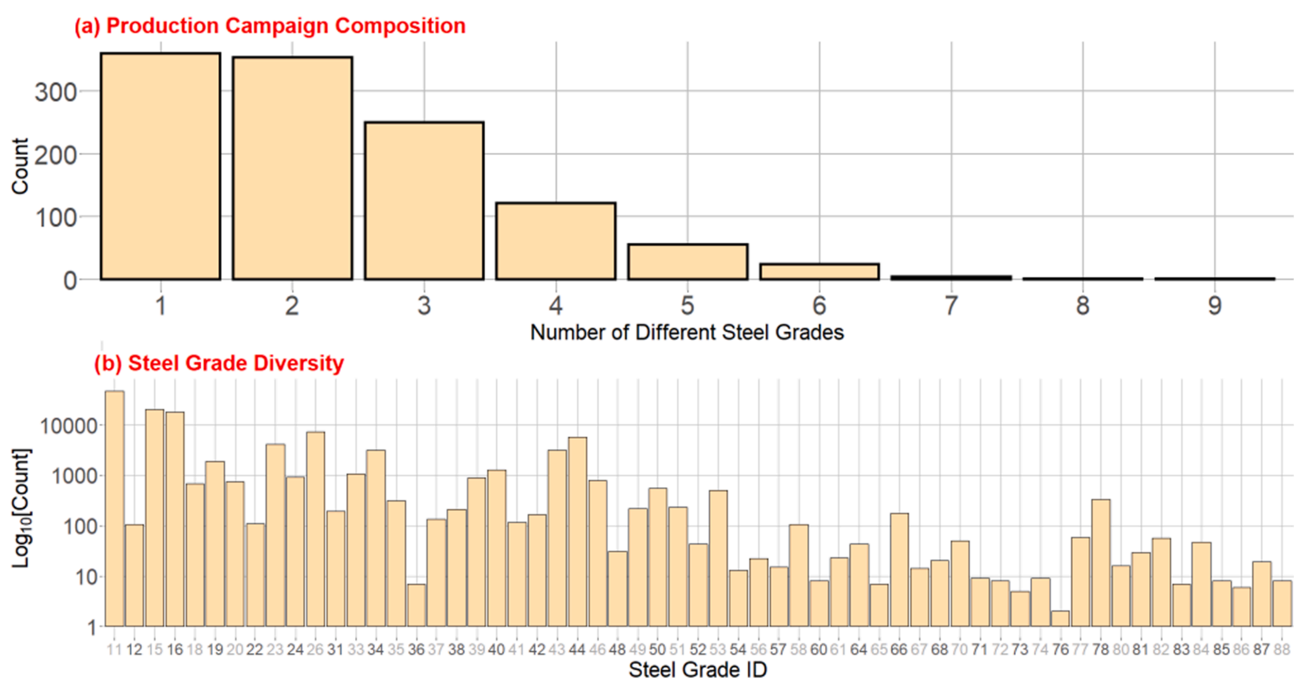

Fig. 2. (a) Histogram of the number of different steel grades per production campaign. (b) logarithmically-scaled histogram of the number of slabs per steel grade in the database.

2.6. Order selection in steel manufacturing

In the past, order selection methods were adopted in the context of manufacturing as well as steel production. Cergibozan and Tasan (2019) review the literature on order picking and batching for different warehouse applications. While a few decision support systems select orders according to the monetary value (Jacobs, Wright, & Cobbs, 1988) user-assigned priority (Cowling, 2003), or simply "under some rules" (Ji & Lu, 2009), others group orders together because of their compatibility in terms of technological constraints. Here, compatibility refers to, inter alia, equal alloy composition (Balakrishnan & Geunes, 2003), similar properties (Chang, Chang, & Hong, 2000), comparable carbon contents (Tang, Wang, Liu, & Liu, 2011), suitable steel grade combinations (Tang, Wang, & Chen, 2014; Tang, Meng, Chen, & Liu, 2016) and homogenous metallurgical characteristics (Tang & Wang, 2008). By deploying these support systems, the pertinent literature promises efficient energy usage (Naphade, Wu, Storer, & Doshi, 2001; Ji & Lu, 2009), reduced costs (Tang, Yang, & Liu, 2011), optimized tundish utilization (Tang & Wang,

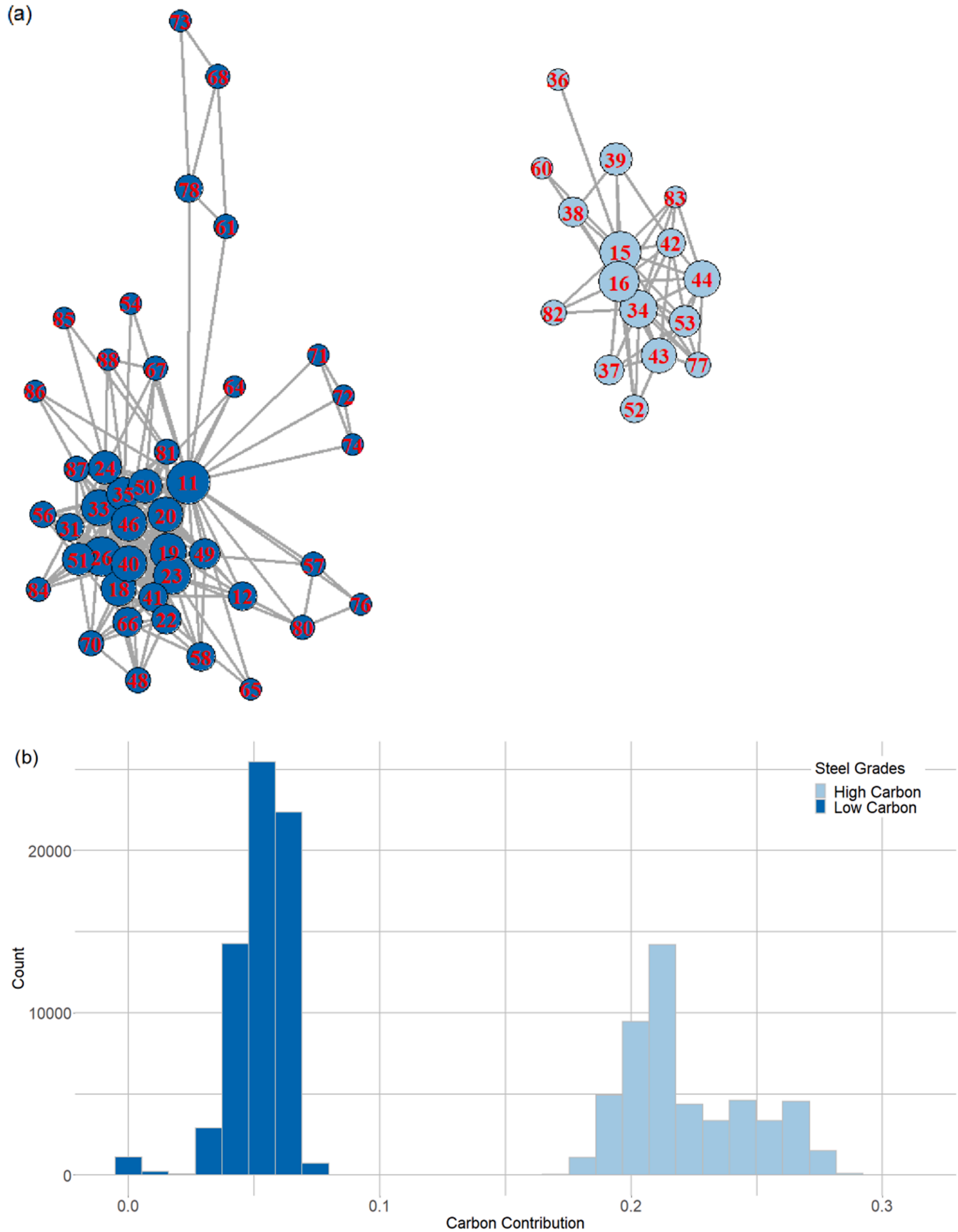

Fig. 3. (a) Steel grade network achieved through association rules mining; nodes (edges) represent steel grades (frequent joint selections of steel grades); the list of association rules leading to this network is reported in the Supplements (see Table S.1); (b) histogram of the slab carbon contribution; the colors (light and dark blue) in (b) correspond to the colors of the steel grade network in (a). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

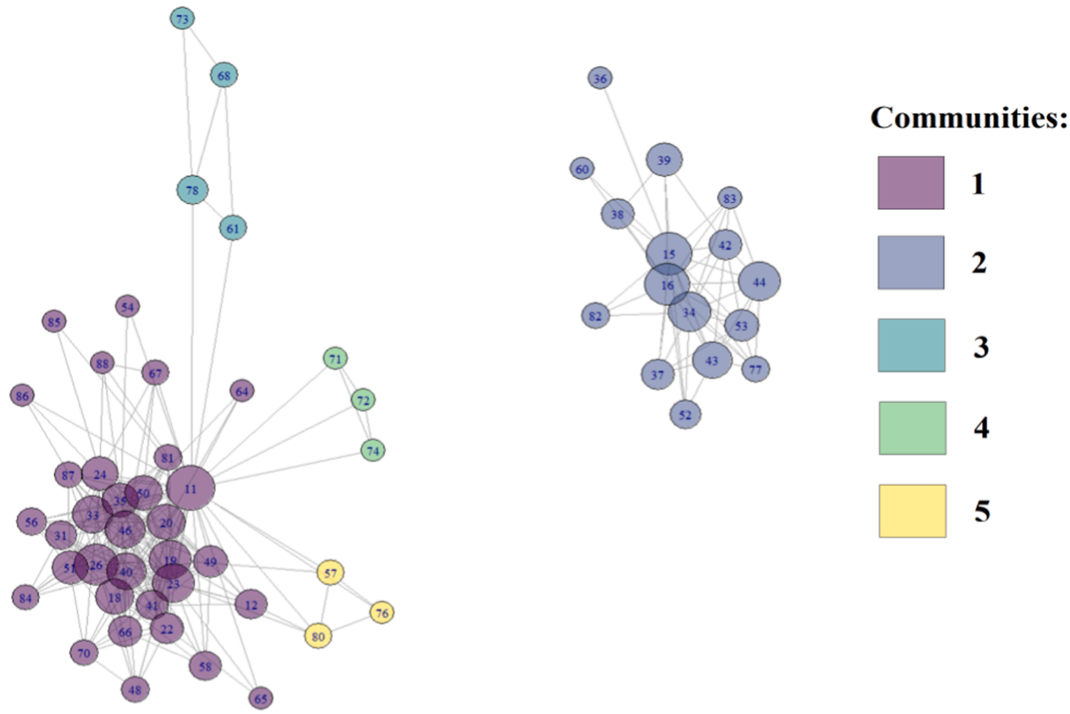

Fig. 4. Results of the community detection algorithm for the steel grade network; the communities were found by repetitively removing the edge with the highest edge betweenness and subsequently calculating the edge betweenness for the new network.

Table 4
Number of different steel grades, relative frequencies of the number of slabs as well as the number of different campaigns which contain steel grades from the respective community plus the mean carbon content for each community of steel grades in Fig. 4.

Community/ Metric	Number of Steel Grades	Slab Frequency	Campaign Frequency	Mean Carbon Content
1 (purple)	33	0.5620	0.5714	0.053
2 (blue / grey)	16	0.4343	0.4277	0.222
3 (turquoise)	4	0.0032	0.0070	0.004
4 (green)	3	0.0002	0.0008	0.004
5 (yellow)	3	0.0003	0.0026	0.056

2008; Tang, Wang, & Chen, 2014), improved product quality (Tang & Wang, 2008), enhanced order punctuality (Naphade, Wu, Storer, & Doshi, 2001), and increased financial benefits (Tang, Meng, Chen, & Liu, 2016).

Most articles in this review do not provide information on how their algorithms select orders in detail. For example, does “suitable steel grade combinations” (Tang, Wang, & Chen, 2014; Tang, Meng, Chen, & Liu, 2016) include every chemical element that is typically comprised in steel? In fact, steel manufacturers rely on very unique steel grade classifications aside from the publicly available industry standards. So, in some cases, a certain steel grade would conform to a precise percentage of an arbitrary element, while in others a large range of content values is implied. Analogously, “comparable carbon contents” (Tang, Wang, Liu, & Liu, 2011) could mean that only marginal carbon fluctuations are permitted within a production campaign or it could correspond to groups of steel grades with mutually exclusive carbon equivalents (i.e. low carbon / high carbon grades). However, in order to make planning support systems implementable in real-life steel factories, it is necessary to answer these issues meticulously, or else these systems will perform worse than fully manual scheduling due to multiple arguments given in the literature: The chemical transitions between consecutively processed steel slabs are not to be modified exceedingly (Tang, Luh, Liu, & Fang, 2002; Tang & Wang, 2008), because variations of the slab hardness deteriorate the wear of the rollers (Chen, Yang, & Wu, 2008) and call for adjustments of the rolling pressure, which in turn are detrimental to the steel quality (Cowling, 2001; Cowling, 2003). Moreover, changing the chemical composition from one slab to the next prompts a transition steel grade (Tang, Wang, & Chen, 2014), which does not meet the customer requirements and consequently is of lower economic value (Lee, Murthy, Haider, & Morse, 1996; Tang & Wang, 2008; Dorn & Slany, 1994). Our experiments (“5. Results and Discussion”) will try to confirm the practical validity of some chemical constraints based on historical production data.

3. Background information and theory

In this chapter, we summarize the theory regarding association rules mining and complex networks. The background information given here will help to understand the “Methods” and “Results” sections.

3.1. Association rules

In 1992 Julander wrote up one of the first studies of association rules as a market basket analysis (Julander, 1992). By evaluating supermarket receipts he was able to infer which articles were usually bought together. Shortly after, Agrawal et al. supplied a mathematical definition of association rules along with a method that efficiently finds them – the so-called Apriori algorithm (Agrawal, Imieliński, & Swami, 1993; Yuan, 2017; Ghafari & Tjortjis, 2019). Since association rules might be unmanageable and untransparent, several sophisticated visualization techniques (Hahsler & Karpienko, 2017) and interest measures (Agrawal, Imieliński, & Swami, 1993; Brin, Motwani, Ullman, & Tsur, 1997; Kotsiantis & Kanellopoulos, 2006) have been established.

As mentioned above, association rules are mined through a market basket analysis. The fundamental concepts in market basket analysis are items i_k and transactions $t_n = \{i_g, i_h, \ldots, i_k\}$, where a transaction consists of items that have been purchased simultaneously. In the context of steel production planning, items and transactions are congruent with

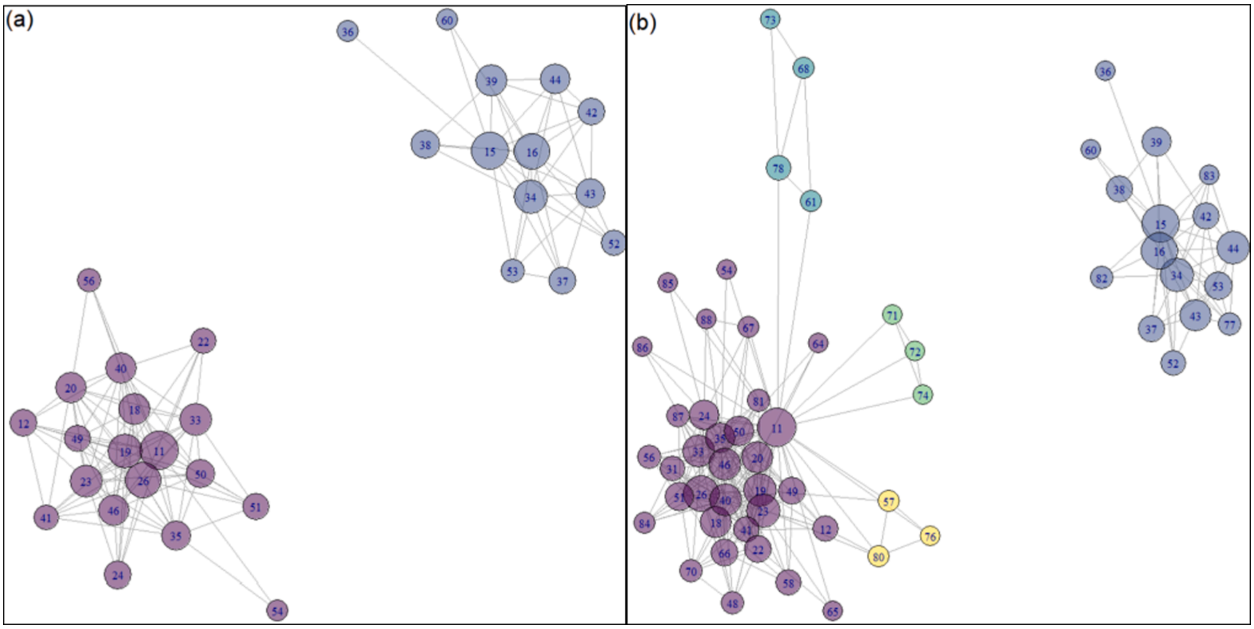

Fig. 5. Results of the community detection algorithm for both the first (a) and final (b) evolutionary stage of the steel grade network; note that Fig. 5 b) is equivalent to Fig. 4.

Table 5
Spearman correlation (degree D vs betweenness centrality BC + clustering coefficient CC vs. betweenness centrality BC) and p-value for the first and final evolutionary stage of the network component associated with lower carbon contents; note that ranking the raw data rows increases the correlations between degree and betweenness centrality as well as clustering coefficient and betweenness centrality tremendously, which could imply that ranked correlation coefficients such as Kendall's Tau and Spearman's Rho may be better suited for our experiments than Pearson's correlation coefficient.

	D vs. BC Start	CC. vs. BC Start	D vs. BC Final	CC vs. BC Final
Correlation	0.93	−0.99	0.80	−0.95
P-Value	$4.2*10^{-9}$	$1.3*10^{-16}$	$6.0*10^{-11}$	$2.5*10^{-15}$

customer orders (or: steel grades) and campaigns of customer orders (or: campaigns of steel grades), respectively. So, when items i_g and i_k are aggregated in transactions, rules in the form of $\{i_g\} \leftrightarrow \{i_k\}$ are extracted from the transaction records. To estimate the accuracy of said rules, market basket analysis resorts to statistical metrics such as support and lift. The support of an item or a group of items is the relative frequency at which the item or the group of items have been selected:

$$Support(i_k) = p(i_k)$$

where $p(i_k)$ denotes the probability that item i_k is selected and.

$$Support(i_g, i_k) = p(i_g, i_k)$$

where $p(i_g, i_k)$ denotes the probability that items i_g and i_k are selected jointly. Resting upon these relative frequencies, the lift (also referred to as "interest") formula is stated here (Brin, Motwani, Ullman, & Tsur, 1997):

$$Lift(i_g, i_k) = \frac{Support(i_g, i_k)}{Support(i_g)*Support(i_k)} = \frac{p(i_g, i_k)}{p(i_g)*p(i_k)}$$

As manifested by this equation, the $Lift(i_g, i_k)$ contrasts the support of an association rule against the hypothetical situation of independently occurring items i_g and i_k. A lift value larger than one means that the corresponding items are co-selected more often than expected by chance.

3.2. Complex networks

The pioneering work of Watts and Strogatz (1998) questioned the popular perception that networks are only seen in one of two very opposite forms: purely ordered or purely disordered. By steadily increasing the total disorder in an otherwise regular network through random edge rewiring, they discovered "small world" networks – a transitional type of network that distinguishes itself by a short characteristic path length similar to random graphs and, at the same time, a high clustering coefficient comparable to regular networks (Watts & Strogatz, 1998; Strogatz, 2001). Milo et al. contrasted complex networks against sets of random graphs to expose few-node sub-graphs objects (network motifs) that appear surprisingly often in complex networks (Milo, et al., 2002). Suitable random graphs were contributed by Erdős & Rényi (1960) and Molly & Reed (1995; 1998). Erdős and Rényi proposed random graphs whose node degree distribution is Poisson-distributed, whereas Molloy and Reed introduced a more adaptable type of network which is dependent on a sequence of node degrees and, therefore, is able to reproduce any kind of degree distribution. An additional third kind is portrayed by random geometric graphs (Dall & Christensen, 2002). They randomly place nodes in a metric space and connect any two nodes that are not further apart than a given cut-off distance.

Girvan and Newman (2002) provided a quantitative, algorithmic framework for identifying network communities – clusters of densely connected nodes (Yang & Leskovec, 2015). As their community detection algorithm yields a complete dendrogram with a vast range of network divisions, it has been suggested to maximize the division's modularity. Modularity specifies the extent to which edges occur in certain parts of the network at a higher frequency than anticipated (Newman & Girvan, 2004; Newman, 2006; Javed, Younis, Latif, & Baig, 2018). Besides, useful network measures, namely the clustering coefficient C_i and the betweenness centrality $b(i)$, were described by Watts & Strogatz (1998) and Freeman (1977), respectively:

$$C_i = \frac{2n}{k_i(k_i - 1)}$$

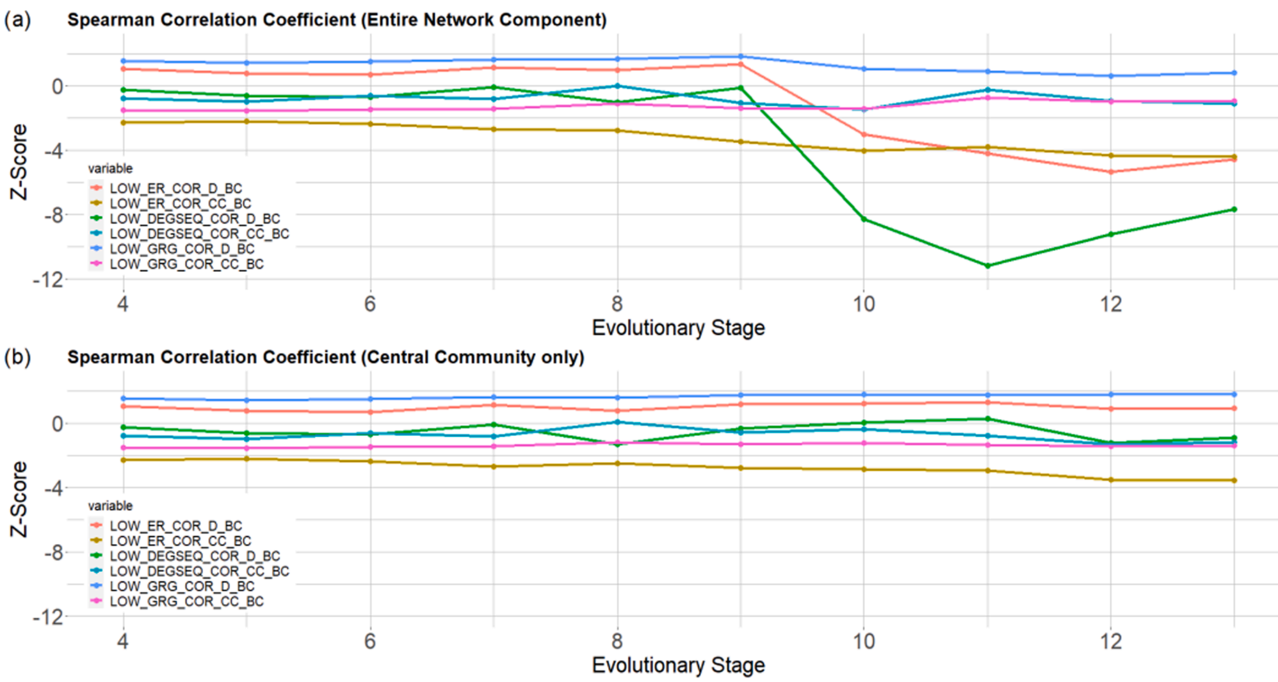

Fig. 6. Z-scores of the entire low-carbon network component (a) / the central community of said network component only (b) for two different Spearman correlations (degree vs. betweenness centrality "COR_D_BC" & clustering coefficients vs. betweenness centrality "COR_CC_BC") and three different types of randomized networks (Erdős-Rényi graph "ER", switch-randomized graph "DEGSEQ", random geometric graph "GRG") against the evolutionary stage; the corresponding Pearson and Kendall correlations are given in the supplements (see Supplements: Fig. S.3 (a) – S.3 (d)).

where k_i / n is the degree / number of nearest neighbors for node i and.

$$b(i) = \sum_{j \neq i \neq l} \frac{s_{jl}(i)}{s_{jl}}$$

where s_{jl} and $s_{jl}(i)$ are the number of shortest paths between nodes j and l in total as well as the number of shortest paths between nodes j and l that go through node i, respectively.

4. Methods

In this section, we shed light on the peculiarities of the data before the exact procedure of our study is clarified.

4.1. Data

The examined production data are made available by a steel production plant where liquid steel is cast into steel slabs and rolled into coils[1]. A sample snapshot of the steel production data is displayed in Table 1. The snapshot contains planning-relevant variables like the customer order's physical dimensions (i.e. width and thickness) and carbon content as well as labels for the respective steel grades and production campaigns. In particular, the grade and campaign labels are extremely valuable to us, as they enable the mining of association rules. While the grade labels represent the chemical ingredients of a customer order, the campaign labels summarize a set of customer orders that were manufactured consecutively. Beyond that, we append a purely theoretical column to the data: To make the temporal analysis of the planning decisions possible, the customer orders are allotted to equally-sized chronological observation windows.

[1] The data are anonymized according to a non-disclosure agreement.

4.2. Exact procedure

For an illustration of the following seven operational steps please refer to the supplements (see Supplements: Fig. S.1). To get an overview of the data, we visually inspect the diversity of the production campaigns concerning the existence of different steel grades. This is accomplished by means of histograms (Step 1: Data visualization). Applying the Apriori algorithm (Agrawal, Imieliński, & Swami, 1993; Yuan, 2017; Ghafari & Tjortjis, 2019) to our production data (with minimum support and confidence values of 10^{-6} each) allows us to construct an association rules network in which the nodes symbolize the steel grades; edges between nodes are drawn for such steel grades that are frequently co-selected (Step 2: Association rules mining). Within this steel grade network, we search for components that may stem from shared external attributes (e.g. chemical composition) of the intra-component nodes. Coloring the network nodes according to those attributes confirms whether the components overlap with changes of the external factors or not (Step 3: Component analysis). Afterward, within these components, we look for non-random topological network fragments such as areas of high edge density (i.e. communities) and we verify their relative contribution to the production output total. If any of the components exhibit intriguing community structures, we proceed to interpret them (Step 4: Community analysis).

Now, we create successive evolutionary versions of the chosen network components by mining association rules in a rolling window approach with increasing window size. Correspondingly, the second evolutionary stage includes the first and second observation window, the third stage includes the first, second, and third window, etc. At first, any nodes that migrate between communities over time are identified. Then, for each node i in our graphs, the degree k_i, the clustering coefficient C_i (Watts & Strogatz, 1998), and the betweenness centrality $b(i)$ (Freeman, 1977) are calculated. Furthermore, we compute the correlations between these quantities as they indicate randomness in networks (Enders, Hütt, & Jeschke, 2018). In order to estimate the magnitude of the detected non-random features (i.e. components / communities), we perform the same correlation evaluation on a large set of randomized

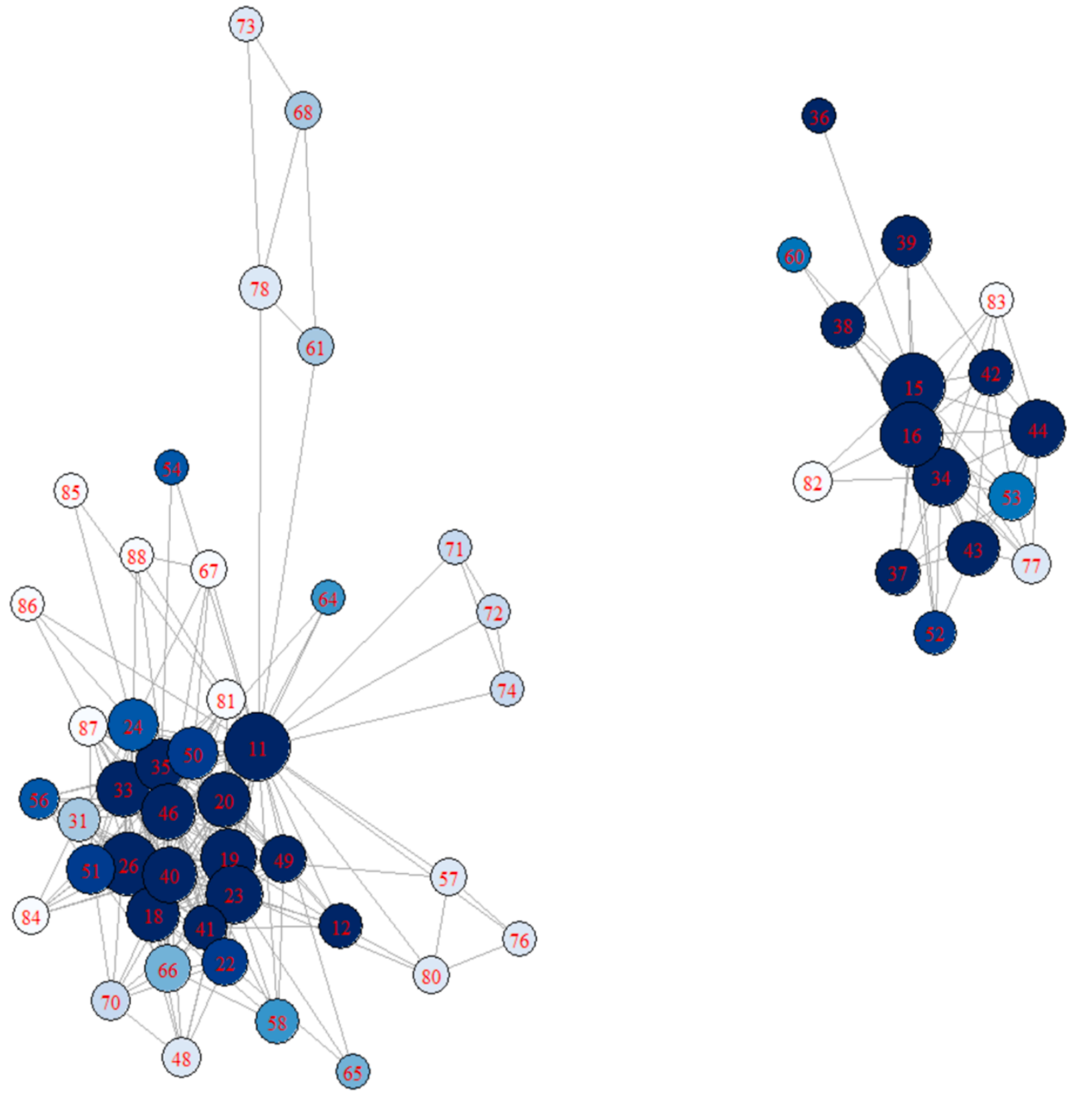

Fig. 7. Steel grade network equivalent to Fig. 4 but instead the nodes are colored corresponding to the node age (i.e. evolutionary stage during which the respective steel grade was introduced; dark blue – old, light blue – young). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

graphs that resemble our steel grade network component as explained in Enders et al. (2018). With regards to this experiment, three distinct types of randomized graphs have been chosen, namely G(n,m)-random graphs according to Erdős and Rényi (1960), switch-randomized graphs (Maslov & Sneppen, 2002) as well as random geometric graphs (Dall & Christensen, 2002). The Erdős-Rényi random graphs are only required to have the same number of nodes (n) and edges (m) as the steel grade network (Erdős & Rényi, 1960); in the case of the switch randomized graphs we conserve the original degree sequence of the steel grade network (Molloy & Reed, 1995; Molloy & Reed, 1998). Conversely, the random geometric graphs only keep the number of nodes constant (Dall & Christensen, 2002). Their cut-off distance is fixed so as to approximately reproduce the total number of edges in the steel grade network.

Consequently, z-scores are determined by quantifying the mean and standard deviation of these correlations for all randomized graphs; we contrast these means against their counterpart-values retrieved from the steel grade network:

$$Z = \frac{X - \mu}{\sigma}$$

where X, μ, and σ are the correlation for the steel grade network, and the mean / standard deviation for all randomized graphs, respectively. The entire procedure is reiterated for different evolutionary stages of the steel grade network, whereby information about the temporal development of the complexity is collected. As we aim to derive planning rules that are valid in the majority of the planning circumstances, we will first concentrate on the dominant communities. Hence, we repetitively prune the network by removing negligible features and we check if the remainder of the network is quantitatively similar to a randomized graph (Step 5: Comparison with random graphs).

Next, we attempt to draw connections between the emergence of the smaller network communities containing some rarer steel grades and the external attributes of these steel grades. Again, this is achieved by coloring the network nodes in compliance with the external parameters. Possible parameters are presented by the average chemical composition of a node or the node age; by node age, we refer to the evolutionary stage during which a given node or steel grade was introduced (Step 6: Complementary analysis).

Once these efforts have yielded universal planning rules, we assess whether it is possible to construct similar steel grade networks by applying comparable rules to simulated data. First, a toy model is deployed which includes a binary canalizing function as the planning rule. The simulated steel grades are essentially multi-dimensional binary vectors where each entry corresponds to a specific chemical element

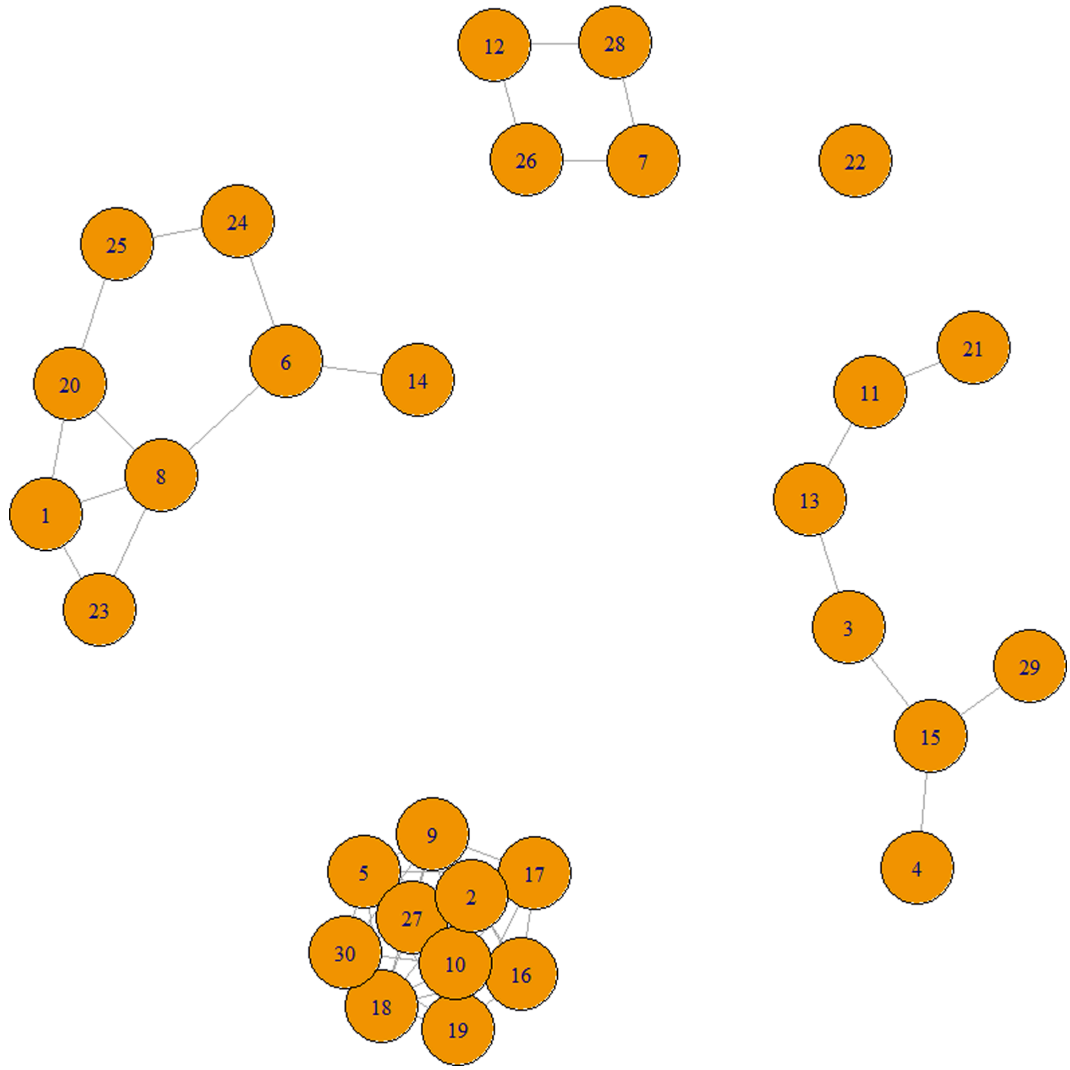

Fig. 8. Synthetic steel grade network resulting from a binary canalizing function; two nodes (steel grades) are connected only if the primary chemical component of both nodes (steel grades) is in the same binary state.

such as carbon or manganese. Now, we obtain a steel grade network by ensuring that steel grades with different entries regarding their primary chemical element (e.g. carbon) cannot be connected. On the other hand, if their primary entries are the same, the respective steel grades may have a link between them as long as at least 50 percent of their remaining entries match each other.

Provided that the simulated steel grade network resembles the actual steel grade network descending from the historical production data, we replace the binary canalizing function by the carbon equivalent (C.E.) formula. The C.E. formula is a weighted sum of multiple elements (e.g. carbon and manganese) that defines the steel's hardness and, thus, its chemical compatibility (Kasuya & Yurioka, 1993; Talaş, 2010):

$$C.E. = C + \frac{Mn}{6} + \frac{Cu + Ni}{15} + \frac{Cr + Mo + V}{5}$$

The letters *C*, *Mn*, *Cu*, *Ni*, *Cr*, *Mo*, and *V* signify the carbon, manganese, copper, nickel, chromium, molybdenum, and vanadium mass percentages of a certain steel grade. For these elements, we generate continuous steel grade data (see sample snapshot in Table 2) instead of binary vectors whereby the distributions of the mass percentages are aligned with our historical production data (see Table 3). For instance, the carbon values come from a bimodal normal distribution while the other elements are unimodally distributed.

At first, based on the steel grade data (see Table 2), we design a single campaign data set similar to the historical production data in Table 1. Thoughout this data set, steel grades g and k are merged in campaigns as long as their C.E. values do not vary significantly. In particular, we match steel grades subject to a probability p_{gk} that linearly depends on the C.E. difference between them. As reference for the maximally allowed C.E. difference, the maximum C.E. transition that appeared within any actual production campaign (=> 0.21 mass percentages) of the historical data is selected:

$$p_{gk} = \begin{cases} \left(1 - \frac{|C.E._{\cdot g} - C.E._{\cdot k}|}{0.21}\right) & if |C.E._{\cdot g} - C.E._{\cdot k}| \leq 0.21 \\ 0 & if |C.E._{\cdot g} - C.E._{\cdot k}| \rangle 0.21 \end{cases}$$

Now, we pick two steel grades from our steel grade data (see Table 2) by chance and combine them in a production campaign if a uniformly $U(0,1)$-distributed random number falls below their respective merging probability. This procedure is repeated until we have reached the target number of production campaigns. As before, association rules are extracted from these synthetic production campaigns and the resulting steel grade network is inspected visually.

Assuming that the synthetic steel grade network resembles the historical steel grade network, we analyze the effect of the maximally allowed C.E. difference on the shape of the network. In dependence of this cut-off distance (0.010 – 0.060 carbon mass percentages), the

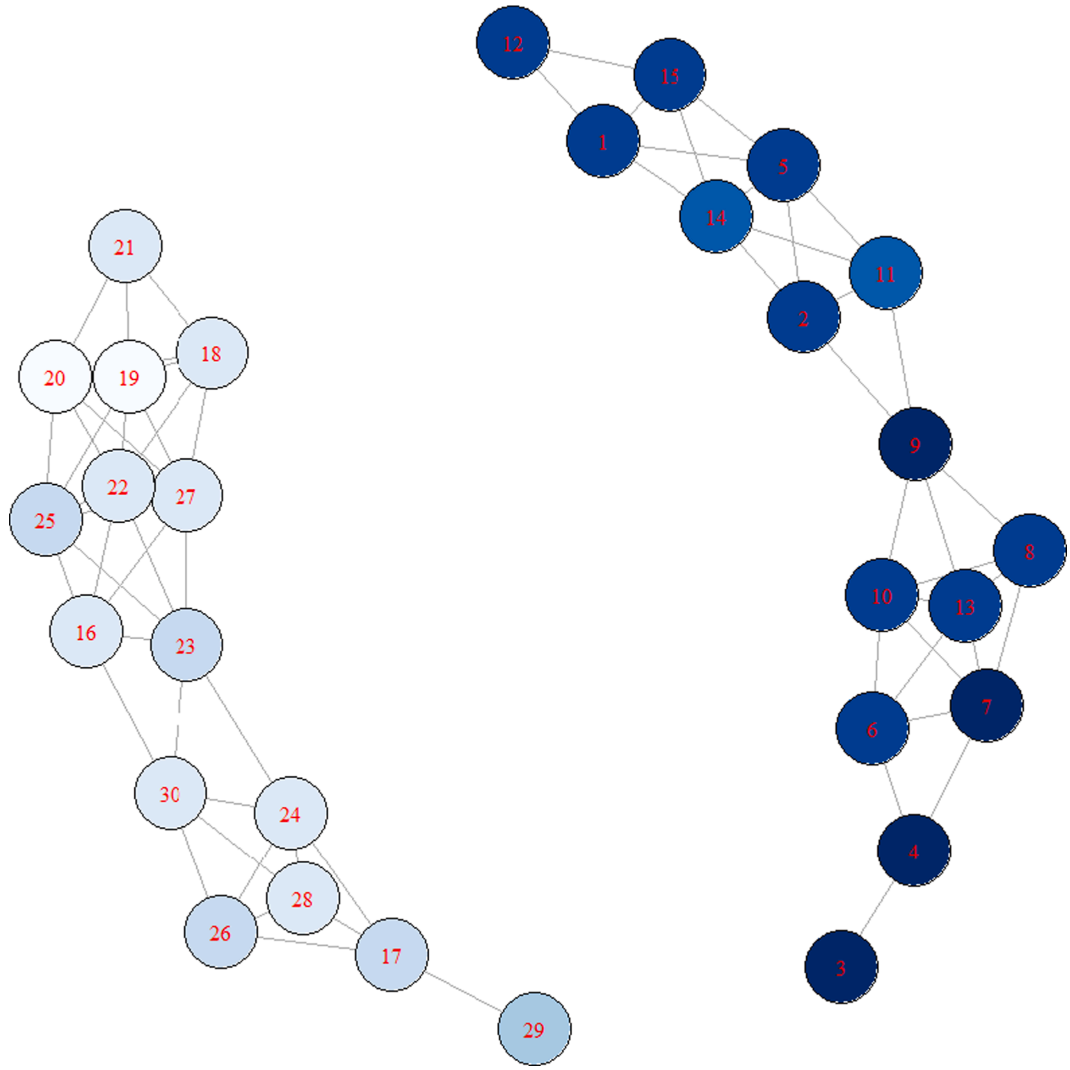

Fig. 9. Synthetic steel grade network resulting from the a canalzing function that is based on the C.E. formula (Kasuya & Yurioka, 1993; Talaş, 2010); two nodes (steel grades) are connected only if the C.E. difference between both grades is smaller than the maximum C.E. difference (=> 0.21 carbon mass percentages) found within any historical production campaign.

components are counted for a large volume of synthetic steel grade networks. Since deducing association rules networks from production data sets is computationally very expensive, we have decided to build graphs from the steel grade data directly. For this purpose, random geometric graphs are formed whereby the distance between nodes corresponds to the C.E. difference between steel grades and links are drawn for such nodes that are no further apart than the cut-off distance (Step 7: Carbon equivalent simulations).

5. Results and discussion

In this chapter, we will demonstrate the results acquired by carrying out the procedural steps from section 4.3.

Step 1 (Data visualization): As mentioned previously, the experiment data entail, inter alia, two crucial features: a label for each (i) steel grade and (ii) production campaign (see Table 1). Normally, one or several steel grades are integrated by the human expert planner into every production campaign (see Fig. 2 (a)). The bar plot in Fig. 2 (b) highlights the dataset composition in terms of steel grades. Note the rich combinatorics arising from the number of different steel grades in a campaign and the variety of steel grades in the whole dataset. Selecting the optimal combination of steel grades might therefore pose a difficult challenge for the human mind. However, visualizing these combinatorics through histograms (or below association rules networks) can help less experience planners to fathom the complexity of both the problem itself as well as the tacit knowledge needed to solve it.

Step 2 (Association rules mining): Mining the patterns of steel grade co-selections discerned in the production data leads to the steel grade network in Fig. 3 (a). The list of association rules for this network is reported in the Supplements (see Table S.1). Besides the rules we display their support and confidence values. In order to reduce automation bias, decision-support systems should incorporate these values and express how confident they are about their advice.

Step 3 (Component analysis): Fig. 3 (a) reveals the existence of two independent steel grade groups whose individual constituents are commonly selected for joint production, whereas no such links exist between those two groups. Interestingly, this separation of steel grades coincides with a transition of carbon contents (see Fig. 3 (b)). Obviously, the first group comprising steel grades 11, 23, 26, and numerous less regularly fabricated steel grades has a lower mean carbon content than the second group (15, 16, 34, 44, etc.). These results align with the academic insights listed earlier, as the hardness of a steel grade – and thereby the carbon content – essentially dictates its linkability with other grades (Kosiba, Wright, & Cobbs, 1992; Chen, Yang, & Wu, 2008). We did not discover equivalent rules for other elements like manganese, silicon, or titanium (see Supplements: Fig. S.2 (b) - S.2 (d)) which is

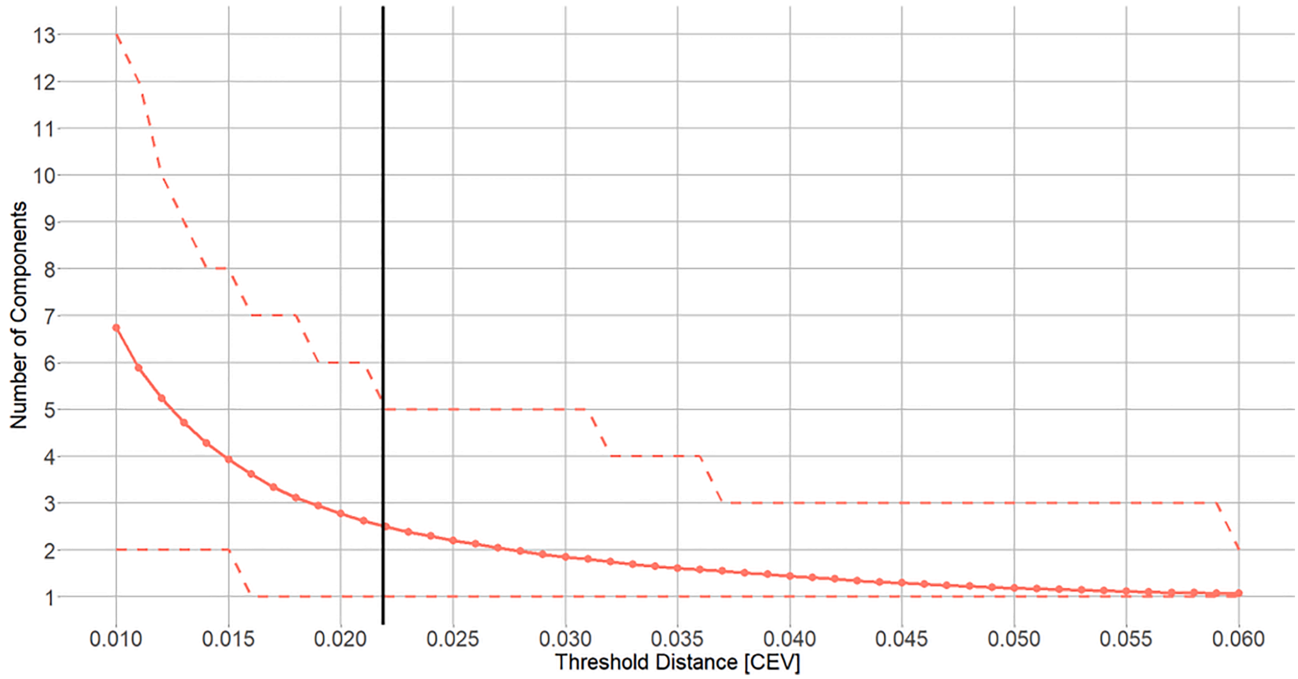

Fig. 10. Number of components vs. C.E. cut-off distance for geometric random graphs where the synthetically generated steel grades are only connected if they are no further apart than the threshold distance; the red full line signifies the mean number of components, while the dashed lines stand for the minimum and maximum number of components for each cut-off distance value; the actual cut-off distance found in the historical production data is marked by the black vertical line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

unexpected since the exact contributions of these elements are considered to be important by the pertinent literature (see Sub-section 2.6).

Step 4 (Community analysis): Nevertheless, how these trace elements influence the decision process could be mirrored in the internal structure of the two carbon-related network components. That is why we break down the steel grade network from Fig. 3 (a) into a number of communities and color its nodes accordingly (see Fig. 4). It becomes apparent, that the network carbon component associated with lower carbon contents exhibits one massive community in the center plus three small peripheral communities. An analysis of the relative frequencies of the steel grades within each community (see Table 4) discloses that the peripheral communities contribute a negligible production output, and, hence, we can focus on the central community first. Under this assumption, we conclude that merely sorting the pending customer orders based on their carbon contents and co-selecting orders with similar carbon contents is a reasonable selection strategy regarding the mixing of steel grades.

Step 5 (Comparison with random graphs): Network communities are only one possible non-random feature of such selection strategies. Other features may be indicative of the impact of trace elements like manganese, titanium and, silicon on the planning procedure. Thus, we want to estimate the network's extent of randomness beyond the already confirmed carbon-related network components by studying the steel grade network as a function of increasing data volume (see Methodology: rolling window approach with increasing window size). To begin with, it is confirmed that there are no nodes that travel between the communities over time (see Supplements: Table S.2). Then, for successive evolutionary stages of the low-carbon network component, we compute every node's degree, clustering coefficient, and betweenness centrality and measure their correlations.

Only the first and the last evolutionary stage of the steel grade network are portrayed here (see Fig. 5 (a) + 5 (b); note that Fig. 5 (b) is equivalent to Fig. 4). Table 5 summarizes the correlations for the ranked distributions of degree, clustering coefficients, and betweenness centralities in both the first and the final evolutionary stage. As all four correlations are quite large, it is safe to assume that the selection of steel grades underlying the low-carbon network component involves an enormous amount of randomness. Whether the decrease in correlation from the first to the last evolutionary stage is accompanied by a more systematic growth of the steel grade network over time and whether this has something to do with trace elements will be addressed in the following paragraph.

Constructing a substantial number of randomized graphs of three types – namely Erdős-Rényi random graphs, switch-randomized graphs as well as random geometric graphs – permits for the assessment of randomness in the low-carbon network component via z-scores. Fig. 6 (a) documents the z-scores of the entire low-carbon component including all four communities for two different Spearman correlations (degree vs. betweenness centrality COR_D_BC & clustering coefficients vs. betweenness centrality COR_CC_BC) and three different types of randomized graphs (Erdős-Rényi graph ER, switch-randomized graph DEGSEQ, random geometric graph GRG) against the evolutionary stage. After the ninth evolutionary stage the z-scores for LOW_ER_COR_D_BC and LOW_DEGSEQ_COR_D_BC experience a downtrend, which does not show itself in Fig. 6 (b) where we calculated the same set of z-scores, but this time we omitted the three peripheral communities. Note that we enclosed the boxplots for the Spearman z-scores of both the first and the final evolutionary stage to the supplements because they offer an intuitive visualization of how z-scores form (see Supplements: Fig. S.4 (a) - S.4 (d)). The fact that the z-scores in Fig. 6 (b) are much closer to zero than in Fig. 6 (a) suggests that, indeed, the non-random features are a consequence of the three peripheral communities. Likewise, since all but one z-score in Fig. 6 (b) persistently have a magnitude below 2 we underscore the great level of randomness in the central community which indicates a lack of universal selection rules in addition to the carbon content selection rule.

Step 6 (Complementary analysis): Still, it is instructive to also study the emergence of other non-random features such as the peripheral communities in the low-carbon network component. We already know that those communities are responsible for only a small fraction of the factory's production output. Moreover, many of the marginal steel grades and the peripheral communities, in particular, vary from the bulk of the steel grades concerning two external attributes: node age (i.e. during what evolutionary stage did the node occur for the first time) and node chemical composition. Fig. 7 displays the same steel grade network as Fig. 4, but instead it colors the nodes according to their age (dark blue - old age, light blue - young age). Evidently, the peripheral nodes were appended to the network later than most central nodes (as previously anticipated by Fig. 6).

Again, this supports the claim that simply complying with the carbon content constraint is already sufficient for the majority of the steel grade selection decisions. On the contrary, Fig. S.2 (b), S.2 (c) and, S.2 (d) testify to the slightly dissimilar chemical compositions of the peripheral steel grades compared to the bulk, as these three figures color the network nodes in agreement with the mean concentrations of the chemical elements manganese, silicon and titanium (dark blue - low content, light blue - high content). So, although the combination strategy of steel grades within the network components is not mainly defined by the concentration of chemical elements other than carbon, these elements might however guide the steel grade selection in individual cases. Besides the prominence of the carbon content, other planning parameters such as the slab thickness and width are also recognized for their effect on selection decisions since their association rules networks have striking non-random features (see Fig. S.5 (a) and S.5 (b)).

Step 7 (Carbon equivalent simulations): At last, we attempt to explicate the shape of the steel grade network through simulations with canalyzing functions such as the carbon equivalent (C.E.) formula. Fig. 8 discloses the results of the earlier established steel grade network toy model (see Section 4: "Methods") that is based on a binary canalizing function. The steel grade network comprises synthetically generated steel grades whose individual chemical elements are merely binary expressions; links between any two steel grades are only drawn if the primary chemical element (e.g. carbon) of both grades is in the same binary state or if at least 50 percent of the other elements concur.

Obviously, the canalizing function of the toy model yields a fragmented network similar to the actual steel grade network from the historic production data (see Fig. 3 (a)). This proves that relying on a simplistic steel grade selection rule (such as not trying to not mix different carbon groups) may cause non-trivial association rules network structures. However, the actual steel grade network only features two components which is why we have decided to repeat this experiment with continuous synthetic variables instead of binary ones (see Fig. 9). In addition, we have replaced the binary canalizing function by the carbon equivalent (C.E.) formula (Kasuya & Yurioka, 1993; Talaş, 2010). As described above, the steel grades are connected via links according to a probability that linearly depends on the C.E. difference between the respective grades (see Section 4: Methods).

Fig. 9 demonstrates that the combination of the C.E. formula and a maximally allowed C.E. difference of 0.21 carbon mass percentages can lead to a steel grade network with only two components. Therefore, the dominance of the carbon content in steel grade selection decisions is further accentuated. Nevertheless, Fig. 9 is of course only a snapshot from a single synthetic production dataset. Hence, we create a number of synthetic datasets and measure the number of components in dependence of the maximally allowed C.E. difference (see Fig. 10).

Fig. 10 verifies that the average number of components for a cut-off distance of 0.21 carbon mass percentages is two and a half which roughly matches the number of components in the actual steel grade network from the historical production data. Given that the theoretically allowed C.E. difference might be greater than the recorded 0.21 carbon mass percentage we can assume that the carbon equivalent and, thus, the steel's hardness governs the steel grade selection most certainly. Ergo, the universal planning rule extracted from our historical production data says "within the same steel campaign, do not combine steel grades whose C.E. values are further apart than 0.21 mass percentages". By braking down the complexity of the grade selection process into such a simple rule, we facilitate the transfer of expert knowledge within the steel industry towards both less informed human planners and automated decision support systems.

6. Conclusion

This article successfully formalizes tacit knowledge entrenched in the steel manufacturing process (to be precise: in the selection of suitable customer orders for immediate production). We have determined the significance of various planning parameters by deploying a mixture of data visualization, association rules mining, complex network methods, and network simulations with canalyzing functions. The central message resulting from these analyses is that, within the same production campaign, the carbon equivalent gap between customer orders is not supposed to exceed ca. 0.21 mass percentages.

To a large extent, our outcomes coincide with common knowledge about the interplay of different chemistry-related factors – with the exception that, in our dataset, elements other than carbon are routinely disregarded during the order selection process. For example, the concentration of trace elements like manganese, silicon, and titanium seems to play a tangential role in real-world factory decisions. This finding contradicts the existing literature about steel production planning constraints, as the exact chemical composition of consecutive steel grades should technically affect the steel quality (Tang, Wang, & Chen, 2014; Lee, Murthy, Haider, & Morse, 1996; Tang & Wang, 2008). Whether the lack of trace element consideration stems from the cognitive inability of the human expert planner to incorporate several planning constraints in the same instance or other commercial planning objectives (e.g. due date) are plainly more important needs to be discussed in future research.

Our results facilitate knowledge management by explaining which planning goals or constraints cannot be relaxed if the schedule preparation appears infeasible. Consequently, if a company's human expert planner is absent, less informed planners could benefit from our experiments and build on the expert planner's know-how. On top of that, our method helps in any situation where an automated order suggestion algorithm has to be configured based on implicit selection criteria that derive from fundamental technological production principles. Thanks to our work, such algorithms should be able to prevent adverse phenomena like automation bias by highlighting the extracted selection criteria that led to a certain order suggestion (Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003; Goddard, Roudsari, & Wyatt, 2012) or by expressing their confidence regarding this suggestion through association rules interest measures (McGuirl & Sarter, 2006; Goddard, Roudsari, & Wyatt, 2012; Wickens, Clegg, Vieane, & Sebok, 2015).

Generally, we advocate for a stronger focus on network-aided planning and scheduling methods since they provide an intuitive representation of the problem circumstances. The above case study has already shown that network-aided methods can effectively elicit tacit manufacturing knowledge which is something that explication interviews between experts and knowledge engineers often fail to do because of human errors (Madni, 1988). Especially when it comes to weighting the importance of several competing planning parameters (e.g. various chemical elements), humans are prone to making mistakes (Madni, 1988). Also, as opposed to occupying the experts for extended periods of time for such interviews, we can effortlessly apply our methods to historical production datasets and, therefore, save time and money.

To put into perspective how much could be saved by transfering the extracted tacit knowledge to less experienced human planners or automated decision-support systems, we have performed some rough calculations: If the amount of devaluated steel is just reduced by one heat (equivalent to ca. 150 tons of steel) per day, then, the respective factory saves more or less 100 thousand dollars daily (=> 36.5 millions yearly) under the current prices for hot-rolled coils. For a factory like the one considered in (Merten, Hütt, & Uygun, 2021) this sums to a reduction of approximately 3.5 percent. In case the respective factory further processed their coils on subsequent production lines such as the pickling or the galvanizing line, this reduction could be even larger due to the increased value of such products.

CRediT authorship contribution statement

Daniel Christopher Merten: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Marc-Thorsten Hütt:** Conceptualization, Methodology, Validation, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Yilmaz Uygun:** Conceptualization, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cie.2022.108120.

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