Technology Introduction

Validation of a Simulation-Based Method of Deriving Optimal Conditions in Induction Hardening

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1 Introduction

The manufacturing industry can only achieve consistent product quality, improved productivity, and reduced costs simultaneously by optimizing various manufacturing conditions. Traditionally, manufacturers relied on experimental methods based on skilled workers' experience and trial and error to determine these conditions. These methods required a significant amount of time and man-hours, which posed a challenge.

However, recent advancements in numerical simulation technology now allow manufacturers to virtually reproduce manufacturing processes and quantitatively evaluate changes in output in response to modifications in conditions. This enables manufacturers to efficiently derive optimal conditions for specific objectives while reducing the number of experiments. This approach is now an almost realistic option.

This report presents a case study that validates the effectiveness of applying simulation to optimize manufacturing conditions. The case study focuses on optimizing induction hardening conditions. The target process involves the induction hardening of the stepped section of a piston rod used in construction machinery. During this process, complex workpieces with external threads undergo stationary heating and moving heating. This combined heat treatment was applied to multiple parts simultaneously. Consequently, the process involved diverse design variables for heating conditions, which made it difficult to derive optimal conditions using conventional experimental methods. Additionally, quality verification and other tasks required enormous man-hours. To address these challenges, we used JMAG® electromagnetic field analysis software (hereinafter, "JMAG®") to explore optimal conditions for induction hardening. We then validated these conditions using the Simcenter HEEDS® design exploration tool (hereinafter, "HEEDS®") or the genetic algorithm built into JMAG®. We then compare and discuss the processes and results of deriving optimal conditions using these approaches individually. Furthermore, we describe our validation of applying a simulation-based optimization calculation to actual operations.

2 Target Process Overview

Fig. 1 shows a schematic diagram of the target process. In this process, a stepped round bar with external threads from turning is subjected to three heating operations for quenching and tempering.

(1) Stationary heating of the small-diameter section ("preheating")
(2) Stationary heating of the large-diameter section ("stationary heating")
(3) Moving heating toward the small-diameter section ("moving heating")

This complex heating process provides heat treatment to workpieces on their different external diameter sections simultaneously. However, due to the diverse design variables involved in the heating conditions, it is difficult to find optimal conditions using conventional experimental methods. Specifically, the process involves nine design variables related to preheating, stationary heating, and moving heating, as illustrated in Fig. 1. These variables significantly affect temperature distribution and heating time when combined. Additionally, the temperature of each workpiece section must be controlled to fall within a prescribed range to ensure the quality of the heat treatment. The target process was required to shorten the cycle time (CT) of the heat treatment process to improve productivity. Substantially changing the conditions was necessary to derive the fastest achievable conditions using the existing heat treatment equipment.

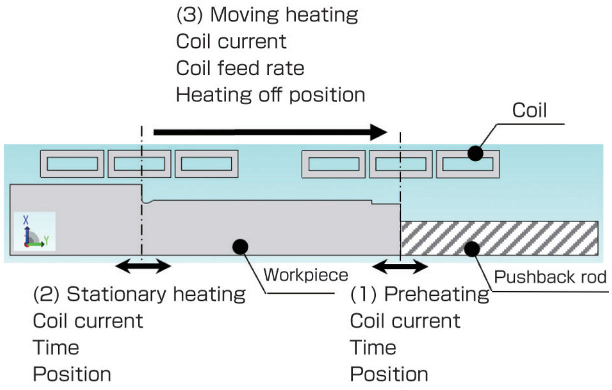

Fig. 1 Schematic diagram of the target process

3 Hardening Basics

Hardening is a typical heat treatment process used to control the mechanical properties of steel. It involves heating the steel to its austenitizing temperature, followed by rapid cooling (quenching) to form a martensitic structure. This improves the steel's hardness and strength.

Inadequate heating can result in improper hardening, while excessive heating can cause grain coarsening, oxidation, and even cracking. Therefore, the temperature at which the parts to be hardened are heated must be controlled within an appropriate range.

In general, quenched steel becomes harder but less tough. Thus, it undergoes tempering, which involves reheating to an appropriate temperature. This process restores toughness and alleviates residual stress. This validation covers quenching only.

4 Overview of the Analysis Model for Validation

Fig. 2 shows the analysis model used for this validation. Focusing on the verification of operational optimization calculations, this validation used a simplified workpiece and heating coil in the target process to minimize the calculation load for a single case. Specifically, a 10-degree axisymmetric segmented model of a stepped round bar with sections of radius r and 2r was adopted. Four temperature measuring points (probes) were placed on the workpiece surface to output the maximum temperature at each point. Fig. 3 shows the probe positions. We used temperature-dependent data for S45C, which was calculated using the JMatPro® material property calculation software as the work material data. For the heating coil data, we used copper data from JMAG®. Since the heating coil is water-cooled by internal channels, we considered the temperature dependency effect to be minimal. Consequently, we omitted the heating conditions and used the initial temperature of 20°C consistently for model simplification.

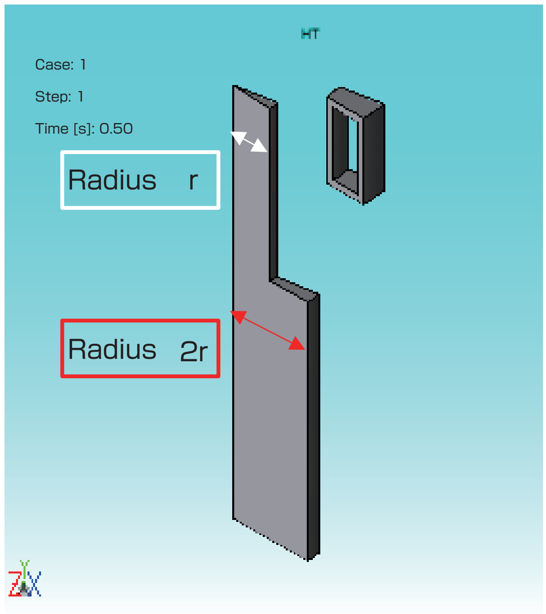

Fig.2 Model used in this validation

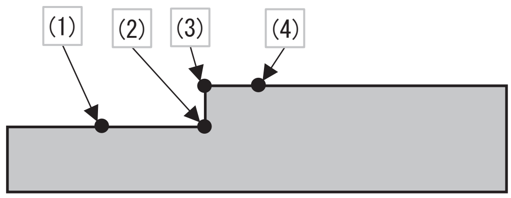

Fig. 3 Probe positions

The mesh size and time step were also fixed at reasonable values to minimize the calculation load. These values were set to enable JMAG® to perform a coupled analysis of the frequency response cross-sectional magnetic field and thermal analyses.

We set nine design variables, which are shown in Fig. 1. Table 1 shows these design variables and their search ranges. For this validation, we assumed a use case that finds conditions enabling uniform hardening within the hardening range while minimizing processing time. We formulated a multi-objective optimization problem with the following objective functions: minimizing the standard deviation of the maximum temperature at each probe point and minimizing the heating time, as shown in Fig. 3. Heating time refers to the time from the start of preheating to the end of moving heating. Constraints were set for the temperature at each probe point and the maximum temperature across the workpiece. Table 2 shows the objective functions and Table 3 shows the constraints.

Table 1 Design variables and search ranges

	Design variable	Min	Max
Preheating	Position [mm]	−10	10
	Time [s]	0	20
	Output [V]	10	60
Stationary heating	Position [mm]	−60	−40
	Time [s]	0	10
	Output [V]	10	40
Moving heating	Output [V]	10	60
	Heating off position [mm]	−10	10
	Coil feed rate [m/s]	0.001	0.01

Table 2 Objective functions

Item	Direction
Standard deviation of maximum temperature at each probe point	Minimize
Heating time	Minimize

Table 3 Constraints

Item	Constraint
Maximum temperature at each probe point [°C]	≧850
Maximum temperature of entire workpiece [°C]	≦1100

5 Overview of Optimization Methods

5. 1 Classification of Search Strategies

Search strategies used in optimization algorithms are generally classified as either local or global.

Local searches focus on exploring the area around the current solution. They converge quickly and are suitable for fine-tuning. However, due to their limited search range, local searches run the risk of becoming stuck in local solutions.

Global searches explore the entire search space extensively, increasing the likelihood of finding better solutions. However, global searches involve higher computational cost and may take a long time to converge.

5. 2 SHERPA Algorithm[1)]

SHERPA (Simultaneously Hybrid Exploration that is Robust, Progressive and Adaptive) is a proprietary optimization algorithm implemented in HEEDS®. SHERPA features a hybrid adaptive search strategy that uses multiple local and global search methods simultaneously. The algorithm runs two to ten search methods in parallel and dynamically adjusts the usage ratio of these methods based on their own effectiveness, thereby improving search efficiency. Additionally, the internal parameters of each search method are automatically adjusted based on information about the design space obtained during the search. This eliminates the need for preliminary tuning by the user. Furthermore, SHERPA® can handle complex design problems by learning the structure of the design space during exploration and flexibly changing the search strategy.

Thanks to these features, SHERPA® tends to derive higher-quality solutions in the same number of evaluations as other typical optimization methods. SHERPA® also demonstrates excellent robustness, exhibiting low standard deviation and stable performance even through multiple trials with randomly varied initial conditions. These advantages enable users without expertise in search methods to efficiently solve optimization problems.

5. 3 Genetic Algorithm

A genetic algorithm is a global search method that imitates the mechanisms of natural selection, crossover, and mutation found in biological evolution. It is a type of probabilistic optimization algorithm. It treats multiple candidate solutions (or "individuals") within the search space as a population and approaches the optimal solution through successive generations. The basic processing steps are as follows[2)]:

(1) Initial population generation: Generate an initial population of individuals randomly within the range of design variables.
(2) Fitness evaluation: Determine the fitness value of each individual based on the objective functions and constraints.
(3) Selection: Select "parent" individuals for the next generation based on fitness.
(4) Crossover: Combine the design variables of the "parent" individuals to generate the "child" individuals.
(5) Mutation: Randomly modify some of the design variables of the "child" individuals.
(6) New generation formation: Create a new population, followed by iterations of evaluation and selection.

Repeating these evolutionary operations extensively explores the entire search space, enabling the derivation of global solutions rather than getting stuck in local ones.

JMAG® implements the Non-dominated Sorting Genetic Algorithm II (NSGA-II) as a multi-objective optimization method with the following characteristics[3) 4)]:

(1) Individual ranking through rapid non-dominated sorting
(2) Diversity preservation through congestion evaluation
(3) Superior individual preservation based on elitism.

These characteristics enable efficient exploration of a population of Pareto-optimal solutions [Note 1)]

(Pareto front Note 2)) that considers the trade-off relationship among multiple objective functions.

Note 1) Solutions that are not dominated by any others [5].

Note 2) A curve configured by Pareto solutions [5].

6 Optimization Calculation Settings and Execution Environment

6. 1 HEEDS® Optimization Calculation Settings

The HEEDS® optimization calculation settings basically consist of the design variables, objective functions, and constraints shown in Tables 1-3, as well as the number of calculations. Table 4 shows the number of calculations for each trial. In the table, "100+100" indicates that 100 calculations are followed by an additional 100 calculations. Archive size refers to the number of cases generated at one time. The results of the calculations in the current archive size are used to generate cases in the next archive size. This process repeats until the specified number of calculations is reached. This series of operations is called a cycle. For this validation, the calculation was executed with the default archive size.

Table 4 Number of calculations for each trial

Trial	Number of calculations	Archive size
1	100 + 100	20 (default)
2	200 + 100	
3	200	
4 Note 3)	5000 (424)	

Note 3) For Trial 4, the computation actually terminated at 424 due to various circumstances, even though the number of calculations was set to 5,000.

6. 2 JMAG® Optimization Calculation Settings

The JMAG® optimization calculation requires the specification of the design variables, objective functions, and constraints listed in Table 1-3. It also requires the specification of the initial case generation method, the number of generations, and the population size. Table 5 shows the settings for each JMAG® optimization trial. When using the "Use existing cases" initial case generation method, each design variable is randomly assigned within the specified search range for that variable, except for the single case generated when setting up the analysis study. The population size and number of generations are based on JMAG®'s recommended values: design variables x 10. For Trial 3, the population size is half the value used in Trials 1 and 2, in order to determine the effect of population size.

Table 5 Settings for each JMAG® optimization trial

Trial	Population size	Number of generations	Initial case
1	96	100	Use existing cases
2	96		
3	48		

6. 3 Execution Environment

Table 6 shows the execution environment for each optimization calculation. The HEEDS® optimization was performed on a standard local PC. Due to the enormous number of cases, the JMAG® optimization used PSL Note 4) and Amazon Elastic Compute Cloud (EC2), a cloud computing service from Amazon Web Services®. For this validation, the number of physical cores of the computational instances was set to match the population size in Table 5. This enables parallel execution of calculations for one generation.

7 Calculation Results and Discussion

7. 1 HEEDS® Optimization Calculation

Fig. 4 shows the distribution of the feasible solutions Note 5) obtained through HEEDS® optimization calculations. Trial 1 produced a set of feasible solutions through the first 100 calculations.

Table 6 Execution environment for optimization calculations

Method	Software	Analysis environment	Remarks
HEEDS® optimization	JMAG v22.1 HEEDS 2304	Local PC	CPU: Intel® Xeon® W-2133 CPU @ 3.60 GHz RAM: 32.0 GB Physical cores: 6 OS: Windows 10
	JMAG v23.1 HEEDS 2404 (Trial 4 only)		
JMAG® optimization	JMAG v23.1	EC2 Compute node: c6a.metal, c6a.24xlarge	PSL usage CPU: AMD EPYC 7R13 RAM: 384 GB (.metal), 192 GB (.24xlarge) Physical cores: 96 (.metal), 48 (.24xlarge) OS: Amazon Linux 2

Note 4) PSL (Power Simulation License): JMAG option license enabling parallel execution of up to 100 cases.

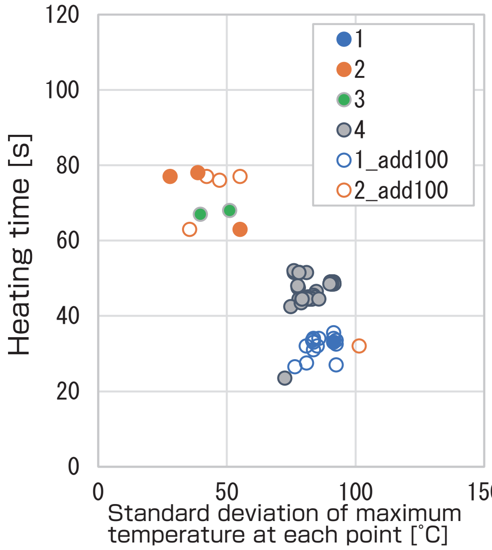

Fig. 4 Distribution of feasible solutions obtained through HEEDS® optimization calculations

Note 5) Solutions that meet all constraints.

The subsequent 100 calculations yielded additional feasible solutions, which were concentrated around the initial set (1_add100). Trial 2 and Trial 3, both of which involved 200 calculations, produced feasible solutions in domains different from those of Trial 1. Specifically, Trial 2's additional 100 calculations produced feasible solutions around those obtained in the initial 200 calculations, as well as around those obtained in Trial 1 (2_add100). Trial 4 also produced feasible solutions in domains different from those in Trials 1, 2, and 3. This is likely due to SHERPA's application of multiple search methods to enable automatic parameter tuning suited to the design space, as described in Chapter 5. Furthermore, the distribution of the feasible solutions obtained through the additional 100 calculations in Trial 2 (2_add100) suggests that HEEDS® tactically used its characteristic multiple local and global search algorithms to explore solutions simultaneously.

Table 7 shows the computation time for each HEEDS® trial. Since the HEEDS® optimization calculations did not involve parallel execution, the generated cases were computed sequentially for this validation. Computation time depends on the number of model elements and steps. For this validation, computing around 300 cases can be completed in about one week when exploring with approximately 6,000 elements for 2D magnetic field analysis and 30,000 elements for 3D thermal analysis with no more than 180 steps.

Table 7 Computation time for each HEEDS® trial

Trial	Number of calculations	Computation time
1	100 + 100	Approx. 72 hrs.
2	200 + 100	Approx. 157 hrs.
3	200	Approx. 92 hrs.
4	424	Approx. 196 hrs.

7.2 JMAG® Optimization Calculation

Fig. 5 shows the distribution of the feasible solutions obtained through JMAG® optimization calculations. The JMAG® optimization produced feasible solutions across a broad domain. Coverage appears to be broadest in the order of Trial 3, Trial 2, and Trial 1. The difference in the distribution of feasible solutions for each trial is likely due to the method used to generate the initial cases. In other words, the search area may vary depending on the solutions output by the randomly generated initial population.

Trial 3 reflects the effect of reducing the population size. Fig. 6 shows the distribution of feasible solutions for Trial 3. According to the figure, Trial 3 yielded few solutions in the area indicated by the red circle. The genetic algorithm generally explores a narrower search space when the population size is reduced. In Trial 3, a possible exploration gap prevented the algorithm from reaching combinations of design variables that should have been feasible solutions. As previously mentioned, the distribution of initial case solutions can affect the final distribution of feasible solutions. Therefore, the population size should not be reduced indiscriminately because domains where search gaps occur are likely random.

Table 8 shows the computation time for each JMAG® trial. JMAG® optimization calculations use PSL and EC2 instances with a number of physical cores corresponding to the number of parallel executions to complete one generation"s worth of calculations in approximately the time required for one case. Thus, the analysis data size for this validation can be computed in approximately two days, even with a scale of 96 populations and 100 generations.

7.3 JMAG® Optimization Calculation Pareto Front and HEEDS® Feasible Solution Distribution

As shown in Fig. 5, JMAG® optimization calculations produce feasible solutions in the form of a Pareto front. Fig. 7 shows the JMAG® Pareto front and the HEEDS® distribution of feasible solutions. The Pareto front was obtained by exploring the range of feasible solutions from minimum to maximum standard deviation of maximum temperature at individual points in 1-unit increments, then extracting the minimum

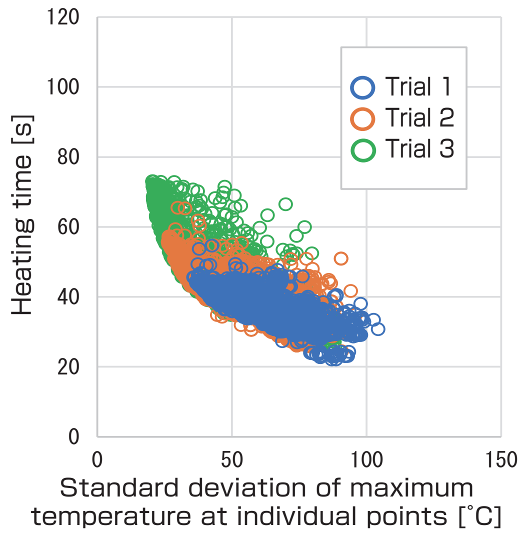

Fig. 5 Distribution of feasible solutions obtained through JMAG® optimization calculations

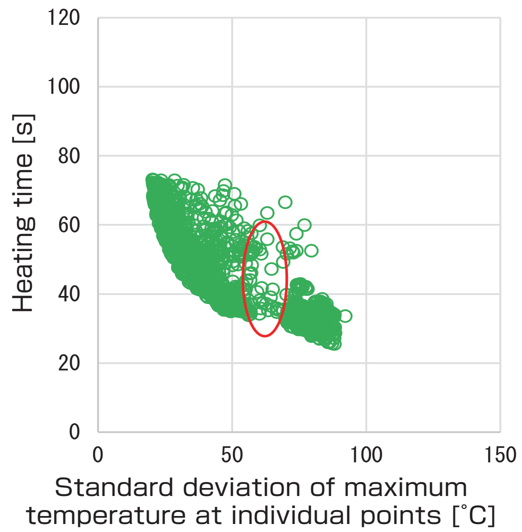

Fig. 6 Distribution of feasible solutions for Trial 3

Table 8 Computation time for each JMAG® trial

Trial	Number of calculations	computation time
1	9696	Approx. 45 hrs.
2	9696	Approx. 49.5 hrs.
3	4848	Approx. 35.5 hrs.

heating time within the search width.

JMAG® produced equivalent Pareto fronts for Trials 1 and 2. However, Trial 3 showed discontinuity in the domain where exploration gaps occurred. Nevertheless, the Pareto front for the longer heating time remained equivalent. Forming Pareto fronts allows designers to identify trade-offs between two objective functions and achieve a limit design with an arbitrary balance.

Conversely, HEEDS® Trials 1 and 4 produced

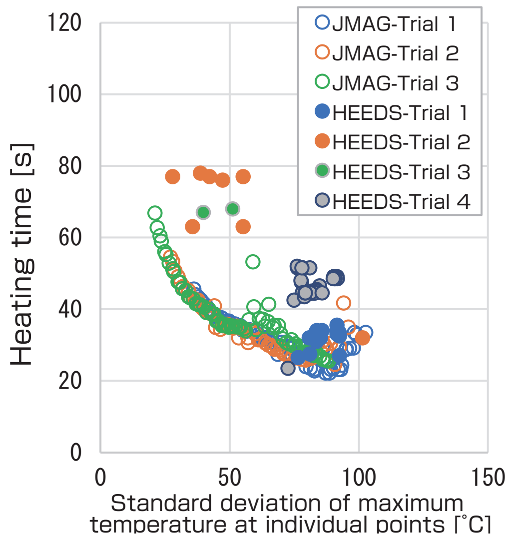

Fig. 7 JMAG® Pareto front and HEEDS® feasible solution distribution

feasible solutions equivalent to or beyond those of the Pareto front derived by JMAG® (solutions in the domain below and to the left of the Pareto front). However, the general distribution of the feasible solutions output by HEEDS® is inferior to the Pareto front derived by JMAG®. Notably, the solution derived by HEEDS® Trial 4 that exceeds the JMAG® Pareto front is located outside the HEEDS® Trial 4 solution set. This indicates that the SHERPA algorithm efficiently explores the design space through combinations of local and global searches, as discussed in Section 7.1. Therefore, it can be concluded that HEEDS® can derive global optimal solutions and Pareto fronts with significantly fewer calculations than exploration using general genetic algorithms.

8 Validation of Applying Optimization Calculations to Actual Operations

Up to Chapter 7, the validation demonstrated the effectiveness of using optimization calculations to derive heat treatment conditions for actual operations in the target process. For this validation, we selected the SHERPA optimization calculation method, which efficiently explored the design space with fewer calculations. We reformulated the problem as a single-objective optimization problem to minimize heating time. This was done by eliminating the standard deviation of the maximum temperature at individual points, which had been set in the earlier validation. As long as the maximum hardening temperature falls within the target temperature range, the quality of the process can be guaranteed. Additionally, we modified the analysis model, search range, and constraints to match the actual machine model.

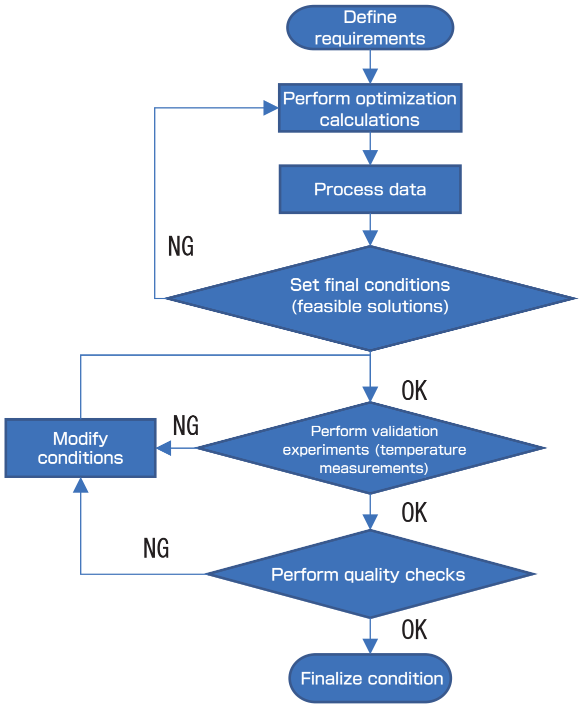

Fig. 8 Flow for determining improvement conditions

Fig. 8 shows the flow for determining improvement conditions. The general steps are as follows:

(1) Set the search range, objective functions, and constraints based on the target cycle time and process constraints. Set the maximum possible number of calculations within the given period, and then perform the optimization calculations.

(2) After the optimization calculations are complete, perform post-processing to extract feasible solutions and set conditions.

(3) Perform hardening on the actual mass production equipment under the set conditions. Measure the surface temperature at locations equivalent to the analysis model and verify that the measurements fall within the target temperature range.

(4) Finalize the conditions if they pass the quality checks.

During validation, we conducted optimization calculations while making model adjustments, totaling 610 calculations. Of these, 264 were performed with the final model, yielding six feasible solutions. We then selected the best conditions and conducted temperature measurement experiments.

Fig. 9 shows the analysis results and the measurement values before and after modifying the conditions. When hardening was performed under the conditions set based purely on the optimization calculation results, the measurement values showed higher temperatures than the analysis results. Additionally, the maximum temperature measured at location 1 exceeded the target temperature range. This is likely due to the JMAG® analysis model being insufficiently fit to reproduce the physical phenomena. The model should be improved in the future. Based on these results, we finally tuned the heat treatment conditions approximately three times and successfully derived heat treatment conditions that kept all sections within the target temperature range. Compared with conventional mass production conditions, we reduced machine cycle time (MCT) by 29% and CO_2 emissions from power consumption by 24%. Of the MCT reduction, the time required for heating, which was the target of the optimization calculation, decreased by 49%.

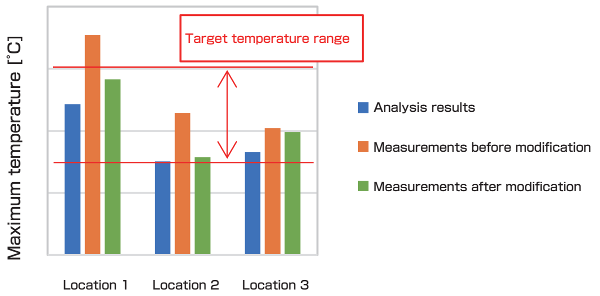

Fig. 9 Analysis results and measurements before and after condition modification

The following compares the time it would take to implement similar improvements through trial and error in experiments with the time it takes using the current method. Specifically, we estimated the man-hours that the responsible personnel spent deriving improvement conditions prior to this validation and compared them with the hours spent applying simulation-based optimization calculations. Fig. 10 shows the comparison of estimated man-hours. As a result, using the optimization calculations reduced man-hours by approximately 76%.

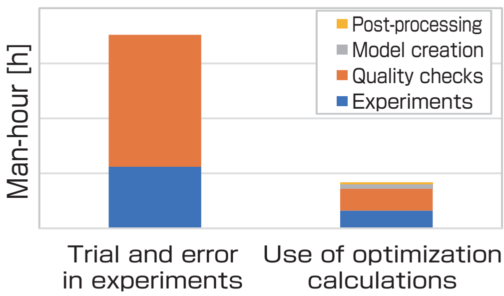

Fig. 10 Comparison of estimated man-hours

The trial-and-error approach to experiments requires identifying individual trends in preheating, stationary heating, and moving heating within the target complex heating process. Then, conditions are combined based on these trends. This approach necessitates numerous experiments and quality checks and relies heavily on the expertise of the personnel. Furthermore, the actual experimental levels are limited by available man-hours and delivery time, which raises doubts about the optimality of the derived conditions.

In contrast, using optimization calculations can substantially reduce the man-hours required for experiments and quality checks, while presenting several hundred patterns of trial results. Regardless of their level of expertise, responsible personnel can establish optimal conditions. Additionally, they can perform other tasks while the optimization calculations are running, thereby improving work efficiency. Furthermore, although this validation uses sequential calculations instead of parallel ones, the cost savings achieved through reduced man-hours could be allocated to computing resources. This would allow for parallel calculations, further reducing the time required for optimization calculations and promoting further design exploration through additional calculations.

The results of this validation show that optimization calculations can determine heat treatment conditions, although there is a discrepancy between the analysis and experimental results. The validation demonstrates the effectiveness of applying optimization calculations .

9 In Closing

We validated the application of simulation-based condition optimization to the high-frequency hardening process for the stepped section of a piston rod used in construction machinery, and we verified its effectiveness. The Production Technology R&D Center has experience optimizing the shape of plating masking fixtures with HEEDS®[6]. Optimization calculations are becoming increasingly popular.

However, Chapter 8 revealed a discrepancy between the analysis and experimental results, requiring fine-tuning of the conditions during the validation experiments. We will address improving analysis accuracy to enhance the reliability of the results.

Optimization calculations can be applied to processing technology, as well as to any kind of design exploration, such as product design and plant simulation. In order to realize digital twins, we will establish simulation technologies for various fields and use optimization calculations to dramatically improve productivity and work efficiency.

Finally, I would like to take this opportunity to express my sincere gratitude to the software vendors who participated in the validation and to the relevant internal departments.

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