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Can AI help in better spare parts demand forecasting?

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Spare parts demand forecasting

- Essential step in service logistics process

- **Many complicating aspects**:
  - type of part (consumable, insurance, rotable)
  - position in supply chain (manf, wholesaler, user)
  - intermittent and lumpy demand,
  - risks: obsolescence, supplier loss

- **Forecasting scientific world**:
  - M-competitions (general)
  - Recent literature reviews spare parts
  - Own research: installed base forecasting, AI

M4,5 Competitions

- **Benchmark data sets** made available to several teams to test their method performance

- **M4** (Makridakis (2018))
  - 100.000 series of data
  - benchmark method Comb (average of Simple, Holt and Damped Exponential Smoothing)
  - evaluation: average of sMAPE, MASE

- **M5** Makridakis et al. (2022) on Kaggle
  - 42.840 time series of retail data (Walmart, store, category, department).
  - weighted root mean squared scaled error evaluation
  - contextual variables added, intermittency

M4,5 Competitions - Results

- **M4**
  - Comb performs good
  - Pure AI methods perform worse than Comb
  - best: hybrid use of a RNN with ES formulas

- **M5** (methods not always revealed)
  - results better than in M4 (>20%)
  - winner depends on aggregation level
  - most winning methods use a combination
    including Light GBM (nonlinear regression using
    gradient boosting trees)
  - contextual variables help.

Recent Review (Pince et al 2021)

- **General methods**: Weighted Average, Exponential Smoothing (ES), Holt, Winter's (address level, trend & season)

  Specific methods: model demand interval and size separately Croston, SBA: - still need distribution assumption

  Non-parametric methods: Willemain, Empirical (distribution)

  Machine learning (AI) methods
  Support Vector Machine, LightGBM, XGBoost,

- **Special**: Installed base, Aggregation of demand, Adjustments

- **Performance measures**
  Mean Square Error based as in M4,5, **OR** Distribution / Inventory Control based (focus on tail: large demand values)

Results Review (Pince et al 2021)

- Results from literature are mixed because of lack of standardization of methods and criteria.

- Evaluation should focus more on inventory control aspects than on forecasting accuracy

- Croston’s method is biased but performs good in inventory control, better than variants and general methods in case of intermittency

- Promising results in Installed Base Forecasting, combining forecasts and aggregation

Installed base Forecasting (IBF)*

- Forecast part demand using forecasts of the installed base (assets) developments

- Example: Fokker Services – keeps track of all Fokker planes (where and flying or not)
  “knows” for each flying hour estimated parts need
  predicts demand location and frequency

- IBF is better in case of changing or moving IB and can prevent part obsolescence
  but keeping track of IB is an issue

- *Dekker et al. (2013), Kim et. Al (2017), Auweraer et al. (2020)

Other own research

- Tuning & selection of forecasting methods in SAP-R3
- Succesfull application of LightGBM in retail sector
- EUR – affiliated company EQI offers commercial general forecasting package FCast
- Application of IBF with Fokker, IBM and Consumer product parts
- Started benchmarking research on using AI – ML methods in spare parts demand (den Haan)

Initial results (Den Haan 2022)

- Four artificial data sets & 3 industrial. Evaluation either on forecast accuracy & inventory performance
- Results vary a lot. No overall winner. Outlier detection (preventive maintenance) is important.
- Syntetos-Boylan (SBA) best for forecasting accuracy Willemain – best in inventory control
- in case of extreme intermittency Multi-layered Perceptron (a NN) and LightGBM performed best in case of inventory control

Open Questions (Den Haan 2022)

- Is there a difference between forecasting for users versus wholesalers / manufacturers?
- Can we identify patterns automatically in data (demand in multiples of 2,3, correlated demands)
- Evaluation of hybrid methods
- Estimation for items with very few data and use of reliability data
- More datasets with more information

Questions?

- Are you interested in sharing experiences and a data set?
- Are you interested in research updates?
- Do you have experience with
  - installed base forecasting?
  - forecast adjustments?
  - own research?