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A Dimension Reduction Method for Efficient Optimization of Manufacturing Performance

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Abstract

Increased competitiveness in the manufacturing industry demands optimizing performance at each level of an enterprise. Optimizing performance in terms of indicators such as manufacturing cost requires knowledge of cost-inducing variables from product design and manufacturing, and optimization of these variables. However, the number of variables that affect manufacturing cost is very high and optimizing all variables is time intensive and computationally difficult. Thus, it is important to identify and optimize select few variables that have high potential for inducing cost. Towards that goal, a dimension reduction method combining dimensional analysis conceptual modelling framework and graph centrality theory is proposed. The proposed method integrates existing knowledge of the cost inducing variables, their interactions, and input-output relationship for different functions or behavior of a system, in the form of a causal graph. Propagation of optimization objectives in the causal graph is checked to identify contradictory influences on the variables in the graph. Following the contradiction analysis, graph centrality theory is used to rank the different regions within the graph based on their relative importance to the optimization problem and to cluster the variables into two optimization groups namely, less important variables and most important variables relative to optimizing cost. The optimization problem is formulated to fix less important variables at their highest or lowest levels based on their interaction to cost and to optimize the more important variables to minimize cost. The proposed dimension reduction method is demonstrated for an optimization problem, to minimize the production cost of the bladder and key mechanism for a high-field superconducting magnet at CERN, capable of producing a 16 Tesla magnetic field. It was found that the graph region representing the electromagnetic force and resultant stress generated during energizing of the magnet ranked highest for influence on the bladder and key manufacturing cost. An optimization of the stress and its associated variables to minimize the manufacturing cost is performed using a genetic algorithm solver in Matlab.

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1. Introduction

Continuous improvement has become means of subsistence for a successful manufacturing enterprise. In recent times, the growth of information and communications technology (ICT) and its integration into manufacturing has further enabled businesses to fulfill customer's needs in an economical and sustainable manner. To remain competitive in the market, manufacturers must ensure optimized utilization of resources, energy and consumables, as well as prolonged life of the product. Thus, optimization of a process or product design for performance improvement is crucial for an enterprise. Manufacturers measure performance with the help of key performance indicators such as cost, quality, productivity, etc. These indicators are often functions of design and manufacturing variables that need to be modelled and optimized. Hence, sufficient knowledge about the product design and manufacturing process is needed to model their influence on performance indicators. Difficulty arises when trying to model these performance indicators, which are inherently complex and span across multiple domains including product behavior, manufacturing process physics, and production planning. Moreover, optimizing a performance indicator require manufacturers to find optimal values for all influencing variables. Choosing optimal values for all variables irrespective of their level of influence on performance is computationally cost intensive. Dimension reduction in the field of design optimization or machine learning is not a new phenomenon. Nevertheless, there is a lack of systematic techniques that embed domain knowledge in manufacturing performance optimization models. Thus, a multi-domain approach is required with the help of conceptual modelling and simulation to optimize performance indicators. Such approaches would help manufacturers 1) to characterize interrelationships between variables in a system to model performance, 2) integrate knowledge of different domains for modelling performance indicators, and 3) to reduce the number of variables that are needed to optimize performance.

This research focuses on developing a new dimension reduction methodology, which combines graph based modelling of performance indicators across different domains using the dimensional analysis conceptual modelling framework (DACM), and variable clustering using the centrality concept in graph theory and network analysis. The method is tested with a case study of manufacturing the key and bladder mechanism for a new superconducting magnet at CERN. The remainder of the manuscript is organized as follows; Section 2 provides a background discussion on conceptual modelling, dimension reduction in optimization, and centrality concept of graph theory and network applications. Section 3 describes the developed methodology applied to the case study and briefly discusses the results of the case study. Finally, Section 4 describes the conclusions of the work and briefly discusses future development efforts.

Nomenclature

B	Magnetic Flux Density (Nm/A) [$MT^{-2}I^{-1}$]
q	Electric charge (C) [IT]
I	Electric current (A) [I]
J	Current density (I/mm^2) [IL^{-2}]
L	Inductance (H) [$ML^2T^{-2}I^{-2}$]
U	Total energy for self-Inductance [ML^2T^{-2}]
n	Number of poles
L_m	Length of the magnet (m) [L]
θ	Angle made by the conductor with the field (degree)
F_L	Lorentz force (N) [MLT^{-2}]
p_m	Magnetic pressure (N/mm^2) [$ML^{-1}T^{-2}$]
μ	Permeability (H m^{-1}) [$MLT^{-2}I^{-2}$]
σ	Normal stress (N/mm^2) [$ML^{-1}T^{-2}$]

σ_v	von Mises stress (N/mm^2) [$ML^{-1}T^{-2}$]
t	Time of current flow (sec) [T]
ε	Normal strain
τ	Shear stress (N/mm^2) [$ML^{-1}T^{-2}$]
δ_l	Elongation of the magnet due to F_L (mm) [L]
d_{key}	Diameter of the stainless steel key (mm) [L]
t_{key}	Thickness of stainless steel key lamination (mm) [L]
A_{key}	Cross-sectional area of the key (mm^2) [L^2]
V_{shell}	Volume of the key (mm^3) [L^3]
ρ_{SS}	Material density of stainless steel [ML^{-3}]
n_{key}	Number of keys
f	Feed rate of milling tool (mm) [LT^{-1}]
v	Velocity of milling tool (mm) [LT^{-1}]
k	Constant representing cost components within low importance variable list X_L
c_t	Tooling cost (€/unit)
c_m	Material cost (€/unit)
c_l	Labour cost (€/unit)
c_o	Overhead cost (€/unit)
t_s	Milling setup time (min)[T]
c_T	Motal cost of manufacturing of keys (€)

2. Background

2.1. Conceptual modelling and simulation

Conceptual modelling is the abstraction of a model from a real or proposed system [1]. DACM framework as a conceptual modelling mechanism originally developed as a specification and verification technique for complex systems, but has been applied to many different cases such as additive manufacturing [2], machine learning [3], and multidisciplinary design optimization [4]. The main aim of DACM is to extract and encode knowledge of different forms (expert literature, empirical/experimental, and equations) in the form of a causal graph. The DACM framework starts with functional modelling of the system and assigning of fundamental variables to the different functions of the model. The functions, associated variables, and representative equations are characterized in the causal graph in the form of the cause-effect relationship between the fundamental variables of the functional model. The mathematical machinery to check propagation of an objective in a causal network is based on the Vashy-Buckingham's Pi (π)-theorem and the dimensional analysis (DA) theory [5], [6]. An adjacency matrix or multiple domain matrix (MDM) can be obtained from the causal network representing multiple domains. A MDM is a systematic extension of the design structure matrix (DSM), popularly used in system decomposition, integration, and design of complex systems. This matrix encodes a rich data structure able to represent knowledge extracted from the multi-domain system variables [7]. In this research, the matrix representation is evaluated qualitatively to check for contradictory influences in the objective imposed by the system variables. The qualitative analysis is followed by a dimension reduction method to rank order the system variables and form the optimization objective function.

2.2. Dimension reduction

High dimensionality is a universal challenge during computational analysis in the field of science and engineering. In manufacturing, computationally expensive and resource demanding optimization methods are needed to simulate high-dimensional problems such as production planning, scheduling, and performance optimization. Shan and Wang [8] provided a survey of popular strategies such as decomposition, which is to break up the optimization problem into simpler and smaller steps, and screening of variables to identify more important and less important variables as potential means to tackle the high dimensionality in engineering problems. In this research, a screening using the graph centrality theory and node ranking is performed to classify variables as either low impact or high impact depending on their influence on the performance objectives. Following the classification, the optimization problem is decomposed into two stages. First, the low impact variables are fixed at their highest or lowest values based on their connection to the target variables in the performance objectives. Second, the optimization is performed for only the high impact variables based on the performance criteria having fixed the low impact variable values. The screening using graph centrality and node ranking is presented in the next subsection 2.3.

2.3. Graph centrality and node ranking

In a graph-based representation of a system consisting of a large number of nodes, the user is often interested to know what the most important nodes are. This helps the user to direct their attention towards that part of the graph (or network) which has the most influence on the system represented. Graph centrality measures are used to rank nodes and find the most influential nodes within a complex network. Its most notable applications include wireless network applications, network traffic reduction, and social media network analysis. Many measures exist for graph centrality, Freeman [9] provides one of the earliest empirically based measures of centrality in complex networks. The author identifies three measures, namely, degree, betweenness, and closeness, which can be used to obtain a score for centrality in a graph. Borgatti and Everett [10] developed a unified framework for measuring centrality scores in complex social networks. They describe centrality as the node's contribution to the cohesiveness of the network. They also provide mathematical expressions for computing the centrality score in complex networks. The method of ranking the different nodes could be automated using a centrality measurement algorithm similar to the PageRank algorithm, proposed by Brin and Page [11] of Google. PageRank is a network ranking method developed to compute ranks of webpages in Google's search engine results. An improved version of this algorithm is used in applications that go beyond search engine ranking, which include impact analysis of graph-based system requirements and graph-based feature selection [12], [13]. In this article, a dimension reduction strategy is developed based on the causal graph representation of the system. Node ranking algorithm along with graph centrality measurements are used to identify most influential variables in the system. The variables in the causal graph are classified into two groups; high ranking/high impact variables and low ranking/low impact variables. Thus, only a smaller subset of the complete variable list that have high impact are used for optimizing the performance objectives, reducing computational cost. The methodology for dimension reduction using node ranking is explained using a case study of manufacturing the key and bladder mechanism for superconducting magnets in Section 3.

3. Combined Conceptual Modelling and Dimension Reduction Methodology

European Center for Nuclear Research (CERN) has been developing prototype designs of superconducting magnets which have the field strength of 16 Tesla (twice as much field strength compared to the current working designs operated in the Large Hadron Collider). In the conceptual design phase, three designs are under consideration for prototype manufacturing; the cosine theta design, the block design, and the common coil design [14]. In these three designs, the magnet and its support structure differ in size, performance, manufacturing, and assembly process. When the superconducting magnet is energized, electromagnetic forces try to expand the coil. The coil itself is unable to support these forces in tension. Hence, to counter these force during operation, and to have good control during assembly, a bladder and key (made of stainless steel, SS) mechanism is proposed by researchers to produce cost effective magnets [15]. The design and manufacturing of the various components which constitute the magnet becomes challenging considering that it is a multi-criteria design optimization problem. Larger the number of design variables, design constraints, material selection requirements, manufacturing parameters, and functional requirements of finished product, the bigger the optimization problem becomes computationally.

In this research, the cosine theta design structure for the magnet is used for the case study. The methodology developed is shown as a three step approach in Figure 1 which include, modelling the system using DACM, dimension reduction approach to find most influential variables, and solving the optimization problem. The DACM framework is used to model the behavior of the magnet (expansion of magnet coil due to electromagnetic force or Lorentz's force) during energizing.

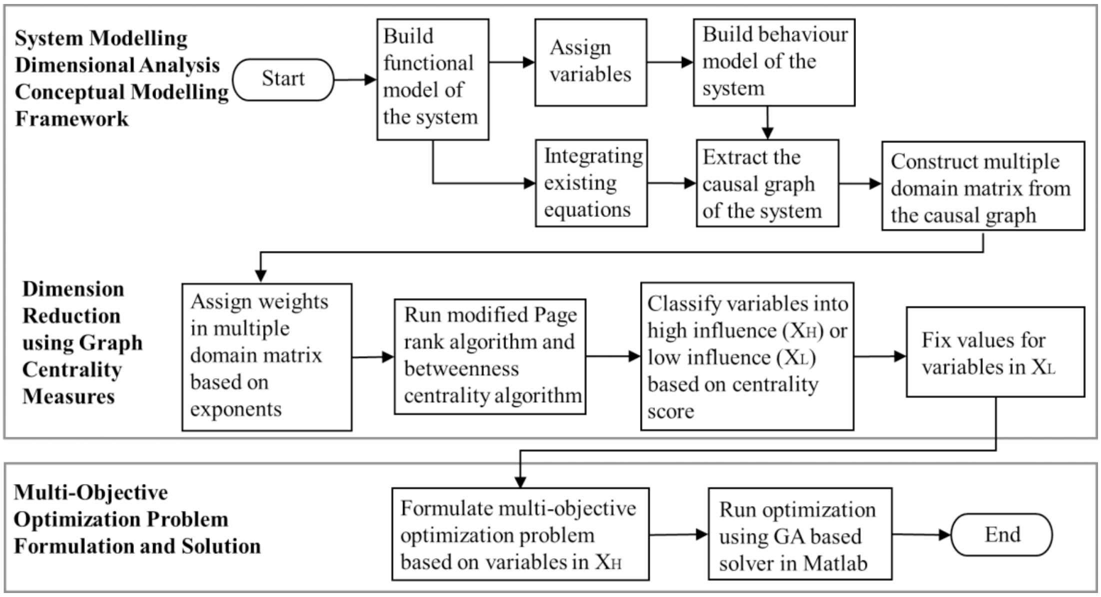

Figure 1: Combined conceptual modelling and dimension reduction methodology

The step-by-step conceptual modelling methodology using DACM is explained in earlier research [5]. The electromagnetic force is counterbalanced by the different support structures of the magnet to prevent magnet displacement. For simplification in this case study, it is assumed that the electromagnetic force is counterbalanced force by the pre-stress provided by the bladder and key mechanism. The functional model of the system is built from an abstract concept to a fidelity model based on elementary phenomena from the domain of classical electrodynamics and theory of failure as shown in Figure 2a. The resultant causal graph of the variables developed based on existing equations representing the different functions of the system is represented in Figure 2b. A simplified version of the cosine theta magnet design used in this case study is shown in Figure 2c. The causal graph maps the variables from the functional domain to the technical domain (used by designers to represent design parameters such as the geometry of the product and material), and from technical domain to process domain (used by manufactures to assign process parameters and compute cost of manufacturing). The nodes are color coded as green (independent variables), blue (intermediate variables), black/grey (exogenous variables), and red (target variables). The arcs that connects the nodes represent the interconnection between different variables as well the exponent of that connection from existing equations. A “+” is assigned on the node connection which denote the relationship, if increase in the n^{th} node increases the $(n+1)^{th}$ node and a “–” relationship if the increase in the n^{th} node decreases the $(n+1)^{th}$ node. Next, a multiple domain matrix is developed from the causal graph. The MDM is a sparse, square matrix representation of the system’s structure that condenses knowledge of all the variables across the functional, design, and manufacturing process domains with their weights obtained from the causal graph (network). The MDM can be considered as a collection of design structure matrices (DSM) in each domain, mapping variables in the domain to itself, as well as variables from other domains to represent the entire structure of the system. The first column of the MDM consists of all the variables in the system. The MDM is a scalable matrix capable of handling very large structures, where each DSM can contain any finite number of variables. The matrix representation of the system facilitates application of ranking algorithms and graph centrality measures to find the most influential variables of the system.

A weighted PageRank algorithm and betweenness centrality scores are used to rank the nodes in the causal network based on the MDM. The PageRank algorithm computes a probabilistic rank vector that provides an importance estimate of all the nodes in the network based on the in-coming and out-going connections of the nodes in the causal graph. The PageRank algorithm is flexible and it can be modified to handle the weights in the causal network. A rank order for the nodes is obtained from the PageRank algorithm based on the measured centrality score. The betweenness centrality score is also computed for the MDM to validate the results obtained from PageRank algorithm.

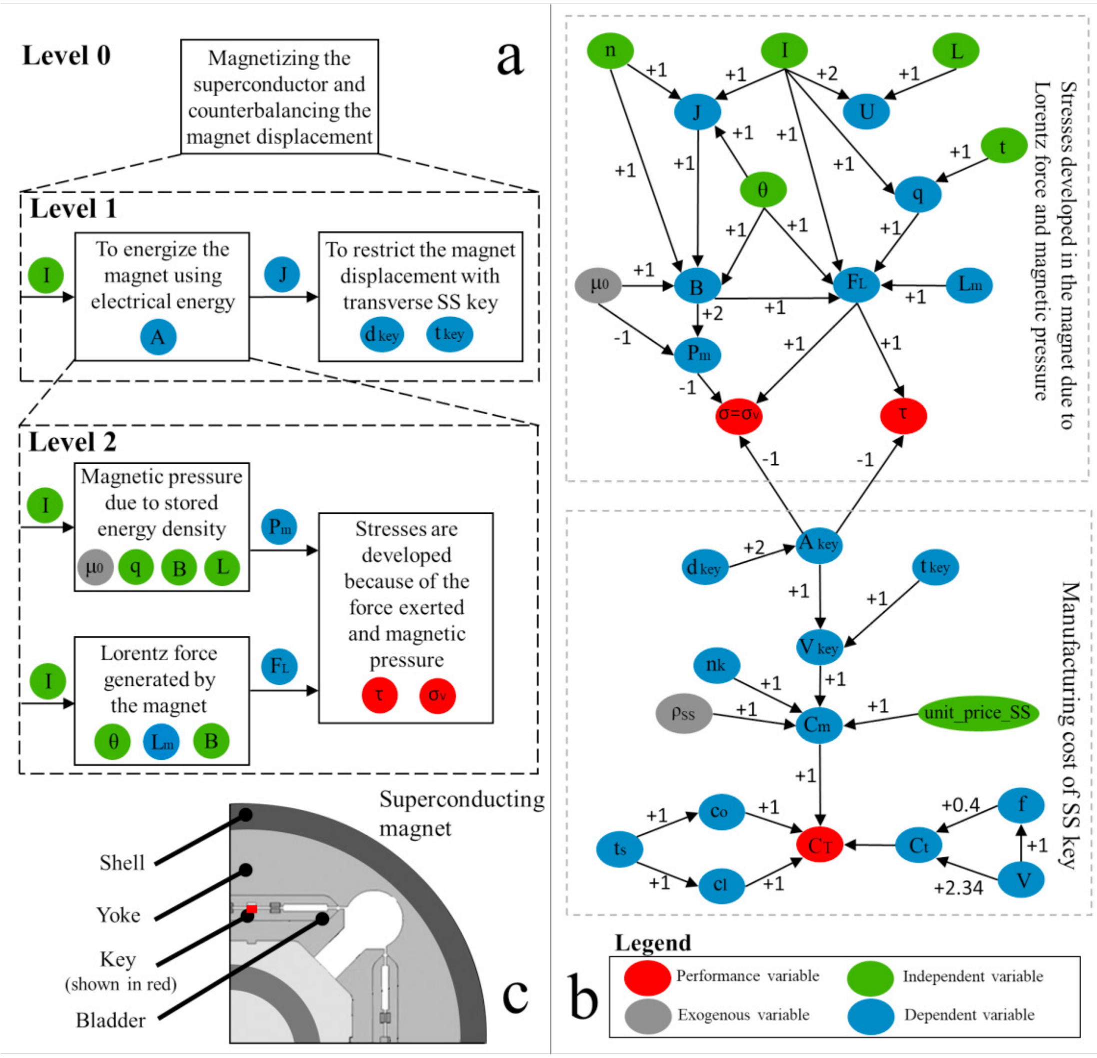

Figure 2: (a) Functional model describing expansion of magnet coil due to electromagnetic force; (b) Causal graph depicting magnet behaviour, and (c) Simplified cosine theta magnet design

Unlike PageRank, which is an Eigen vector centrality measure, the betweenness centrality is a measure of influence a node in a network has over the spread of information throughout the network [16]. The score measures the extent to which a node lies in the shortest path between the hub and the objective node. Higher the betweenness score implies the node is more central to the hub and objective nodes. Hence, betweenness score affirms the categorization of nodes as high importance and low importance nodes. The results of the PageRank algorithm and betweenness score are used to classify the variables into matrices X_H (high influence variables) and X_L (low influence variables). The results of weighted PageRank and betweenness scores of the variables are shown in Fig 3. A variable is considered to be of high importance if it has high score in both PageRank and betweenness centrality measures. The ranks are normalized based on the highest ranking node and a threshold of 0.3 is selected based on the distribution of ranks to categorize the variables. The high scoring variables are stored in X_H matrix and low scoring variables are stored in the X_L matrix. The X_L has low impact on the objective hence, the value of the variables are kept constant at its maximum or minimum depending on whether increase in the variable increases or reduces the performance objective (cost function). The variables in X_H matrix, i.e. $X_H = [B, F_L, \tau, \sigma_v, A_{key}, V_{key}, c_t, c_m, C_T]$, are considered for optimization of the total cost of manufacturing of the stainless steel key against the stress induced due to Lorentz force per magnet.

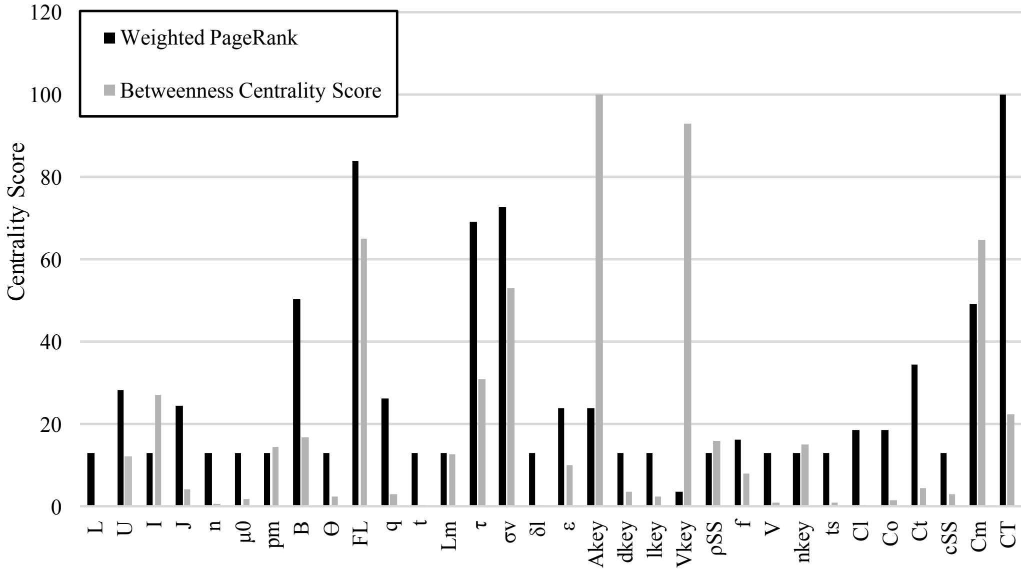

Figure 3: Centrality measure using PageRank algorithm and betweenness centrality score

The optimization problem is then formulated based on the mathematical function for cost of milling the key and the stress generated in the bladder and key mechanism due to the Lorentz force. The data used for optimization can be found in [14], [15]. The objective function for milling the key is as follows:

$$
\begin{aligned}
& f(X_H) \\
& \text{objective 1} \\
& \quad \min f(\sigma) \\
& \quad \text{where, } \sigma = \frac{4F_L}{\pi d_{key}^{\,2}} \\
& \text{objective 2} \\
& \quad \min f(C_T) \\
& \quad \text{where } C_T = c_m + c_t \\
& C_T \approx \frac{1}{4}(\pi d_{key}^{\,2}).l_{key}.\rho_{SS}.\text{unit\_price\_SS} + k \\
& \text{subjected to, } F_L \le 12000 \\
& \qquad\qquad\quad l_{key} \le 890 \\
& \qquad\qquad\quad d_{key} \le 1.5
\end{aligned}
$$

The variables are; $x_1=d_{key}$, $x_2=l_{key}$, the material is considered as stainless steel, SS304 and having standard values of density, unit price, and standard CNC milling parameters with carbide tools. The optimization is run with 'gamultiobj' (a genetic algorithm based solver in Matlab) solver to find manufacturing cost estimate against various levels of stress during energizing of the magnet using the high influence variables in X_H and for fixed values of low influence variables in X_L. From the optimization, the lowest cost obtained from crossover for machining all keys of a magnet was found to be €13.225,51 for a stress value of 191.083 MPa.

4. Conclusions and Future Work

Dimension reduction enables faster and cheaper optimization in the field of engineering design and manufacturing performance measurement. In this research, a dimension reduction methodology is proposed using the DACM framework and graph centrality theory to estimate and optimize the manufacturing cost of new products in the conceptual design stage. The proposed method decomposes the optimization problem into two steps by categorizing variables into low importance variables whose values are prefixed during optimization step 1, and high importance variables, which are optimized using a solver (step 2). The methodology is demonstrated for optimizing the manufacturing cost of the bladder and key mechanism of a new high field superconducting magnet used by CERN. The two step optimization process reduces the effective number of variables that need to be optimized to get minimum manufacturing cost. The reduced variable list reduces the computation time during optimization and hence enables cheaper and faster optimization. Future research focusses on expanding the case study to include other components of 16 Tesla magnet and validation using real data from CERN's prototype magnet manufacturing.

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