Visualizing and mitigating delivery schedule deficiencies and inaccuracies using big data analytics

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Abstract
The purpose of this paper is to describe and categorize deficiencies and inaccuracies in delivery schedules shared in European automotive supply chains, and to propose how to monitor and mitigate delivery schedule deficiencies and inaccuracies. We analyse 2.9 million schedule records received by a supplier during two years. Findings do not identify any critical data deficiencies but describes the existence of time and volume related schedule inaccuracies. It proposes mitigation strategies for monitoring these two inaccuracy types, and strategies for handling inaccuracies and schedule groups with perfect forecasts.

Keywords: Big data, Information sharing, delivery schedules, Supply chain management

Introduction
Studies show that delivery schedules are commonly used for supply chain information sharing (Wang et al., 2016a), but due to schedule quality deficiencies (e.g. missing values, incorrect coding) and inaccuracies (i.e. deviation between planned and ordered volumes) the information is not used as intended (Jonsson and Myrelid, 2017) and/or result in unnecessary rescheduling, reworking, safety mechanisms, backlogs and follow-ups (Myrelid, 2017). Studies also show that schedule inaccuracies may escalate upstream supply chain tiers (Forslund and Jonsson, 2007), and that the extent depends on item commonality, planning frequency, planning period, frozen period (e.g. Myrelid, 2017). Consequently, studies identify that delivery schedules are widely adopted in practice and that they are associated with deficiencies and inaccuracies. Still, no identified study has detailed and empirically analyzed the commonality or severance of deficiencies and inaccuracies, their distribution between item categories, or identified their major causes. Such studies would be necessary in order to design and suggest mitigation strategies to improve delivery schedule quality and its efficient and effective supply chain usage. Delivery schedule data contain a large amount of records (normally millions of records a year for a supplier in the automotive industry – as this study focuses on), and is updated on a daily basis. Consequently, this data is big in terms of volume and velocity (Wang et al., 2016b). Both analyzing delivery schedule data, and mitigating schedule deficiencies and inaccuracies, therefore, calls for big data related analytics. The purpose of this paper is to describe and categorize deficiencies and inaccuracies in delivery schedules shared in European automotive supply chains, and to propose how to mitigate delivery schedule deficiencies and inaccuracies.

Literature review

This study focuses on sharing delivery schedule information in supply chains. A delivery schedule is defined as 'the required or agreed time or rate of delivery of goods and services purchased for a future period' (Blackstone, 2010). Delivery schedules contain planned order and call-off information on various planning horizons. The order information can be expressed in different planning buckets – normally varying between days, weeks and months. Common way of transmitting delivery schedules is through electronic data interchange (EDI), which allows for automatic data interfaces between sender and receiver. The following sub-sections define delivery schedule deficiency and inaccuracy and generates the research questions to guide the case analysis and discussion.

Defining delivery schedule deficiency and inaccuracy

For value adding information sharing in supply chains it is not enough to widely visualize and share information, for example, by sharing delivery schedules using EDI. Information also needs to be of high quality (Forslund and Jonsson, 2007) and be used by the information receiver as discussed by, for example, Jonsson and Myrelid (2016). Literature has presented several dimensions of information quality (Gustavsson and Wänström, 2009). For delivery schedules, as this study focuses on, we distinguish between delivery schedule data deficiency and delivery schedule inaccuracy. A schedule deficiency is a formal error in a delivery schedule record. It could, for example, be incorrect or lack of relevant item number or delivery date. Delivery schedule deficiency relates to what literature refers to as information quality incompleteness or inconsistency (e.g. Gustavsson and Wänström, 2009). Delivery schedule inaccuracy is defined as forecast inaccuracy and corresponds to the information quality dimensions of accuracy or reliability (Gustavsson and Wänström, 2009). Delivery schedule inaccurate can be inaccurate in two ways: Firstly, it can have large volume changes, which normally is expresses as forecast accuracy. Here we call this type of inaccuracy for volume inaccuracy, and define schedule information to have large volume change if the standard deviation of the schedules for a specific item to a specific shipping address and specific delivery date is larger than a specific reference volume (e.g. the mean of all schedules). Secondly, it can have late volume changes. Late volume changes are especially problematic if occurring within the receiving organisation's frozen period. We call this second type of inaccuracy time inaccuracy, and measure it as a changed volume (no matter size of change) within the receiving organisation's frozen planning period. .

Analysing and improving delivery schedule sharing – research questions

Literature indicate that delivery schedules communicated in supply chains contain large variations on item level. A study of Swedish suppliers in the automotive industry show that about 10% of all items included in delivery schedules have very high volume uncertainty (Bystedt, 2015). Literature also indicate that no formal schedule accuracy measurement is carried out or communicated in supply chains which share delivery schedule information. A reason for this is the lack of in industry standards and IT tools to measure, monitor and communicate schedule inaccuracies. As emphasized by for example APICS (2018) and Barratt and Oke (2007), visualizing and communicating plan and schedule variations and uncertainties in supply chains are central for being able to proactively plan for existing inaccuracies, in for example what-if and scenario analysis. It is also necessary for being able to identify and eliminate unnecessary deficiencies and inaccuracies. The problems of varying and inaccurate delivery schedules have especially been identified in the automotive industry where its use is widely spread. For example, Wang et a., (2016a) and VDA (2010) identify problems with EDI based delivery schedule sharing and call for analyses of schedule variations and new ways of communicating future demand in automotive supply chains.

Delivery schedule data contains a large amount of data records and is normally updated on a daily basis. Just for one company, millions of delivery schedule records can be received during a year. Consequently, delivery schedule can be defined as big data – fulfilling the volume and velocity dimensions of common big data definitions (e.g. Wang et al., 2016b).

Consequently, we see a potential in analyzing existing delivery schedule data to explore what type of deficiencies and inaccuracies it contains for a supplier in the automotive industry. Such analysis and insights should be important input for suggesting accuracy measurement, schedule monitoring and mitigation design propositions. Because of the large amount of data, both analyzing delivery schedule data, and carrying out proposed designs therefore, call for big data related analytics. The following research questions are generated to guide our empirical analysis and discussion:

RQ1: What is the amount and type of data deficiencies in current automotive supply chain delivery schedules?

RQ2: To what extent are delivery schedules inaccurate, and what characterize delivery schedules with low relative accuracy?

RQ3: How could delivery schedule (a) deficiencies and (b) inaccuracies be mitigated?

Methodology

A case research approach is used to analyse two years' (2015-2016) delivery schedule records received by a global supplier of safety systems in the automotive industry (an industry using delivery schedules to a large extent). The supplier acts as first-, second- and third-tier supplier, so this set up allows us to conduct comparative analysis between schedules received from OEMs and suppliers. We apply a mixed-method approach combining quantitative analysis of a large set of delivery schedule data received during two calendar years, internal customer and item data records, and qualitative data analysis of schedule usage at the supplier. To discuss and validate our findings we conducted workshops with representatives of the studied supplier and a consultancy firm working with delivery schedules at the supplier and with other companies in the automotive industry.

Quantitative data collection, data cleansing and data preparation

Data was collected from all delivery schedules received from the supplier's customers (OEMs and 1st and 2nd tier suppliers) during 2015 and 2016, and from internal data records at the supplier.

The following 11 variables were extracted from delivery schedules: (1) *Customer number*, (2) *Item number*, (3) *Ship to gate address* (Same customer may have multiple shipping sites), (4) *Order number*, (5) *Forecast indicator* (1=Firm number, 2=Commitment raw material, 3=Commitment production, 4=Forecasting), (6) *Demand date* (The date on which the item should arrive at the shipping address), (7) *Plan received date* (The date when the plan is received), (8) *Delivery schedule ID* (An ID assigned to each delivery schedule), (9) *Quantity* (Number of units requested). (10) *Demand bucket* (This field indicates the time period covered by the demand in the delivery schedule. 1=daily demand, 2=weekly demand, 3=monthly demand, 4=yearly demand, 5=Biweekly demand) (11) *Status* (99=Historical status, 90=Historical status, has been replaced with a new plan/demand, 20=The plan/demand is current/active, and 00=Plan/demand is not activated yet).

The raw delivery schedule data contained 3,534,782 total records/rows. After eliminating complete duplicates (2841) and records with missing demand date (12), we ended up in 3,532,824 unique records in the dataset. Next, in order to eliminate the risk of duplicating any data and to analyse all data on the same level of aggregation, we filtered the data by the demand bucket variable. The 19% of all records expressed in weekly, monthly, biweekly or yearly buckets, were excluded, i.e. 2,858,299 individual records with daily demand buckets were remaining.

Each record in the data corresponds to the information of one delivery schedule received on some plan received date. For a fixed demand date, these individual delivery schedules are repeated on various plan received dates. To be able to analyse schedules targeting unique deliveries, we grouped the 2,858,299 individual records into 270,450 schedule groups, where all schedules in a group contain the same Demand date, Customer, Item, and Shipping address. 2,496,884 individual records were remaining after excluding multiple schedules received for the same demand date, and schedule groups with only zero-quantity records. These were combined into 179,874 unique delivery schedule groups.

The internal data used in this analysis consists of (1) *Customer* (10 categories) and *item group* (112 categories) categories defined by the supplier. When category is not available for some customer or item, it has been labeled as missing.

Qualitative data collection and analysis

The qualitative interview- and workshop-based analysis is conducted to analyse the supplier's schedule usage. This analyses is to understand and categorize deficiencies and inaccuracies, and to propose mitigation strategies. Altogether, we conducted three workshops with two different representatives of the supplier and the manager of the consultancy firms.

Data analysis

The quantitative data analysis of RQ1 was based on the individual schedule records, while those of RQs 2 and 3 were based on the schedule group data. The time accuracy (late changes) analysis focuses on two weeks planning horizon, which roughly corresponds to the frozen planning period at the supplier. Within this time zone, a changed delivery date between individual days in a week will disrupt production. On longer planning horizons, the consequence of changing delivery dates within a given week or month may not be as serious. On this horizon it is also necessary to study quantity changes with daily time buckets. The volume accuracy is studied without constraining for any planning horizon. A delivery schedule group is considered having large schedule changes if the standard deviation of the received delivery schedule quantities is equal to and greater than the mean value of them.

Findings

Schedule deficiencies

In the quantitative data analysis of RQ1 (schedule deficiencies) we analysed potential data deficiencies related to demand values expressed as a past date, demand values always being zero, and demand values being exact duplicates or null values. 164,196 of all records (5.74%) contain the same delivery data as at least one other record in a schedule group. These are combined into 56,232 schedule groups (2.04% of all groups). 107,964 (3.78%) of these records are, consequently, potentially deficient. 9751 (0.34% of all records) refer to a demand date in the past. These are included in 4441 (1.64% of all) schedule groups. These records are considered to be back-orders, but some delivery dates may also be inaccurately recorded. Finally, we analysed schedule groups where all included record quantities are zero. In total 86,444 (31.96%) of the groups contained records with only zero quantities. These represented 198,085 (6.93%) individual records. In total, we consequently identified that 315,800 of the individual schedule records (11.05%) are potentially inaccurate in regard to demand date, quantity, or complete duplicates.

Volume inaccurate schedules

To analyse RQs 2 and 3 we focus on the defined delivery schedule groups. 28,430 of the records (corresponding to 15.81% of all schedule groups) are plans received only once for a certain delivery date, and 18,116 of the records (5.66% of all schedule groups) are received only twice. This leaves 151,444 schedule groups with at least two records, and 133,328 groups with at least three records. The volume inaccuracy analysis is conducted for schedule groups with two individual records, and for schedule groups with three or more records. For both these data sets, volume inaccuracy is defined and measured as the standard deviation being equal or larger than the mean.

For 5466 of the groups with only two records (30.17% of all groups with only two records) and for 7543 of the groups with at least three records (5.66% of all groups with at least three records), the standard deviation is at least equal to the mean. Consequently, 8.59% ((5466+7543)/151444) of the schedule groups with at least two records are inaccurate according to the volume inaccuracy criterion.

Table 1 shows detailed characteristics of volume inaccurate schedule groups with at least two schedules, and Table 2 shows it for those with more than two records.

Table 1 - Volume inaccuracies for schedule groups with two records

	Item group (n=61)	Customer group (n=10)	Item group AND customer group (n=123)
Groups representing 30% of inaccuracies	1 (1.6%)	1 (10.0%)	2 (1.6%)
Groups represent 50% of inaccuracies	2 (3.3%)	1 (10.0%)	2 (1.6%)
Groups represent 80% of inaccuracies	14 (23.0%)	2 (20.0%)	9 (7.3%)
Groups with >80% inaccurate schedule groups	7 (11.5%)	2 (20%)	11 (8.9%)
Groups with >50% inaccurate schedule groups	10 (16.4%)	1 (10%)	17 (13.8%)
Groups with >25% inaccurate schedule groups	19 (31.1%)	1 (10%)	32 (26.0%)
Groups with >10% inaccurate schedule groups	28 (45.9%)	1 (10.0%)	50 (40.6%)
Groups with any inaccurate schedule group	40 (65.6%)	8 (80.0%)	67 (54.5%)

Table 1 shows that one OEM makes up 72% of the two-group volume inaccuracies (n=3960 out of a total of 4268 schedule groups), and two large item groups (3% of all item groups) represent more than half of the inaccuracies. When combining item group and customer group, we identify that 2 combinations (2% of all) represent more than 50% of the inaccuracies and 9 combinations (7% of all) represent more than 80% of the inaccuracies.

Table 2 - Volume inaccuracies for schedule groups with at least three records

	Item group (n=61)	Customer group (n=10)	Item group AND customer group (n=123)
Groups representing 30% of inaccuracies	3 (4.9%)	2 (20.0%)	4 (3.2%)
Groups represent 50% of inaccuracies	6 (9.8%)	2 (20.0%)	9 (7.3%)
Groups represent 80% of inaccuracies	14 (23.0%)	4 (40.0%)	19 (15.4%)
Groups with >80% inaccurate schedule groups	0	0	0
Groups with >50% inaccurate schedule groups	0	0	1 (0.8%)
Groups with >25% inaccurate schedule groups	0	0	3 (2.4%)
Groups with >10% inaccurate schedule groups	7 (11.5%)	2 (20.0%)	13 (10.6%)
Groups with any inaccurate schedule group	38 (62.3%)	9 (90.0%)	68 (55.3%)

For schedule groups with at least two records, roughly the same item groups represent the largest inaccuracies, but the inaccuracies are distributed among more item groups and more OEMs compared to the two records groups. There are fewer item group and customer combinations with large proportions of inaccurate schedules compared to the two item groups. Three combinations (2% of all) have more than 25% inaccurate groups. The corresponding figure for the two record groups was 32 (26%).

Consequently, a large proportion of all inaccuracies in the two record schedule groups are caused by a small number of OEMs and item group-customer combinations. For the two record groups there are also several item group-customer combinations with very high proportions of inaccurate schedules. For the schedule groups with more than two records, the amount and proportions of inaccuracies are spread out to more item groups and customers. Still, a limited amount of item group-customer combinations stand for a large proportion of all volume inaccuracies: 15% of all item group-customer combinations stand for more than 80% of the inaccuracies.

Time inaccurate schedules

The time inaccuracy analysis is also conducted for two data sets. Firstly, schedules received only once are considered time inaccurate if the plan receive date is within two weeks from the delivery date. Secondly, schedule groups are considered inaccurate if delivery quantities are changed within two weeks from the delivery date. This analysis is conducted for groups with more than two records.

For 21,707 of the schedule groups with at least three records, the quantity changes within two weeks from the delivery date, which corresponds to 16.28% of all groups with at least three records. Corresponding changes within four weeks are 24,739 (19%) and within six weeks 27,200 (20%). 7324 (33.7%) of the 21,707 changes within two weeks are from non-zero to zero values, and 2371 (10.9%) are from zero to non-zero-values. Table 3 shows detailed characteristics of the two weeks' time inaccurate schedule groups.

Table 3 - Time inaccuracies for schedule groups with at least three records

	Item group (n=61)	Customer group (n=10)	Item group AND customer group (n=123)
Groups representing 30% of inaccuracies	4 (6.6%)	1 (10.0%)	4 (3.2%)
Groups represent 50% of inaccuracies	7 (11.5%)	2 (20.0%)	9 (7.3%)
Groups represent 80% of inaccuracies	17 (27.9%)	4 (40.0%)	19 (15.4%)
Groups with >80% inaccurate schedule groups	1 (1.6%)	0	0
Groups with >50% inaccurate schedule groups	6 (9.8%)	0	1 (0.8%)
Groups with >25% inaccurate schedule groups	18 (29.5%)	3 (30%)	3 (2.4%)
Groups with >10% inaccurate schedule groups	32 (52.5%)	8 (10.0%)	13 (10.6%)
Groups with any inaccurate schedule group	51 (83.6%)	9 (90.0%)	68 (55.3%)

From Table 3 we see that the distribution of time inaccuracies is very similar to that of the volume inaccuracies in Table 2. Also for time inaccuracies, 19 (15%) of all item group-customer combinations stand for more than 80% of the inaccuracies.

Combined volume and time inaccurate schedules

To further explore the combined effect of item group and customer combinations on volume and time accuracies, we have in Figure 1 plotted all 123 item group-customer combinations along their impact on time inaccuracy (LATE schedule changes) and volume inaccuracies (LARGE schedule changes).

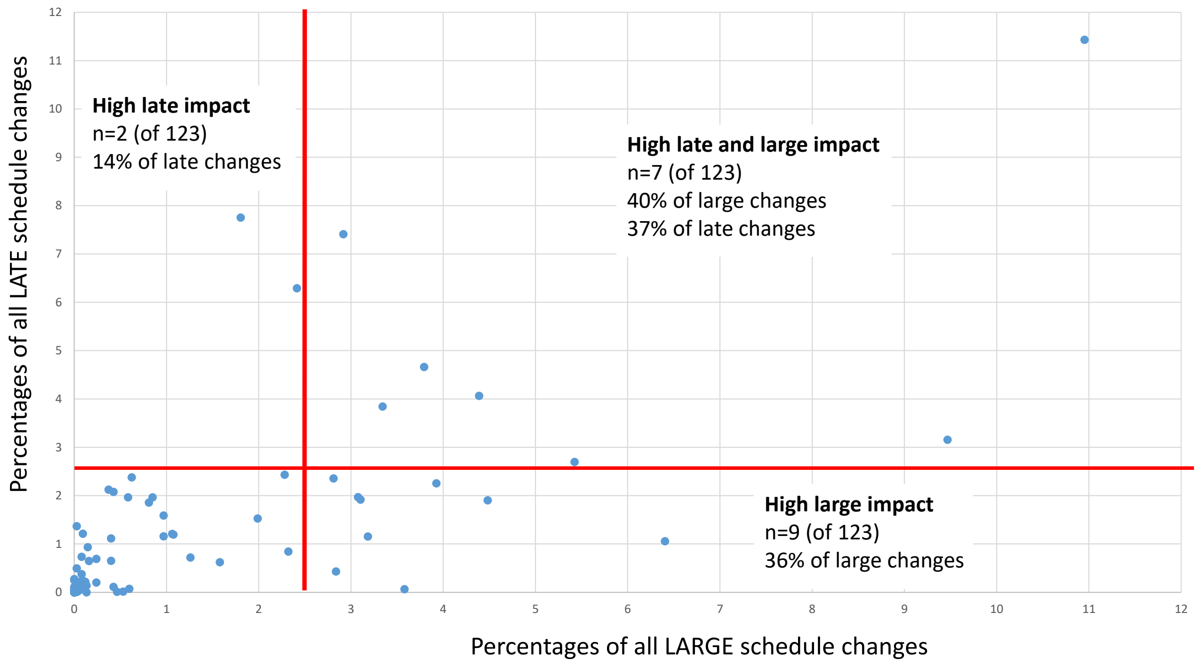

Figure 1. Combined effect on time inaccuracy (LATE change) and volume inaccuracy (LARGE change)

Figure 1 shows that 7 item group-customer combinations stand for about 40% of the time inaccuracies and volume inaccuracies. 2 combinations stand for 14% of the time inaccuracies, and 9 stand for 36% of the volume inaccuracies. Altogether, these 18 combinations (15% of all) stand for very large proportions of the total schedule inaccuracies.

Schedules with perfect forecasts

We also identified schedules representing perfect forecasts. For 58,289 of the schedule groups with at least two records (32.41% of all group schedules and 38.49% of those with at least two records), the individual records always have the same quantity. Corresponding, figure for groups with at least three records is 47,533 (35.65%). These 35-38% of the schedule groups consequently represent groups with perfect forecasts. Excluding the 58,289 perfect schedule groups from the 151,444 groups with at least two records gives that

For the further analysis we explore what characterize the perfect forecast groups with at least three individual schedule records. Table 4 shows detailed characteristics of schedule groups with perfect forecast and at least three schedule records. Also this analysis indicate that a few item groups and item group-customer combinations represent a large proportion of all perfect forecasts. 19 item group-customer combinations (15%) stand for more than 80% of all perfect schedule groups.

Table 4 - Perfect forecasts for schedule groups with at least three records

	Item group (n=61)	Customer group (n=10)	Item group AND customer group (n=123)
Groups representing 30% of accuracies	1 (1.6%)	1 (10.0%)	1 (1%)
Groups represent 50% of accuracies	2 (3.3%)	1 (10.0%)	2 (1.6%)
Groups represent 80% of accuracies	12 (19.7%)	3 (30.0%)	19 (15.4%)
Groups with >80% accurate schedule groups	7 (11.5%)	0	18 (14.6%)
Groups with >50% accurate schedule groups	16 (26.2%)	2 (20%)	38 (30.9%)
Groups with >25% accurate schedule groups	31 (50.8%)	6 (60%)	63 (51.2%)
Groups with >10% accurate schedule groups	49 (80.3%)	9 (90.0%)	88 (71.5%)

Discussion and conclusions

Our findings related to RQ 1 (What is the amount and type of data deficiencies in current automotive supply chain delivery schedules?) identified potential data deficiencies in the schedule data, but our analysis could not identify any negative effect of any of these potential deficiencies. They could be related to backorders (delivery date being a date in the past) or were not affecting the schedules registered and used by the supplier (zero schedules or duplicates). Duplicated schedules expresses both in daily and weekly buckets are not analysed. We have only analysed the 80% of the schedules were expressed in daily buckets. How to combine schedule information expressed in different bucket sizes is left for further research.

For RQ 2(To what extent are delivery schedules inaccurate, and what characterize delivery schedules with low relative accuracy?) we analysed two types of delivery schedule inaccuracies: volume (large changes) and time (late changes) inaccuracies. About 9% of all schedule groups have large variations (standard deviation > mean) and about 16% have late variations (within the supplier's frozen period). Further, we identified that for schedule groups with only two records (schedules) large variations are caused by a very limited number of customers and item group-customer combinations. For schedule groups with more than two records, the inaccuracies are caused by more item groups and customers causing. Still, we identify that categorizing items and customers into unique item group-customer combinations allows us to identify a few combinations that stand for a large proportion of inaccuracies.

For RQ3 (How could delivery schedule deficiencies and inaccuracies be mitigated?) we first conclude that data deficiencies in automotive delivery schedules are not creating any critical impact on the receiving organisation's planning process or delivery performances. Delivery schedule data deficiencies do consequently not constitute any larger problem on the delivery schedule information sharing. Therefore, *no mitigation strategy concerning schedule data deficiencies is proposed*.

For analysing delivery schedule inaccuracies we propose and have shown that the large amount of delivery schedule records received by a supplier (or sent by an OEM) can be analysed for inaccuracies if first *generating a delivery schedule database with a unique delivery schedule group identifier defined by the four schedule variables: Demand date, Customer, Item, and Shipping address*. To be able to monitor and mitigate inaccuracies, additional internal data about customers and item groups are required. *This database is consequently part of the designs here proposed to monitor and mitigate delivery schedule deficiencies and inaccuracies in supply chains*.

For the monitoring and mitigation of schedule volume inaccuracies we first propose to *distinguish between schedule groups with only two records and schedule groups with more than two records*. We also propose *segmentation according to item group-customer combinations*. The following strategies to monitor and segment in regards to inaccuracies are proposed: (1) *Item groups-customer combinations for schedule groups with more than two records with high impact on volume and time inaccuracies are coded very critical* (in the study 5.6% of the combinations were very critical). (2) *Item groups-customer combinations with high impact on volume inaccuracies, but not high impact on time inaccuracies, in the two- and more than two-records schedule groups are coded volume critical* (in this study 1.6% and 7.3% respectively of all combinations are volume critical). (3) *Item groups-customer combinations with high impact on time inaccuracies, but not on volume inaccuracies, in the two- and more than two-records schedule groups are coded time critical* (in this study 1.6% of all combinations). These proposed monitoring and coding are proposed to be done on a continuous basis. (4) For the time inaccuracy we also propose generating *alerts when a late change occur* (in the study defined as within two weeks from the delivery time). Both sending and receiving units should be alerted. Further, (5) schedule groups with perfect forecast, i.e. no volume variation at all, constitute an obvious group to be considered for *fully automated planning*.

Our findings contribute to the fields of supply chain information sharing, information quality and operations planning and control by presenting a detailed empirical analysis of real schedule data and categorizing types of deficiencies and inaccuracies. The proposed mitigation strategies contribute to the calls in the literature (e.g. Jonsson and Holmström, 2016; Wang et al. 2016b) to conduct practically relevant and empirically based big data related studies. Our study design has limitations: It only analyses delivery schedules with daily planning buckets, and is only analysing short-term inaccuracies. To analyse longer-term inaccuracies, only focusing on daily planning buckets would not suffice. But this is a first study of this kind. Further analysis should also assess the effects of applying proposed mitigation strategies, and also analyse data from other companies. Analysis using other planning horizons, planning buckets, etc., are also needed to validate and further develop this work.

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