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Process Mining in production to optimize milling tool usage

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1. Problem statement

- High costs for milling tools in machining (Fig. 1) and missing root cause:
  - No transparency about real tool wear
  - Different operating lifetimes due to heuristics-based setup and exchange of milling tools by workers
- Task: Perform association analysis to determine relationships and influencing factors on tools' lifetime* and determin suitable measures to optimize tool usage in machining

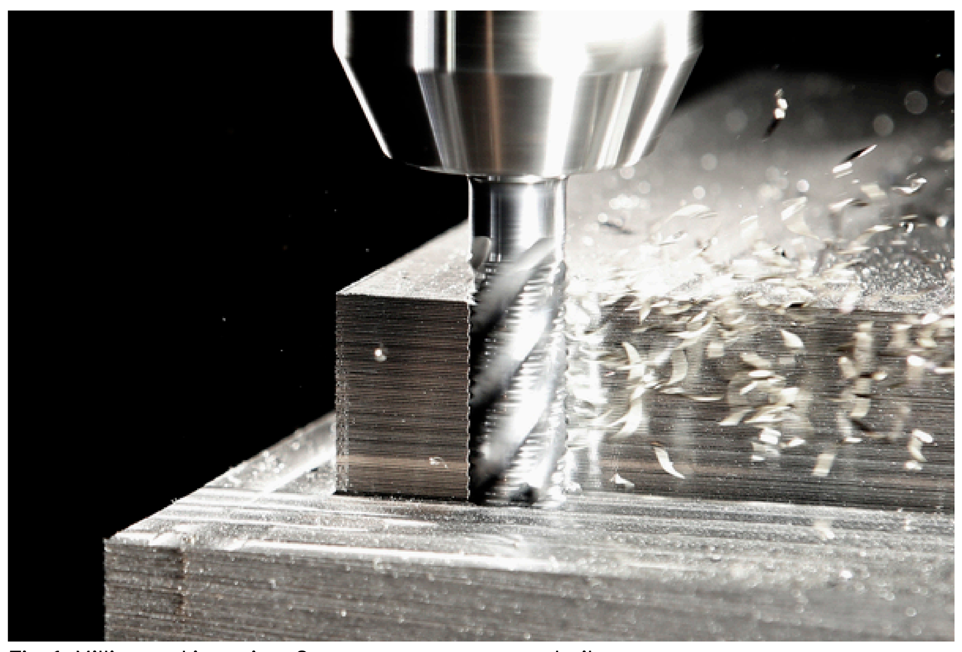

Fig. 1: Milling tool in action. Source: zerspanungstechnik.at

*measured by parts produced during lifetime

2. Data processing

Table 1: Raw data from machining before processing.

	wpd	werkzeug	wechseltyp	auftrittszeitpunkt	aenderung_um	ist	soll	cycle
0	331348	2024	abnutzung	2020-01-08 16:13:00	-1	866	2000	1
1	331348	2005	abnutzung	2020-01-08 16:13:00	-1	85	200	1
2	331348	2021	abnutzung	2020-01-08 16:13:00	-1	190	300	1
3	331348	2017	abnutzung	2020-01-08 16:13:00	-1	3	100	1
4	331348	2030	abnutzung	2020-01-08 16:13:00	-1	448	1500	1
...	...	...	...	...	...	...	...	...
224528	367402	2027	abnutzung	2019-10-24 00:15:00	-1	25	300	64
224529	367402	2027	abnutzung	2019-10-24 00:17:00	-1	24	300	64
224530	367402	2027	abnutzung	2019-10-24 00:20:00	-1	23	300	64
224531	367402	2027	abnutzung	2019-10-24 00:22:00	-1	22	300	64
224532	367402	2027	abnutzung	2019-10-24 00:24:00	-1	21	300	64

224533 rows × 8 columns

Data processing

- Adding cycle and lifetime values
- Discretize lifetime groups (A, B, C)
- Clean data and remove outliers

Table 2: Prepared data to perform association analysis

	wpd	werkzeug	wechseltyp	auftrittszeitpunkt	aenderung_um	ist	soll	cycle	lifetime	ltgroup	year	month	weekday	shift
0	331348	2005	gratbildung	2020-01-09 00:56:00	151	200	200	2	252	A	2020	January	Thursday	night
1	331301	2005	verschleiss	2020-02-28 00:01:00	190	200	200	3	72	C	2020	February	Friday	night
2	331301	2005	gratbildung	2020-02-28 05:45:00	72	200	200	4	167	C	2020	February	Friday	early
3	331301	2005	undefiniert	2020-02-28 21:47:00	167	200	200	5	231	A	2020	February	Friday	late
4	331301	2005	verschleiss	2020-02-29 19:57:00	199	200	200	6	328	A	2020	February	Saturday	late
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
825	331003	2006	verschleiss	2019-11-05 16:12:00	130	130	130	50	176	A	2019	November	Tuesday	late
826	331003	2006	verschleiss	2019-11-06 19:11:00	128	130	130	51	127	B	2019	November	Wednesday	late
827	331003	2006	verschleiss	2019-11-07 15:22:00	127	130	130	52	137	A	2019	November	Thursday	late
828	331003	2006	verschleiss	2019-11-08 14:40:00	125	130	130	53	154	A	2019	November	Friday	late
829	367023	2006	gratbildung	2019-11-29 01:47:00	117	130	130	54	110	C	2019	November	Friday	night

830 rows × 14 columns

3. Method

- Association analysis based on apriori algorithm (Fig. 2):
  - Support: $$Support\ (X \rightarrow Y) = \frac{X \cup Y}{n}$$
    → Frequency on how often X (premise) und Y (Consequence) appear together in data (i.e. all tools used)
  - Confidence: $$Confidence\ (X \rightarrow Y) = \frac{supp(X \rightarrow Y)}{supp(X)}$$
    → Frequency on how often Y appears if X appears
  - Lift: $$Lift\ (X \rightarrow Y) = \frac{supp(X \rightarrow Y)}{supp(X) * supp(Y)}$$
    → Factor of increase in expectation that Y appears with X

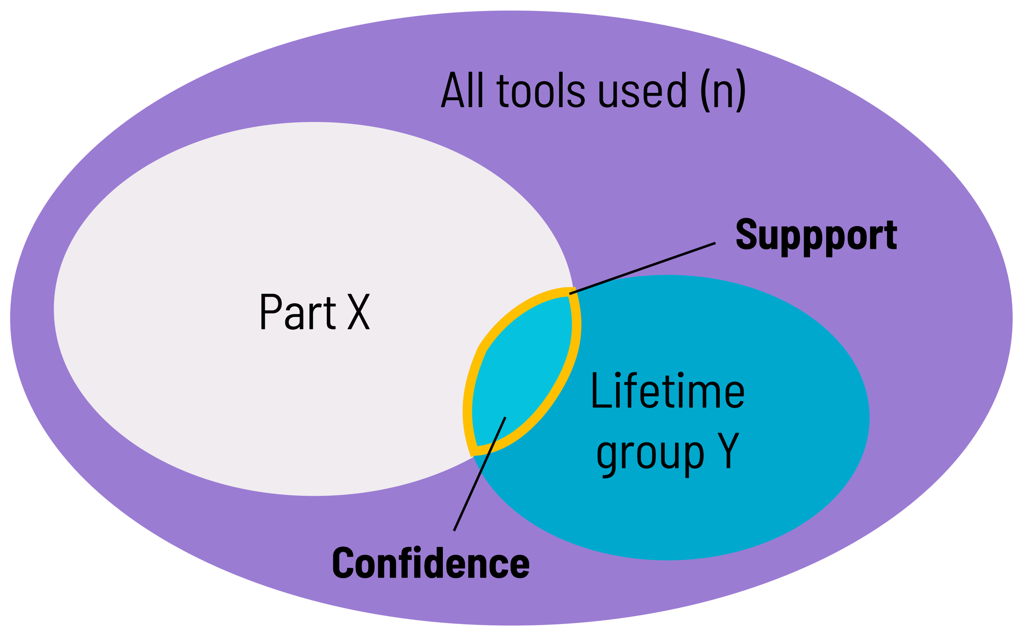

Fig. 2: Venn-Diagram of association analysis figures. Own representation.

4. Results

Table 3: Exemplary results of association analysis.

antecedents	consequents	support	confidence	lift
1 ({Part A, 'Tool 1'})	({'C'})	0,09264305	0,83950617	2,307855921
({'Tool 2', Part B})	({'C'})	0,00681199	0,83333333	2,29088639
({'Tool 3', Part C})	({'C'})	0,01226158	0,75	2,061797753
({'Tool 4', Part C})	({'C'})	0,01226158	0,75	2,061797753
2 ({Part D, 'Tool 5'})	({'B'})	0,00817439	0,75	2,274793388
({'Tool 6', Part A})	({'B'})	0,01362398	0,66666667	2,022038567
({'Tool 7', Part E})	({'A'})	0,00953678	0,63636364	2,075959596
({'Tool 3', Part F})	({'C'})	0,01089918	0,61538462	1,691731489
({'Tool 8', Part E})	({'B'})	0,01089918	0,61538462	1,866497139
({'Tool 7', Part C})	({'A'})	0,01498638	0,57894737	1,888654971
({'Tool 6', Part F})	({'B'})	0,01089918	0,57142857	1,733175915
({Part A, 'Tool 9'})	({'C'})	0,02316076	0,56666667	1,557802747
({'Tool 10', Part C})	({'A'})	0,01362398	0,55555556	1,812345679
({Part D, 'Tool 11'})	({'B'})	0,00817439	0,54545455	1,654395192

Interpretation:

1 84% of tool 1 which produced part A had lifetimes below 95% of setpoint (=lifetime group C). The combination of part A, tool 1 and lifetime group C appears in almost 10% of the data (support) and it is 2,3 times more likely that the combination will happen again.

2 75% of tool 5 which produced part D had lifetimes around 95% to 105% of setpoint (=lifetime group B). The combination of part D, tool 5 and lifetime group B appears in less than 1% of the data (support) and it is 2,3 times more likely that the combination will happen again.

5. Future Perspective

- Individual tool settings for each tool-part-combination to optimize tool usage
- Use of model as data-based decision support regarding tool exchanges and tool life adjustments which could also be replenished by cost/time optimized tool changes (Fig. 4)

Fig. 3: Visualization of data-based decision support.

Literature

Sasse, J. (2020): *Process Mining in der Produktion – Durchführung einer Datenanalyse in der spanenden Fertigung*. Master Thesis, RWU.

Cleve, J. & Lämmel, U. (2016): *Data Mining*. De Gruyter Studium, 2nd ed., Berlin: De Gruyter.

Kröckel, J. (2019). *Data Analytics in Produktion und Logistik*. 1. Auflage, Vogel Communications Group GmbH & Co. KG.