Industrialization of 16T Nb3Sn magnet production for HE-LHC and FCC

FCC WEEK 2019, Brussels, Belgium

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Introduction

• Cost-effective manufacturing of Nb3Sn magnets for FCC and HE-LHC can be achieved by optimization of current HL-LHC magnet manufacturing performance using key performance indicators (KPI)

• Statistical modeling and simulation of Nb3Sn manufacturing system (winding house)

• Surrogate-based analysis and optimization of manufacturing systems with Dimensional Analysis Conceptual Modeling (DACM[1]) framework and Bayesian Networks

Statistical M&S of Nb3Sn magnet manufacturing system

Winding house simulation at LMF
Statistical modeling of Nb3Sn magnet manufacturing (11 T dipole – winding house)

Time data as per coil no- HCMBH_C005-CR000007 (2017)
Simulation Results

<table>
<thead>
<tr>
<th>WnC process parameters</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimated process throughput (coils)</td>
<td>23</td>
</tr>
<tr>
<td>Average winding time (hrs)</td>
<td>83.738</td>
</tr>
<tr>
<td>Winding machine utilization (%)</td>
<td>93.32</td>
</tr>
<tr>
<td>Curing press utilization (%)</td>
<td>79.29</td>
</tr>
</tbody>
</table>

![Graphs and charts showing simulation results](image-url)
Surrogate-based analysis and optimization of Manufacturing Systems with DACM Framework and Bayesian Networks (BN)
DACM Framework

- DACM is a conceptual modeling mechanism for complex systems
- The main goal of DACM is to extract and encode knowledge of different forms in the system with the help of causal representation
- DACM has been successfully applied to case studies in the domain of additive manufacturing (AM), product design and multidisciplinary design optimization (MDO)
Probabilistic Cost Models with BN

Results

Manufacturing Decisions → Effect on performance targets

<table>
<thead>
<tr>
<th>Product Type</th>
<th>Facility Cost</th>
<th>Manufacturing Process Cost</th>
<th>Labour Cost</th>
<th>Raw Material Cost</th>
<th>Supplier Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tallippe</td>
<td>54.52%</td>
<td>45.52%</td>
<td>44.4%</td>
<td>50.86%</td>
<td>37.56%</td>
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<tr>
<td>Small</td>
<td>50.86%</td>
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<td>37.56%</td>
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<table>
<thead>
<tr>
<th>Transportation</th>
<th>Cost of Material Transportation</th>
<th>Order-to-Delivery Lead Time</th>
<th>Delivery Cost</th>
<th>Maintenance Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rail</td>
<td>30.94%</td>
<td>54.73%</td>
<td>54.73%</td>
<td>54.73%</td>
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<tr>
<td>Road</td>
<td>25.96%</td>
<td>25.96%</td>
<td>25.96%</td>
<td>25.96%</td>
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<tr>
<td>Sea</td>
<td>50.86%</td>
<td>50.86%</td>
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</table>

<table>
<thead>
<tr>
<th>Capital Cost</th>
<th>Order-to-Delivery Lead Time</th>
<th>Maintenance Cost</th>
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<tbody>
<tr>
<td>2323.851</td>
<td>2323.536</td>
<td>35.85%</td>
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6/20/2019
Results Contd.

Suggested manufacturing decisions

Predefined performance targets
Dimensionality Reduction

Figure 1: Combined framework for the developed methodologies
Graph centrality scores

- Weighted PageRank
- Betweenness Centrality Score
Adoption of Industry 4.0 tools and techniques in magnet production
Need for digitalization in HL-LHC production

Top 5 functionalities according to interview scores:

1. Tracking stock levels of all magnet parts
2. Tracking critical coil quality parameters
3. Alerting process variations
4. Tracking of total man hours spent per magnet
5. Integration with existing IT infrastructure
• Complete traceability of components
• Production process status info (in phases)
• Detailed production cost breakdown
• Live status of the device: running, idle, off-line
• Quality risks, reliability of delivery related risks
• Anomaly detection

Flowtag installations in production for machine vibration tracking – example from a pilot case in Finland

Production visualization – example from a pilot case study in Finland
Conclusion

• Statistical modeling and simulation of Nb3Sn magnet manufacturing is conducted to predict coil production parameters

• Surrogate-based analysis and optimization models for manufacturing cost are built and tested with various case studies

• Adoption of Industry 4.0 tools and techniques in SC magnet production are discussed