DEUTSCHE TELEKOM AG
INDIVIDUAL SOLUTIONS & PRODUCTS
OPTIMIZED PREDICTIVE PLANNING WITH KNIME

Michael Schaarschmidt

Christian Gräber

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LIFE IS FOR SHARING.

OPTIMIZED PREDICTIVE PLANNING WITH KNIME

FROM BUSINESS PROBLEM TO MODELING AND IMPLEMENTATION

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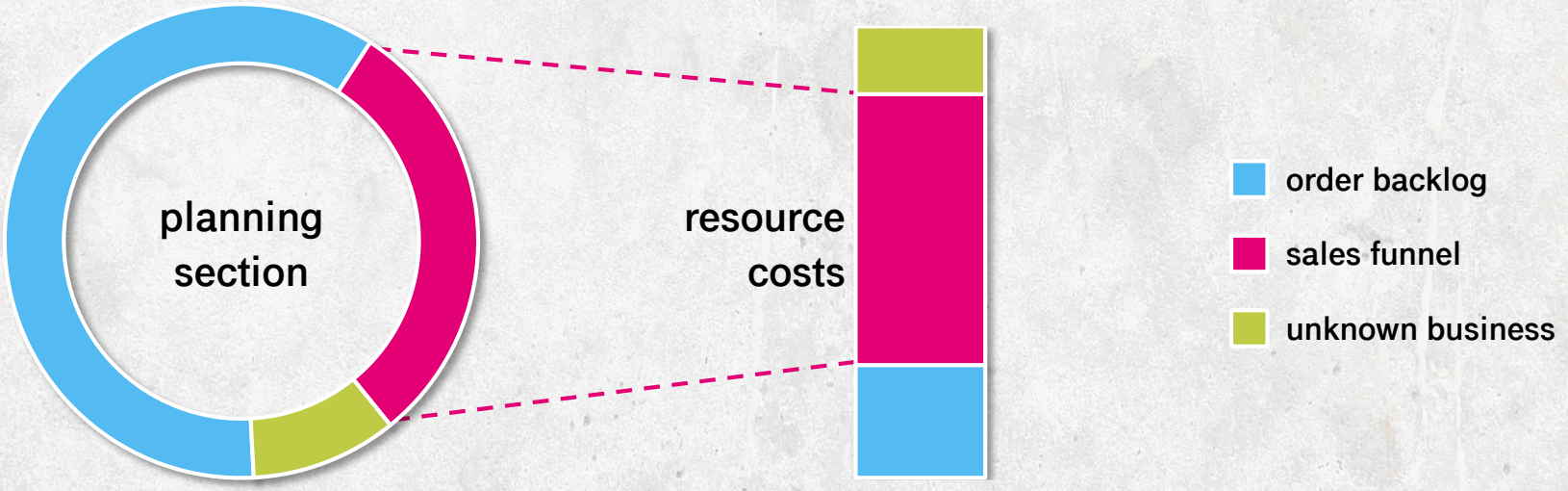
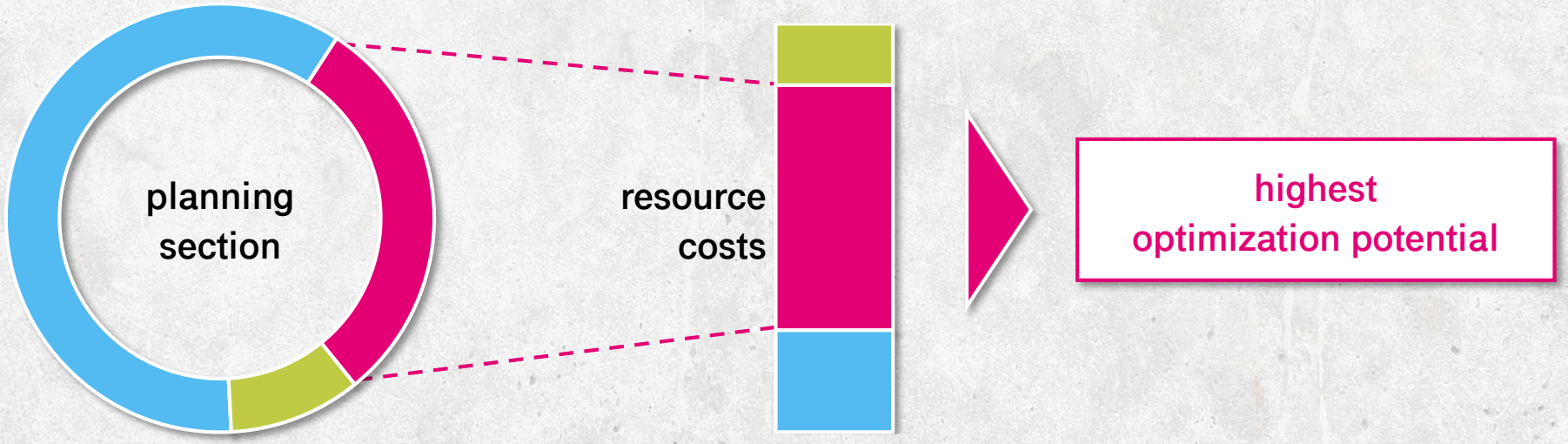
BUSINESS PROBLEM



BUSINESS PROBLEM



- Manuell planning time is too high in relation to the budget
- Consideration of the planning part with the highest resource requirements and lowest validity

order backlog | sales funnel | unknown business

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DECISION ELEMENTS

Regression Modell

Cluster & Similarities

Probability of orders

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EXAMPLES OF UNDERLYING DATA

Customer Dimension

- Sales Region
- Letter of Intent True/False

System Information

- Duration per Stage
- Number of offer versions

Time Dimension

- Quarter of the planned project start
- Condition per Stage

Financial Information

- project volume
- term of contract

Technology & Portfolio

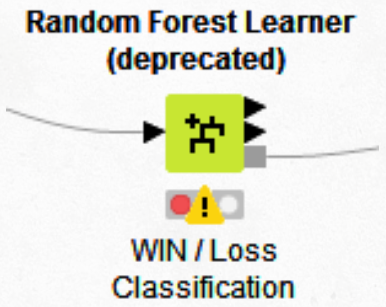
- technology portfolio
- ITIL Type

OPTIMIZED PREDICTIVE PLANNING WITH KNIME

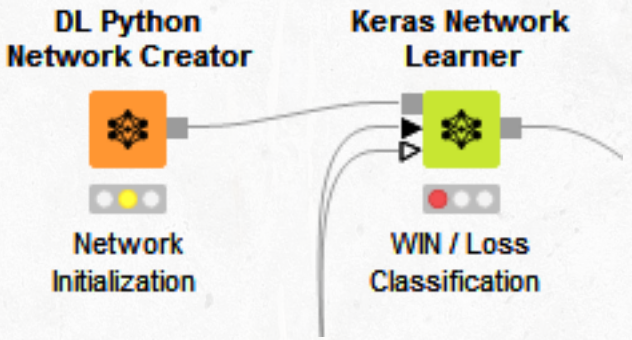
FROM BUSINESS PROBLEM TO MODELING AND IMPLEMENTATION

EVOLUTION OF THE MODEL FROM SIMPLE TO COMPLEX

1 Random Forest Learner



2 Python & Keras Network Learner



EVOLUTION OF THE MODEL FROM SIMPLE TO COMPLEX

1 Random Forest Learner

Easy to implement

- ⊕ Can handle categorical values
- ⊕ No special data preparation required
- ⊕ Successful training even with smaller data sets

Retrain creates a new model each time

- ⊖ Small changes in the training data set can have a big impact on the model.

2 Python & Keras Network Learner

Retrain optimizes the existing model

- ⊕ Can recognize even complex relationships
- ⊕ Stable result even after retrain

High resource requirements for training

- ⊖ Special data preparation required
- ⊖ Scaling to range from -1 to 1 required
- ⊖ Requires sufficient data for initial training (approx. 1,000 data rows per feature)

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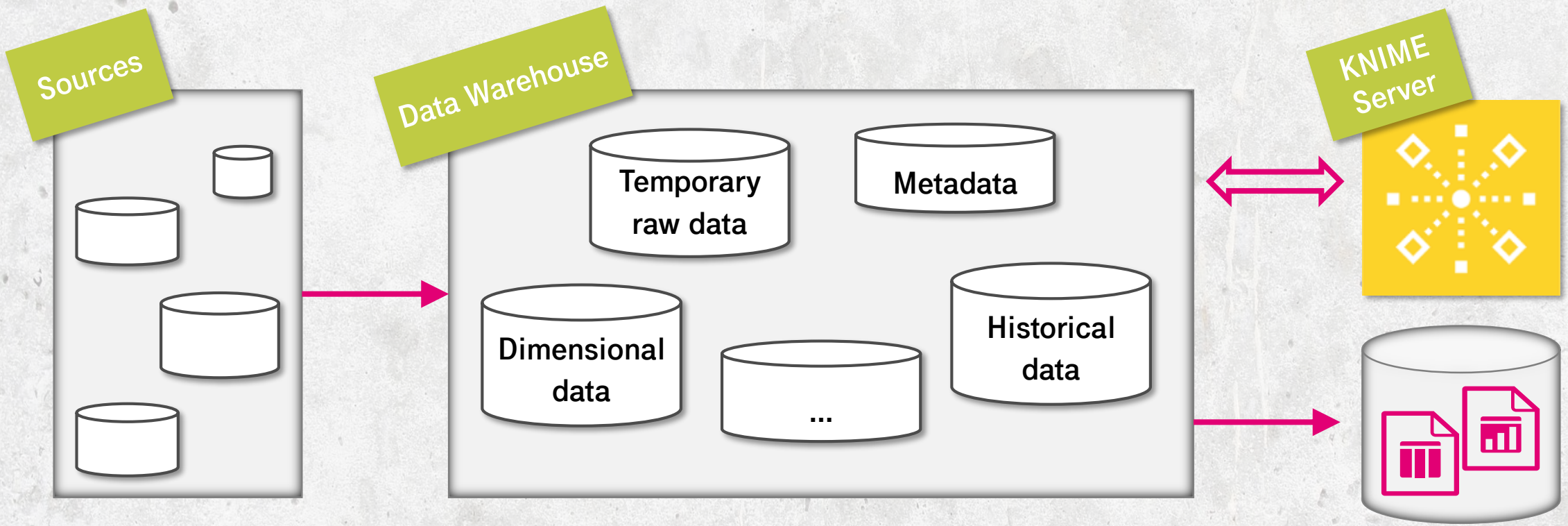
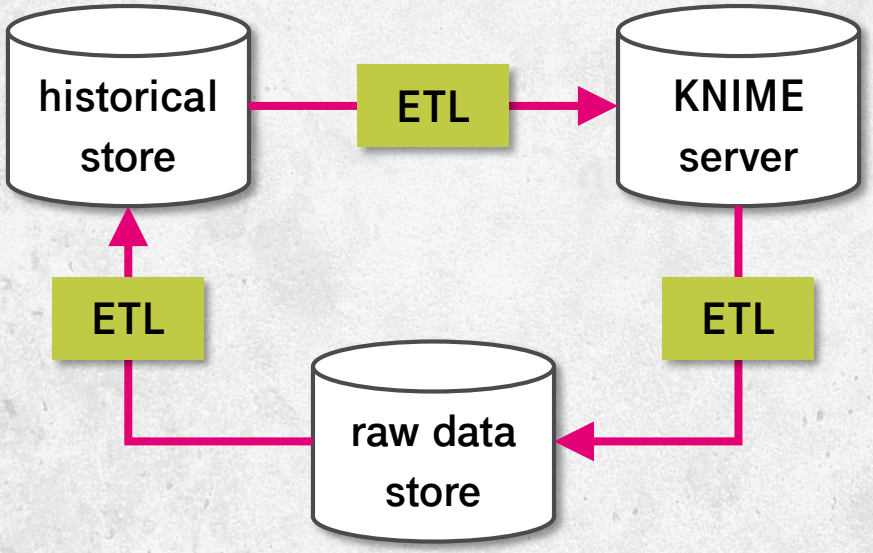
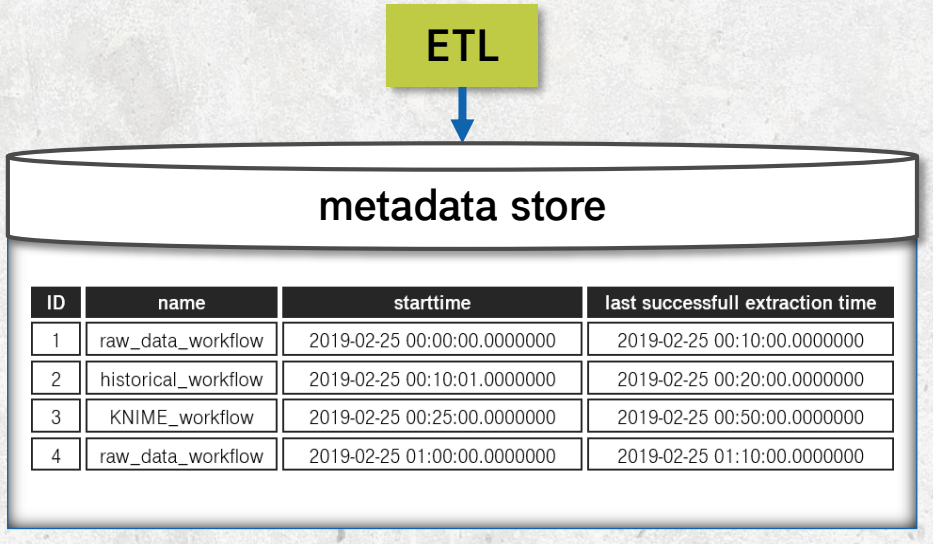
PLATFORM ARCHITECTURE



INTEGRATION INTO DATA WAREHOUSE





ID	name	starttime	last successfull extraction time
1	raw_data_workflow	2019-02-25 00:00:00.0000000	2019-02-25 00:10:00.0000000
2	historical_workflow	2019-02-25 00:10:01.0000000	2019-02-25 00:20:00.0000000
3	KNIME_workflow	2019-02-25 00:25:00.0000000	2019-02-25 00:50:00.0000000
4	raw_data_workflow	2019-02-25 01:00:00.0000000	2019-02-25 01:10:00.0000000

- execution times of individual Extract Load Transform (ETL) processes are defined in metadata management
- each transaction is traceable system-wide
- workflows of the individual processes read metadata, metadata controls workflows of individual processes

ADDITIONAL FRAMEWORKS SUPPORTING DEEP LEARNING

KNIME Server

PYTHON & ANACONDA

- Installation of Python & custom Anaconda environment
- Defining the Uniform Configuration for the KNIME Server Executor

TENSORFLOW

- Underlying framework
- Currently as CPU version, GPU planned 2nd half of 2019

KERAS

- Implemented with Tensorflow backend

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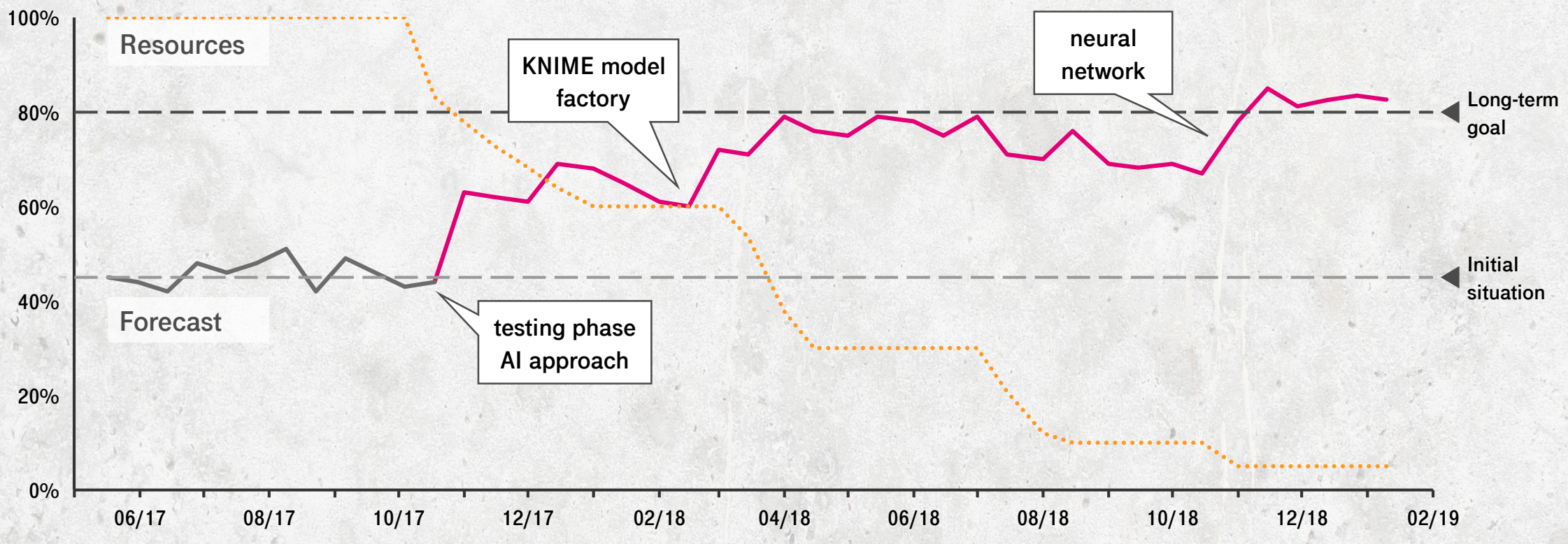

→ Increase of accuracy of forecast and decrease of resources needed

THANK YOU FOR YOUR ATTENTION.