Product report: Optimizing production processes in real-time or planning and simulation scenarios

Predictive Optimization with Deep Qualicision

Deep Qualicision connects the Qualicision decision and optimization engine with neural networks and machine learning based on goal conflicts. This solution principle learns to efficiently adjust parameters so that they can be optimized in advance.

The Deep Qualicision application can be used to efficiently determine multi-criteria decision-making based on individual decisions, consistently taking into account goal conflicts in the business processes being optimized. In addition, the criteria priorities can be learned so that consistent priority settings for criteria and goals (KPIs) are automatically recommended (see Figure 1).

Deep Qualicision allows a deeper connection between individual decisions and the goal criteria to be established using software. When applying this principle to the topic of scheduling production orders, the user may optimize the production process either in real-time or for the purposes of planning or simulating.

Balancing differences

A scenario which occurs very frequently in practice is that now and then there are significant differences between the assumptions made in the process about the performance parameters of production resources and the reality of day-to-day operations.

Numerous industrial applications confirm that Qualicision real-time optimization can successfully balance these differences. However, for instance differences between planned and actual sequences, are often the subject of avoidable efforts that could possibly be treated preventively.

Studies show that the deviations mentioned above are partly a result of a mixture of process anomalies that occur spontaneously. These anomalies arise as a result of unpredictable lack of resources, quality-related stoppages or failures in the supply chain and definitely as a result of spontaneous changes of the order mix.

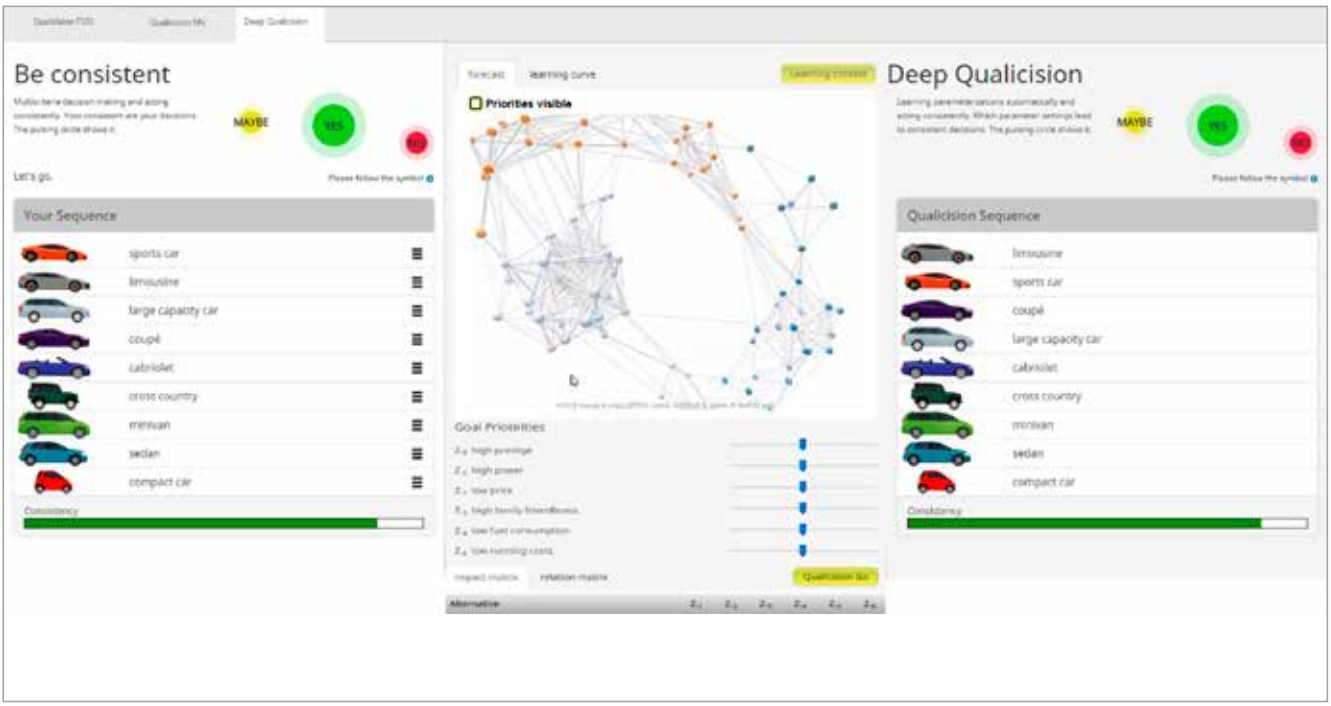

Figure 1 shows consistent priority settings for the criteria and goals (KPIs) in Deep Qualicision.

Learning from Historic Data

On the other hand the same studies show that in addition to the spontaneous anomalies structurally-conditioned deviations between the planned process and the actual process exist which usually become apparent to the process operators only

afterwards. It would be better if the regular structural anomalies of historic data could be learned automatically.

With Deep Qualicision-based predictive prevention, previous production sequences are analyzed and linked to the KPI-oriented optimizations contained in the original Qualicision solutions. The Qualicision goal conflict analysis is extended by the automatic detection of anomalies.

Machine learning is used to learn property classes of products and resources from previous production sequences that come along with structural anomalies. The learned classes represent the systematic anomalies. It is then possible to translate the anomalies into optimization goals for the Qualicision optimization algorithm. This ensures that the optimization also balances the systematic anomalies given that the resources for the production process being optimized are available. The anomalies will be corrected with the help of the learned relations, so to speak.

The example shown in Figure 2 is a simple demonstration of how the learned classification is applied. The example consists of the vehicle sequences formed for the ranking related to processes around making a decision to purchase a car.

Ranking of decision alternatives

The decisions that need to be modeled here are based on creating a ranking of decision alternatives for car types so that the ranking fulfills as many criteria as possible that are important to a car purchasing decision. In simple terms, a ranking of this type can be compared to a production sequence in which the car types are arranged according to the ranking.

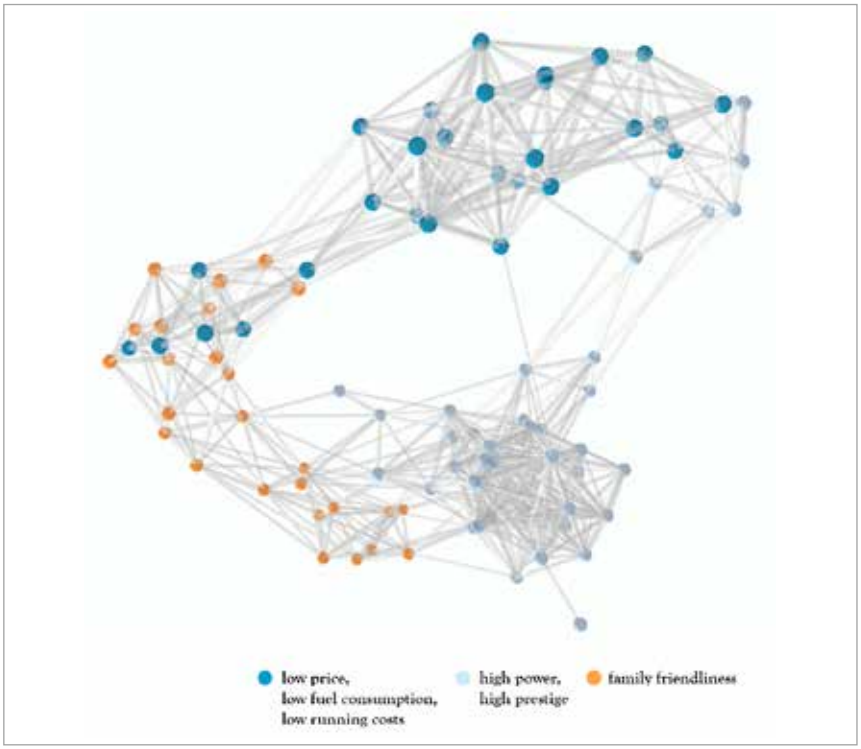

Figure 2 shows the consistent classes of decision alternatives and rankings.

The types of car are compact car, coupé, cabriolet, sedan, limousine, large-capacity car, minivan, sports car and cross country. In the example demonstrated, the criteria that play a role when making the decision are low price, high performance, low consumption, family-friendliness, high prestige and low running costs (see Figure 2). These criteria can be compared to production criteria according to which the sequence is formed.

If the decision maker ranks the car type alternatives by one decision goal then with the ranking the remaining criteria are more or less implicitly fulfilled or not fulfilled as individual decision goals.. As a result, certain other goals are therefore indirectly negated or disregarded. For example, a ranking which prioritizes compact car and sedan tends more towards low price, low consumption and possibly slightly towards family-friendliness.

Rankings which prioritize sports car and cabriolet tend more towards high performance and, perhaps, a desire for a higher prestige, and disregard the low price criterion. In this instance, the low price goal is even negated in some way. If a ranking generates sequences that imply negated criteria, the process automatically identifies them as inconsistent anomalies and learns their structure.

Overall, the Deep Qualicision-based method for the predictive sequencing combines previous benefits gained from Qualicision optimizations with the possibility of automatically learning systematic anomalies in production processes. The first application scenarios with real production data are already proving to be successful.

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