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Multistage Parameter Optimization for Rule Generation for Multistage Manufacturing Processes

Ida Wahyuni, Chin-Chun Chang, *Member, IEEE*, Hua-Sheng Yang, Wei-Jen Wang, *Member, IEEE*, and Deron Liang

***Abstract*—Defects in multistage manufacturing processes (MMPs) decrease profitability and product quality. Therefore, MMP parameter optimization within a range is essential to prevent defects, achieve dynamic accuracy, and accommodate manufacturing tolerances. However, existing studies only focused on optimization in a single manufacturing stage of MMP, such as the weaving stage in fabric manufacturing. Furthermore, existing methods optimize for a single value rather than a range. Thus, we propose a novel approach called multistage parameter optimization for rule generation (MPORG) to prevent the occurrence of defects in MMPs. In the proposed approach, key parameters are identified and optimized to a range for each defect type. Subsequently, the optimized parameters for each defect type are merged. Our approach is novel because it optimizes parameters to a range rather than a single value, allowing engineers to select a value in this range according to their experience. It also provides results that are specific to a product type. Our approach outperformed the classification and regression tree (CART) algorithm and multiresponse CART method in experiments on an empirical fabric manufacturing dataset that we gathered. The experimental results demonstrated that the MPORG approach can prevent the occurrence of single-type or multiple-type defects by approximately 89%.**

***Index Terms*—Fabric manufacturing, industrial data mining, multiple type defects, multistage manufacturing processes, parameter optimization in value range.**

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Nomenclature

Symbol	Description
C_m	Rule condition of R_{m} comprising a set of parameters $\{x_{i;m} \mid \forall i \in \{1,\ldots,I_m\}\}$, with $x_{i;m} \in [a_{i;m},\, b_{i;m}]$. C_m is called the global condition, $m = \{1,\ldots,M\}$.
$x_{i;m}$	Value of the ith parameter of C_{m}, $i = \{1,\ \ldots, I_m\}$.
$a_{i;m}$	Lower limit of ith parameter value, $i = \{1,\ldots,I_m\}$.
$b_{i;m}$	Upper limit of ith parameter value, $i = \{1,\ldots,I_m\}$.
I_{m}	Total parameter or element of C_{m}, $m = \{1,\ldots,M\}$.
Y'_m	Estimated total number of defects after using C_{m}, $m = \{1,\ldots,M\}$.
g	Instance in the dataset.
G	Dataset.
$E(C_m)$	Set of compliant instances.
$\lvert E(C_m)\rvert$	Cardinality of $\mathrm{E}(\mathrm{C}_m)$, or the number of elements in $\mathrm{E}(\mathrm{C}_m)$.
h_m	Total number of noncompliant instances.
$F(C_m)$	Total actual number of defects from the compliant instances.
$FN(C_m)$	Total estimated number of defects of noncompliant instances after implementing the C_m of R_m.
R_{m}	Format of mth rule: IF product type = "A" THEN solution$_A = C_m$, $m = \{1,\ldots,M\}$.
$\mathrm{EB}(C_m)$	Estimated benefit or estimated defect prevention when implementing the condition C_m.
J	Number of instances in the dataset.
y_j	Number of defects for jth instances, $j = \{1,\ldots,J\}$.
Y	Total actual number of defects (defects density).
P	Total number of MMP parameters.
D	Total number of defect types.
$y_{j;d}$	Total number of defects for jth instances, $j = \{1,\ldots,J\}$, and the dth defect type, $d = \{1,\ldots,D\}$.
$w_{j;d}$	Predicted total number of defects for jth instances, $j = \{1,\ldots,J\}$, and for the dth defect type, $d = \{1,\ \ldots,\ D\}$, after using the regression condition from the CART algorithm.

IC_d Individual conditions of the dth defect type, $d = \{1, \ldots, D\}$.

M Total number of condition combinations after merging.

I. Introduction

MULTISTAGE manufacturing processes (MMPs) are highly common in industry [1] because high-quality products cannot be produced through a single-stage process [2], [3]. However, MMPs are susceptible to single-type or multiple-type defects [4], which reduce manufacturing quality and thus profitability [5]. MMPs are common in fabric manufacturing. Specifically, yarns are processed into fabric over several stages, including warping, sizing, beaming, and weaving (see Fig. 1). In this process, defects, such as color spots, misprints [5], knots, broken ends, holes, thick bars, and thin bars [6], are common. These defects reduce the value of finished fabric by as much as 45–65% and thus severely erode profit margins [7]. Therefore, zero-defect manufacturing (ZDM) is highly useful for the fabric industry.

In general, ZDM involves detection, prediction, repair, and prevention, all of which are interconnected [8]. However, ZDM studies have only focused on the detection and repair of defects [9], [10]. Whereas, methods for defect prevention reduce delays [11], costs [12], and defect frequency, especially in MMPs. Therefore, ZDM methods for MMPs must be further improved [13].

Numerous studies have proposed defect prevention approaches for fabric manufacturing. For example, Dema et al. [14] proposed a machine vision method for evaluating the wicking quality of fabric. However, their method, as is the case with device-based optimization in general, is expensive and requires considerable maintenance, making it impractical and only suited to some and not all stages of an MMP. In addition, Dong et al. [15] used association rules in their method, and Mukhopadhyay et al. [16] used evolutionary algorithms to address the weaknesses and, thus, improve the performance of linear regression (LR). However, their approaches only yield a single value for each parameter; flexible parameter values are crucial to achieving dynamic accuracy and accounting for tolerances in manufacturing devices [17]. Therefore, an approach that optimizes parameters to a range rather than a single value (such as weft density being optimized to a range of 79.5 PPI $<$ weft density $\leq$ 109 PPI) is required [18]. Although several methods, such as those proposed by Zhang et al. [19] and Nejat et al. [20], optimize parameters to a range based on fuzzy numbers, continual tweaking by experts is required for the implementation of these methods.

Studies on manufacturing optimization for the fabric industry have only focused on optimization in a single manufacturing stage, such as sizing [19], weaving [16], [20], or finishing [14], [15]. Single-stage optimization methods have also been implemented in the manufacturing processes of other industries, including the metalworking [21] and semiconductor [22] industries. However, single-stage optimization in an MMP is generally insufficient for achieving ZDM [23]. Nonetheless, preventing

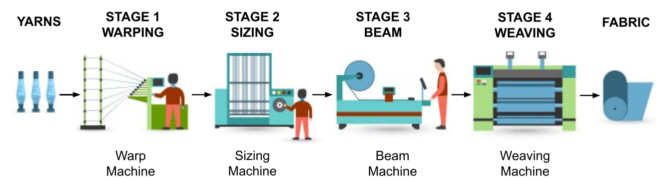

Fig. 1. MMP in fabric manufacturing.

defects in every stage is impractical because an MMP involves many stages [24]. Typically, defect prevention methods are only applied when production machines are subject to inspection or when the finished product rolls off the production line [11]. However, defects can occur in the intermediate stages of an MMP [25], and optimization processes for a single stage may interfere with each other when implemented simultaneously [26]. Moreover, if the information is unavailable as to the manufacturing stages at which defects occur, the stages in which optimization is required cannot be determined. Therefore, preventing defects in an MMP is challenging due to the complex range of machines involved in manufacturing [27].

All-in-one multistage optimization offers a solution to this problem [11]. However, studies on defect prevention in MMPs (e.g., those in fabric manufacturing) are scarce. We noted two gaps in the literature. First, few studies have investigated multistage optimization for MMPs in fabric manufacturing. Second, studies have not conducted the multiple batteries of tests required for evaluating multistage optimization methods for MMPs. In general, such a method must be capable of determining the ranges of parameters required for defect prevention in the absence of information on the manufacturing stages at which defects tend to occur.

In response to these problems, this study formulated a novel method called multistage parameter optimization for rule generation (MPORG). This method outputs parameter ranges for defect prevention in an MMP that are specific to a product type, which MMP engineers can adopt. Conceptually, MPORG proceeds in two main steps. First, sequential backward selection (SBS) is used to identify key parameters from a large set of MMP parameters. Then, the classification and regression tree (CART) algorithm is used to optimize every key parameter to a range [28], and these optimization results are specific to particular defect types. Second and finally, the optimization results for each parameter are merged into a set comprising the optimal ranges of all parameters (called the global condition).

This study evaluated the performance of the algorithm on a real-world I-Manufacturing dataset, which this study compiled, in terms of the estimated benefit (EB) and the number of manufacturing instances $|E(C_m)|$ where the optimized global condition is applied; specifically, better performance is indicated by a higher EB with a reliable $|E(C_m)|$ (defined in this study as an $|E(C_m)|$ of at least 5%–10% of testing dataset). This dataset contained data on 17 584 batches of products collected over approximately 5 years (2015–2019) on 2 yarn-related and 19 machine-related parameters. The dataset also contained information on single-type and multiple-type defects in each batch of products. We adopted forward-chaining cross validation because the dataset was a time series.

The main contributions of this work are summarized as follows.

1) Our MPORG method is the first to cover multiple types of defects over multiple stages in fabric manufacturing MMPs. Therefore, it differs from existing single-stage optimization approaches for fabric manufacturing.
2) Our MPORG method is the first to optimize parameters to a range rather than to a single value, with no need for expert input. This allows engineers to adjust MMP parameters to a specific value within this range on the basis of their expertise and the tolerances in production machinery.
3) In experiments, the MPORG could prevent the occurrence of approximately 89% of single-type or multiple-type defects.

The rest of this article is organized as follows. Section II formalizes the problem of fabric manufacturing on the basis of real-world experience and details the proposed approach. Section III describes the evaluation experiments, where the proposed approach was evaluated against several competing methods. Section IV discusses the proposed approach and the experimental results. Finally, Section V concludes this article.

II. Proposed Approach

Section II-A formalizes the problem of defect prevention, and Section II-B details the MPORG.

A. Problem Formulation

Two assumptions are made. First, the manufacturer initially uses nonoptimal parameter values in the MMPs; thus, single-type or multiple-type defects are common. Second, no information is available as to the manufacturing stage at which defects tend to occur.

An optimized condition C_m is defined as a set of optimized parameters for all manufacturing stages as follows.

Definition of optimized condition $\boldsymbol{C_m}$: C_m is a set of ranges of key parameters $\{x_{i;m} \mid \forall i \in \{1, \ldots, I_m\}\}$. Each key parameter has an optimized range $[a_{i;m},\ b_{i;m}]$, where $a_{i;m}$ and $b_{i;m}$ are known values. For example, $C_m = \{(a_{1;m} < x_{1;m} \leq b_{1;m}),\ (a_{2;m} < x_{2;m} \leq b_{2;m}),\ \ldots,\ (a_{i;m} < x_{i;m} \leq b_{i;m})\}$.

In the proposed approach, the number of defects Y'_m when condition C_m is realized is estimated in three main steps. First, a definition of compliance between C_m and the parameter values in each empirical instance of manufacturing g is established. Second, the number of defects in compliant instances $F(C_m)$ is calculated, and the average value of $F(C_m)$ is taken as the estimated number of defects in every noncompliant instance $\mathrm{FN}(C_m)$. Third, the value of Y'_m is calculated by summing the number of defects in $\mathrm{F}(C_m)$ and the number of defects in $\mathrm{FN}(C_m)$. Specifically, in the first step, compliance is defined as follows.

Definition of compliance: An instance g of the dataset G is compliant with C_m if and only if every parameter $x_{i;m}$ in g lies within the range $[a_{i;m},\ b_{i;m}]$.

Note that all instances are either compliant or noncompliant. Thus, (1) and (2) follow, where h_m is the number of noncompliant instances

$$E(C_m) = \{g \mid g \in G \wedge g \text{ complies with } C_m\} \tag{1}$$

$$h_m = J - |E(C_m)|. \tag{2}$$

In the second step, we assume that C_m has been applied to optimize the production process. Then, we estimate the number of defects in noncompliant instances (i.e., instances where C_m has not been applied). This estimation proceeds on the assumption that the number of defects in every noncompliant instance is equal to the average number of defects in compliant instances. In this case, the total number of defects in the compliant instances $F(C_m)$ must be calculated using (3). The total number of noncompliant instances $\mathrm{FN}(C_m)$ can then be calculated using (4) as follows:

$$F\left(C_m\right) = \sum_{g_j \in E(C_m)} y_j \tag{3}$$

$$\mathrm{FN}(C_m) = \frac{F(C_m)}{|E(C_m)|} \times h_m. \tag{4}$$

In the third step, the total number of defects after the implementation of C_m (in the second step) can be estimated by summing $F(C_m)$ and $\mathrm{FN}(C_m)$, as written in

$$Y'_m = F(C_m) + \mathrm{FN}(C_m). \tag{5}$$

We describe our problem by using an if–then rule [29], where the antecedent is a product type and the consequent is the C_m condition corresponding to that product type. Thus, a rule (R) is defined as follows.

Definition of rule $\boldsymbol{R}$: R is an if–then statement that takes a product type as the antecedent and a particular instance of C_m as the consequent.

The optimality of C_m in defect prevention is evaluated in terms of the EB, which ranges between 0 and 1. Specifically, the EB is the estimated number of defects that is prevented by the implementation of C_m. Although the EB is an estimate, this study adopted the EB because direct measurements of reductions in defect frequency due to C_m are prohibitively costly and time-consuming.

The EB is defined in (6), where Y is the total actual number of defects and Y'_m is the total number of estimated defects after C_m is implemented. In the evaluation experiments of this study, we calculated Y from the I-Manufacturing dataset, where Y is the sum of the number of defects in each instance of the dataset. Thus, we aim to find an instance of C_m that maximizes EB (i.e., an instance of C_m that is truly optimal)

$$\max_{C_m} \mathrm{EB}\left(C_m\right) = \frac{Y - Y'_m}{Y}. \tag{6}$$

Specifically, better performance is indicated by a higher EB with a reliable $|E(C_m)|$ of at least 5%–10% of testing dataset.

TABLE I
STYLIZED EXAMPLE OF ESTIMATED TOTAL NUMBER OF DEFECTS AFTER GLOBAL CONDITION IS APPLIED

Index	Warp Speed	Weaving Speed	Y	Status	Y'_m
1	370	415	1	Compliant	1
2	360	410	0	Compliant	0
3	380	410	1	Compliant	1
4	430	480	5	Noncompliant	0.7
5	300	450	10	Noncompliant	0.7
6	290	520	5	Noncompliant	0.7
7	440	480	5	Noncompliant	0.7
8	320	500	5	Noncompliant	0.7
9	300	520	5	Noncompliant	0.7
10	410	430	1	Noncompliant	0.7
Total	-	-	38	-	6.9

Algorithm 1: MPORG.

Input: training dataset = $\{x_i, y_d\} \mid 1 \le i \le P$ and $1 \le d \le D$.
Output: C_m

```
1  #Procedure SBS-CART.
2  For each d do
3    F = {all parameters in x_i}
4    ϵ = Mean validation MSE of CART on F by k-fold cross-validation
5    key_parameters_d = F
6    While |F| > 1 do
7      F′, ϵ′ = SBS_CART(F)
       #F′: parameter set selected by SBS
       #ϵ′: mean validation MSE associated with F′
8      If ϵ′ < ϵ then
9        key_parameters_d = F′
10       ϵ = ϵ′
11     End If
12     F = F′
13   End While
14   IC_d = build CART using the training dataset on key_parameters_d
15   Assign IC_d to IC_CART_Set
16 End For
17 #Procedure Merging.
18 For conditions = 1 to M do
19   C_m = Merge all possible combination of IC_d from IC_CART_Set
20   If the same parameter found then
21     Merged the range using the union or intersection operations
22   End If
23 End For
24 Return C_m
```

Table I illustrates the calculation of EB in a stylized example where $C_m = \{(350 < \text{warp speed} \le 400), (400 < \text{weaving speed} \le 420)\}$ for a testing dataset with 10 instances. In this example, EB is equal to 0.82.

B. Proposed MPORG Method

In the MPORG method, the aim is to minimize the occurrence of defects Y by optimizing key MMP parameters to a specific range. To achieve this, an EB-maximizing instance of C_m is determined in three steps. First, the key MMP parameters (in a larger set of parameters) are determined. Second, optimal ranges (denoted IC_d) for the specific parameters affecting the likelihood of a specific type of defect are calculated. These two steps are executed using the SBS [30] and CART [28] algorithms, and a stable regression tree model is selected on the basis of the mean squared error (MSE) as an evaluation metric, which is defined in (7). Third, all IC_d conditions from the model are merged to form C_m. Subsequently, the C_m with a high EB is selected to minimize the likelihood of defects

$$\mathrm{MSE} = \frac{1}{J}\sum_{j=1}^{J}\left(y_{j;d} - w_{j;d}\right)^2. \tag{7}$$

1) Selecting Key Parameters and Finding the Value Range:

As mentioned in the introduction, optimization to a range rather than to a single value is advantageous for MMPs, and fuzzy numbers and the CART algorithm can be used to do so. This study chose the CART algorithm because it requires minimal human involvement and is applicable to classification and regression problems [31]. In general, the CART algorithm is used to construct a classification tree to solve problems where the response variable is discrete or nominal. When the response is continuous, the CART algorithm is used to construct a regression tree.

In our MPORG method, the SBS-CART algorithm is used to construct a regression tree model for each defect type. First, as described in Algorithm 1, the fabric dataset comprising data on some MMP parameters and defects is prepared. For each defect type, the training dataset is split into five folds of subtraining and validation datasets through the use of forward-chaining cross validation.

CART is then used to determine the key parameters, which are defined as those that are most influential in the optimization process [32]. However, the CART algorithm cannot determine whether a set of key parameters as opposed to another set yields the lowest (i.e., best) validation MSE. Thus, the feature selection method SBS is used to identify the optimal key-parameter set for a given defect by testing that parameter set on a validation dataset [33] (lines 3–13 in Algorithm 1). As illustrated in Fig. 2, at each iteration, the SBS algorithm removes the least significant parameter with the lowest average CART-determined validation MSE in k-fold cross validation (line 7). Subsequently, the key-parameter set with the lowest validation MSE is chosen (lines 8–11). Selecting a regression tree model with the lowest validation MSE is crucial. In this case, the IC_d that correlates with a lower defect value is more likely to be discovered as a result. Ultimately, it may lead to a significant reduction in defects.

Subsequently, the CART algorithm constructs regression tree model using the key parameters for each defect type (lines 14–15). An example of a regression tree model for broken warp defects in microfiber fabric with three leaf nodes for the parameter of oil wax speed is illustrated in Fig. 3. The regression tree is read by branching to the left or right from the top node (the root node) all the way to the bottom (ending at the leaf nodes). Because it has three leaf nodes, this regression tree has three individual conditions: (1) oil wax speed ≤ 10, (2) $10 <$ oil wax speed ≤ 25, and (3) oil wax speed > 25.

The number of IC_d conditions generated by the CART algorithm varies with the number of parameters selected using SBS for each defect type. In the proposed approach, all generated IC_d conditions from each defect type (see Table II for examples) are merged. Lines 18–23 of Algorithm 1 describe the merging process, which is detailed in Section II-B-2.

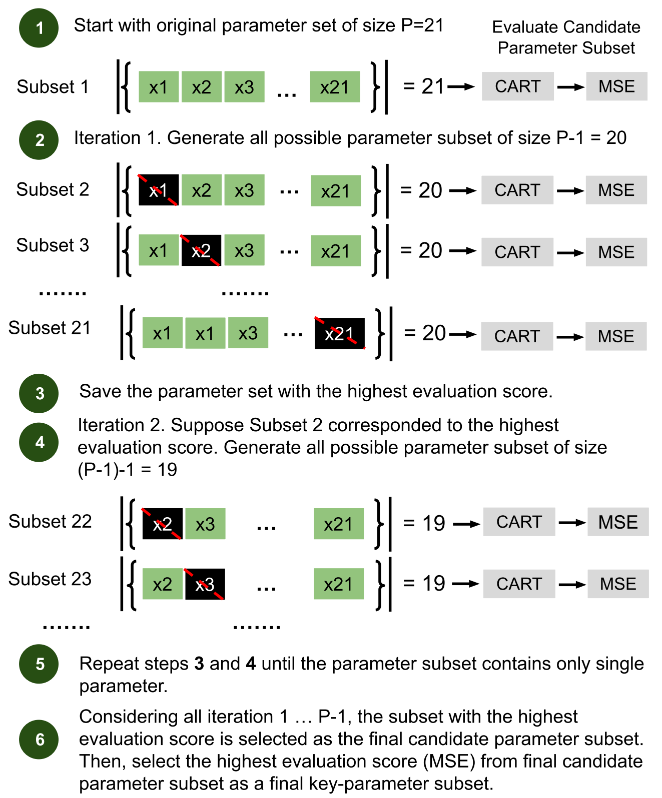

Fig. 2. Steps of SBS-CART.

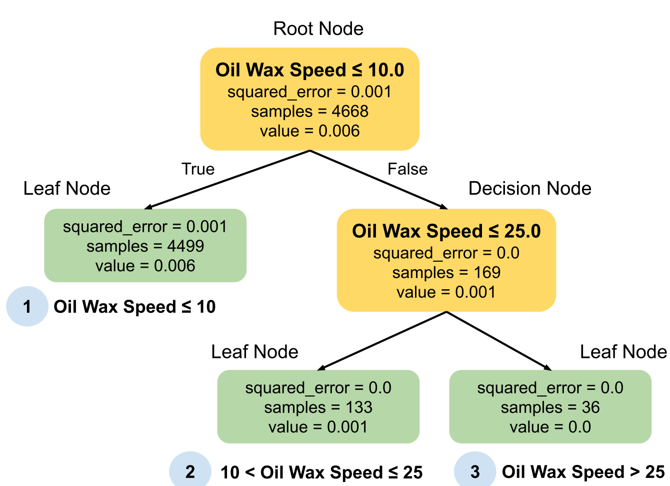

Fig. 3. Example of regression tree.

TABLE II
EXAMPLE OF CONDITIONS GENERATED BY THE CART ALGORITHM

Conditions	Symbol	List of Individual Condition
Conditions of first defect type	IC_1	$IC_{1:1}$: (126 < Fiber Base ≤ 168) and (57 < Reed Width ≤ 85) …
Conditions of second defect type	IC_2	$IC_{2:1}$: (120 < Fiber Base ≤ 135) and (Weft Density > 111) …
Conditions of Dth defect type	IC_D	$IC_{D:1}$: … …

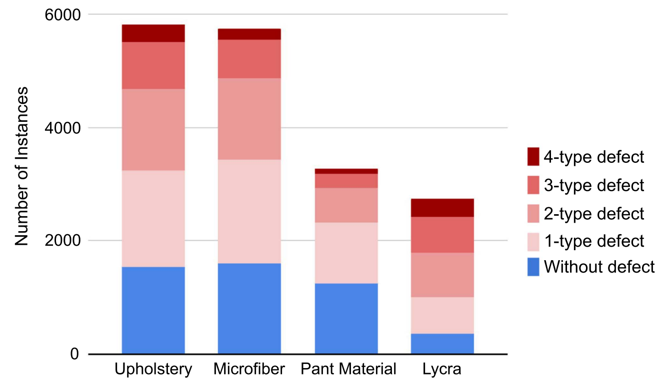

Fig. 4. Defect distribution per fabric type.

2) Merging Methods: Generally, in an MMP, especially in fabric manufacturing, multiple types of defects occur simultaneously and are distributed unevenly (see Fig. 4). However, the SBS–CART algorithm only outputs IC_d conditions that each cover one type of defect. Moreover, insufficient data on specific defect types may result in poor model training. Therefore, our MPORG method merges these individual IC_d conditions into a global condition C_m.

In general, for d defects, conditions for 2 to d defects can be merged. However, the merging of conditions for all d defects may not yield the most favorable results. Thus, we conducted a sensitivity analysis to determine the number of defects to be used in the merge. We only restricted our tests to the merger of two to four defects because our I-Manufacturing dataset only covered four defects. Our sensitivity analysis covered all possible combinations of parameters for all possible numbers of defects (i.e., two to four defects).

Furthermore, we tested whether the ranges (for the same parameter) in the individual conditions should be merged using the set union or set intersection operations. In rare cases, where the intersection of ranges was empty, we used both ranges in evaluations of whether the intersection operation resulted in a global condition C_m with a high EB. The union and intersection operations are defined in

$$\text{Union}\left(\{[a_{i;m},\ b_{i;m}]\}\right) = \{[\min(\{a_{i;m}\}), \max\left(\{b_{i;m}\}\right)]\} \quad (8)$$

$$\text{Intersection}\left(\{[a_{i;m},\ b_{i;m}]\}\right) = \{[\max(\{a_{i;m}\}), \min\left(\{b_{i;m}\}\right)]\}. \quad (9)$$

In general, the set union of several ranges is more expansive than the constituent ranges. Therefore, we tested whether the MSE of merged C_m conditions increased for the training dataset after the set union operation. Subsequently, filtering was conducted, where C_m was applied if and only if its MSE was lower than or equal to the average MSE of its constituent individual conditions.

For both set operations, parameters that are in one condition but not any other have their ranges included in C_m as is. An example of such merging for two defects sharing only the parameter "fiber base" is given in Table III. This example also

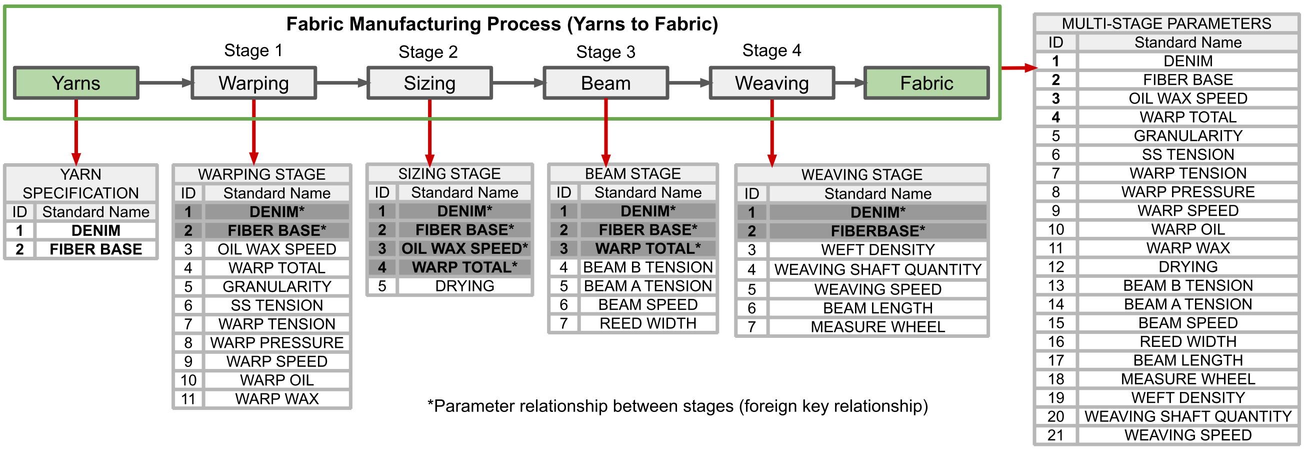

Fig. 5. Manufacturing stage that each parameter corresponded to in the I-Manufacturing dataset.

TABLE III
EXAMPLE OF A CANDIDATE GLOBAL CONDITION

Condition	Example Combination of $IC_{1:1}$ and $IC_{2:1}$
Condition C_m using Union	C_m: (120 < Fiber Base ≤ 168) and (57 < Reed Width ≤ 85) and (Weft Density > 111)
Condition C_m using Intersection	C_m: (126 < Fiber Base ≤ 135) and (57 < Reed Width ≤ 85) and (Weft Density > 111)

involves the parameters of reed width and weft density. All these parameters implicate multiple stages of the manufacturing process; this indicates that the MPORG can be used by engineers for the optimization of the multiple stages in MMPs. Finally, the consequent of rule R is the merged C_m condition with the highest EB and reliable $|E(C)|$.

III. Evaluation Experiments

Section III-A describes the dataset used in this study's evaluation experiments, Section III-B presents results on the MPORG's performance, and Section III-C–F presents results on the MPORG's performance relative to competing methods.

A. Datasets

In this study, we used an empirical dataset called I-Manufacturing on fabric production that we gathered and processed as follows. First, we gathered data by collecting paperwork records of manufacturing machine parameters for each stage of the manufacturing process from engineers in fabric manufacturing plants; we also collected records on time points at which production began and ended, and fabric inspection results. These data were then digitized. Subsequently, we merged the data into a single dataset and then cleaned the data (i.e., removed noise from negative data and factory simulation data and removed duplicates).

The dataset was for the period of 2015–2019 and covered 17 584 batches (i.e., manufacturing instances) of upholstery, microfiber, pant material, and Lycra products. This dataset had records of 12 846 defects of either low or high density. Thus,

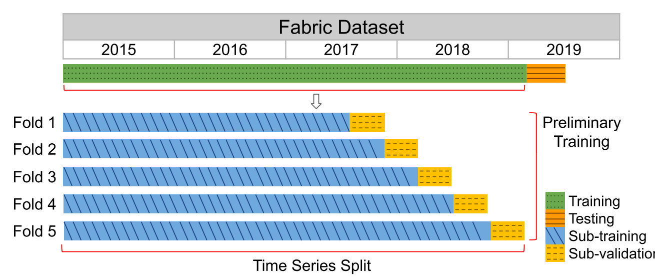

Fig. 6. Splitting of dataset into training, validation, and testing data.

approximately 73% of the products had single-type or multiple-type defects, with the four most common defects being broken warp, intermittent warp, missing weft, and parking mark defects. The dataset contained data on 2 yarn-related parameters and 19 machine-related parameters. The stages to which each parameter corresponded are illustrated in Fig. 5.

We conducted separate experiments for each fabric type to determine each type's optimal parameter settings. Because our dataset was a time series, we applied walk-forward validation, where the training data were sorted to be chronologically prior to the testing data. Moreover, we used k-fold forward-chaining cross validation in the training data for preliminary training (see Fig. 6). The training data were split into five folds for preliminary training, which was performed to select the key parameters with the lowest MSE. These parameters were then used by the CART algorithm to determine the conditions on the basis of the training dataset, as presented in Algorithm 1. After the global condition was established, we tested the MPORG on testing data in terms of the EB.

The fabric types were unevenly represented in the training versus testing data; this is because the amount of each fabric type that is manufactured is different on different days. Thus, the training and testing data sets had a large range of sizes. Data from January 2015 to February 2019 were used for training, and data from March 2019 to May 2019 were used for testing (see Table IV). For consistency, we also used the average defects per

TABLE IV
CHARACTERISTICS OF TRAINING AND TESTING DATA

Fabric Dataset	Training Instances	Testing Instances	Y* of Testing Data
Microfiber	4 668	360	5.80
Upholstery	4 999	274	5.46
Pant material	2 931	116	0.66
Lycra	2 317	141	7.02

*Y = Number of defects per 10 yards

TABLE V
PERFORMANCE OF MPORG FOR SET UNION OPERATION

Fabric Dataset	Number of IC_d*	M	M After Filtering	Number of Candidates C_m	Running Time (s)
Microfiber	7; 20; 16; 64	3 324	737	183	53
Upholstery	94; 30; 8; 115	18 992	2 108	556	143
Pant Material	9; 37; 9; 6	1 077	380	61	68
Lycra	6; 34; 54; 38	5 936	1 168	232	67

*d: broken warp; intermittent warp; missing weft; parking mark

10 yards in our experiments because the fabric length differed between instances.

B. Performance of Proposed Approach

The merging of conditions for two defects yielded the best results in our sensitivity analysis. The best C_m value from the C_m sets for each dataset was used. In addition to the EB, $|E(C_m)|$ was used to indicate the performance of a candidate C_m condition; specifically, a candidate C_m condition performs well if instances that comply with C_m have few defects. A low $F(C_m)$ indicates the presence of few defects when C_m is implemented.

1) Set Union Operation: Table V presents results on the number of individual conditions IC_d generated by CART for each fabric type and defect type and the number of merged C_m conditions (from the merging of conditions for two defects). The number of all possible merged combinations of C_m conditions (denoted M) and number of M after filtering are shown. Meanwhile, the numbers of merged C_m conditions with EB > 0 and $|E(C_m)| > 0$ (candidate C_m conditions) are stated. Thus, approximately 5% of all merged C_m conditions yielded a reduction in the number of defects. The time taken to generate the C_m conditions and calculate their respective EBs in seconds is also presented. The computing time was similar between the union and intersection operations.

In general, EB and $|E(C_m)|$ were inversely correlated; for example, except for those for data on upholstery, the highest EBs $(0.9-1)$ corresponded to $|E(C_m)|$ values of ≤ 3 (see Table VI). In practice, C_m conditions that perform well on one metric and poorly on another should be avoided. C_m conditions such as that on the microfiber data with a reliable $|E(C_m)|$ of 31 and a high EB of 0.82 should be chosen (potential solutions with high EB were ≥ 0.8). Therefore, C_m conditions with $|E(C_m)|$ values that were less than $5\%-10\%$ were considered to be too unreliable and, thus, excluded from consideration.

The average EB of the best C_m conditions formed using the set union operation for the four datasets was 0.99. However, when C_m conditions with unreliable $|E(C_m)|$ were excluded, this average decreased to 0.89, meaning that an average of

TABLE VI
DISTRIBUTION OF $|E(C_m)|$ FOR CANDIDATE C_m CONDITIONS OBTAINED USING SET UNION

Range of EB	Highest Number of $\lvert E(C_m)\rvert$			
	Microfiber	Upholstery	Pant Material	Lycra
0−0.1	2	36	49	4
0.1−0.2	10	27	69	53
0.2−0.3	-	47	42	61
0.3−0.4	-	37	48	8
0.4−0.5	122	54	18	5
0.5−0.6	13	109	4	26
0.6−0.7	11	18	21	3
0.7−0.8	44	9	-	7
0.8−0.9	**31**	**30**	**7**	**7**
0.9−1	**1**	**16**	**2**	**3**

* Bold entities indicate the potential solution with high EB

TABLE VII
PERFORMANCE RESULTS OF MPORG (SET UNION)

Fabric Dataset	MPORG (Multistage)				
	$\lvert E(C)\rvert$	$F(C)$	Y'	EB	I
Microfiber	31	0.089	1.03	0.82	3
Upholstery	16	0.016	0.28	0.95	4
Pant Material	5	0.003	0.07	0.89	2
Lycra	7	0.040	0.81	0.88	4
Mean	-	-	-	0.89	-
STDEV	-	-	-	0.05	-

TABLE VIII
FINAL GLOBAL SOLUTION (SET UNION)

Fabric Type	Global Rule R
Microfiber	IF Product Type = Microfiber THEN $Solution_{\text{Microfiber}}$ = (108 < Fiber Base ≤ 168) AND (Warp Tension > 5.5) AND (108.5 < Measure Wheel ≤ 117)
Upholstery	IF Product Type = Upholstery THEN $Solution_{\text{Upholstery}}$ = (4634 < Warp Total ≤ 4684) AND (Granularity > 681) AND (Weft Density ≤ 69) AND (Weaving Speed > 435)
Pant Material	IF Product Type = Pant THEN $Solution_{\text{Pant}}$ = (90 < Fiber Base ≤ 102) AND (1.5 < Weaving Shaft Quantity ≤ 2.5)
Lycra	IF Product Type = Lycra THEN $Solution_{\text{Lycra}}$ = (57 < Denim ≤ 88.5) AND (Warp Total ≤ 7358) AND (139 < Beam Tension ≤ 242) AND (Warp Speed > 135)

89% of defects were prevented in the testing data upon the implementation of C_m (see Table VII).

These reliable C_m conditions are presented as the consequent of rule R (see Table VIII) and should be implemented in the manufacturing process. Suppose that microfiber is manufactured, and the engineers, using their knowledge and the tolerances of the manufacturing machinery, can use the microfiber rule and alter the MMPs parameters to a specific value within the range. The parameters also covered various aspects and stages of manufacturing. For example, for microfiber manufacturing, the fiber base parameter pertains to the yarn, the warp tension parameter pertains to the warping stage, and the measure wheel parameter pertains to the weaving stage. Similarly, for upholstery manufacturing, the granularity parameter pertains to the warping stage and the weft density and weaving speed parameters pertain to the weaving stages.

TABLE IX
DISTRIBUTION OF $|E(C_m)|$ FOR CANDIDATE C_m CONDITIONS OBTAINED USING SET INTERSECTION

Range of EB	Maximum Number of $\|E(C_m)\|$			
	Microfiber	Upholstery	Pant Material	Lycra
0–0.1	34	18	45	5
0.1–0.2	10	27	-	53
0.2–0.3	-	36	-	-
0.3–0.4	55	17	48	2
0.4–0.5	122	53	26	5
0.5–0.6	176	31	-	21
0.6–0.7	54	9	21	-
0.7–0.8	3	9	7	-
0.8–0.9	**30**	**30**	**9**	**4**
0.9–1	**1**	**16**	**1**	**3**

* Bold entities indicate the potential solution with high EB

TABLE X
PERFORMANCE RESULTS OF MPORG (SET INTERSECTION)

Fabric Dataset	MPORG (Multistage)				
	$\|E(C)\|$	$F(C)$	Y'	EB	I
Microfiber	30	0.086	1.04	0.82	3
Upholstery	16	0.016	0.28	0.95	4
Pant Material	5	0.003	0.07	0.89	2
Lycra	4	0.031	1.10	0.84	5
Mean	-	-	-	0.88	-
STDEV	-	-	-	0.06	-

TABLE XI
FINAL GLOBAL SOLUTION (SET INTERSECTION)

Fabric Type	Global Rule R
Microfiber	IF Product Type = Microfiber THEN $Solution_{\text{Microfiber}}$ = (68.5 < Reed Width ≤ 70.5) AND (Beam Speed > 90), (490< Weaving Speed ≤ 535)
Upholstery	IF Product Type = Upholstery THEN $Solution_{\text{Upholstery}}$ = (4634 < Warp Total ≤ 4684) AND (Granularity > 681) AND (Weft Density ≤ 69) AND (Weaving Speed > 435)
Pant Material	IF Product Type = Pant THEN $Solution_{\text{Pant}}$ = (90 < Fiber Base ≤ 102) AND (1.5 < Weaving Shaft Quantity ≤ 2.5)
Lycra	IF Product Type = Lycra THEN $Solution_{\text{Lycra}}$ = (85.5 < Denim ≤ 88.5) AND (Measure Wheel ≤ 110) AND (Warp Total ≤ 6700) AND (139 < Beam Tension ≤ 242) AND (Warp Speed > 135)

2) Set Intersection Operation: In general, the set intersection of several ranges is less expansive than the constituent ranges. Thus, the MSE for the C_m condition does not increase after the set intersection operation.

$|E(C_m)|$ tended to be smaller when the intersection, as opposed to the union, was used (see Table IX). Moreover, only 2% of all possible C_m conditions were such that EB > 0 and $|E(C_m)| > 0$. The average EB of the best C_m conditions formed using the set intersection operation for the four datasets was 0.99. However, when C_m conditions with unreliable $|E(C_m)|$ were excluded, this average decreased to 0.88. On the other hand, the number of $E(C)$ decreased slightly as opposed to the union (see Table X).

The best performing C_m conditions for each fabric type using intersection are presented in Table XI. The set intersection operation gives narrower ranges than the set union operation and, thus, provides closer, and potentially more useful, guidance to engineers. For example, for Lycra manufacturing, the denim parameter had a much narrower recommended range of 85.5–88.5 from the intersection operation as opposed to 57–88.5 from the union operation.

TABLE XII
PERFORMANCE RESULTS OF CART ALGORITHM

Fabric Dataset	CART (Multistage)				
	$\|E(C)\|$	$F(C)$	Y'	EB	I
Microfiber	31	0.109	1.26	0.78	5
Upholstery	30	0.105	0.96	0.82	6
Pant Material	59	0.176	0.35	0.48	5
Lycra	7	0.087	1.75	0.75	6
Mean	-	-	-	0.71	-
STDEV	-	-	-	0.16	-

C. Performance of CART Algorithm

Our proposed MPORG method was also compared against several methods.

The first competing method was the CART algorithm with no feature selection (SBS) but with two-defect, set-intersection merging. Performance was indicated by reliable $|E(C_m)|$ and EB-maximizing C_m conditions on the same dataset with a similar number of parameters (i.e., multistage parameters). The results also indicated the difference in EB before versus after feature selection in SBS was applied.

In several cases (i.e., microfiber, pant material, and Lycra), the CART algorithm failed to find EB $\geq$ 0.8 with reliable $|E(C_m)|$ (see Table XII). Thus, the MPORG method outperformed the CART algorithm: the average EBs of reliable C_m conditions for the four datasets were 0.88 for the MPORG method but 0.71 for the CART algorithm. Moreover, the CART algorithm generally used more key parameters I relative to the MPORG method.

D. Performance of MR-CART Method

The second competing method was the multiresponse CART (MR-CART) method [31], which outputs predictions of multiple response variables simultaneously. The MR-CART method had four sequentially listed response variables in the experiment, namely the broken warp, intermittent warp, missing weft, and parking mark defects. The MR-CART method can be extended to multiresponse optimization in multistage processes [31], which is the problem addressed in the present study.

Because the global condition generated by MR-CART is designed to prevent multiple types of defects, merging was not executed in our implementation of MR-CART. In the experiment, MR-CART performed poorly with a paltry average EB of 0.32 for all reliable C_m conditions for the four datasets (see Table XIII). This is because the MR-CART method failed to find EB$\geq$0.8 with reliable $|E(C_m)|$. Our experiment also had 21 input parameters, much more than the 11 input parameters used in [31]; this suggests that MR-CART has limited applicability when numerous parameters are present.

TABLE XIII
PERFORMANCE RESULTS OF MR-CART METHOD

Fabric Dataset	MR-CART (Multistage)				
	$\|E(C)\|$	$F(C)$	Y'	EB	I
Microfiber	178	1.221	2.47	0.57	5
Upholstery	123	1.353	3.01	0.45	3
Pant Material	116	0.661	0.66	0.00	3
Lycra	16	0.579	5.10	0.27	3
Mean	-	-	-	0.32	-
STDEV	-	-	-	0.25	-

TABLE XIV
PERFORMANCE RESULTS OF SBS-MR-CART METHOD

Fabric Dataset	SBS-MRCART (Multistage)				
	$\|E(C)\|$	$F(C)$	Y'	EB	I
Microfiber	33	0.119	1.30	0.78	3
Upholstery	20	0.051	0.69	0.87	2
Pant Material	108	0.556	0.60	0.10	1
Lycra	141	7.018	7.02	0.00	1
Mean	-	-	-	0.44	-
STDEV	-	-	-	0.45	-

E. Performance of SBS-MR-CART Method

The third competing method was a combination of the SBS method and MR-CART; we incorporated SBS to boost the performance of MR-CART. However, this combination performed poorly on the pant material and Lycra datasets (see Table XIV); this may be due to the small size of these datasets.

In general, the MR-CART method is unstable for small datasets [31]. Moreover, the regression tree model seemed to be overfitted because it had more than six layers; this may be due to highly imbalanced data among the defect types. The SBS-MR-CART method should be improved upon in future studies to enable a fairer comparison with our method.

F. Performance of Linear Regression Method

The fourth competing method was LR. In [16], LR was used to optimize only one manufacturing stage (the weaving stage). We, thus, examined whether the MPORG method outperformed LR in optimization for a single stage, namely the weaving stage. In our experiments, this stage had five parameters; redundant parameters (i.e., parameters that had a "foreign key" status) were ignored (see Fig. 5).

The LR method only provided single-value parameters based on an LR equation for each defect type. Note that $E(C)$ values cannot be obtained from the LR results because no instance in the historical data complies perfectly with the conditions stated in the LR equations. Therefore, we calculated the EB using the Y' value predicted in the LR equation. Because merging was not implemented for LR, we averaged the EBs in the LR equations for the four defect types of each fabric type.

Our MPORG method outperformed LR in terms of average reliable EB on some but not all datasets; for example, LR performed much better than the MPORG method on the Lycra dataset (see Table XV). Nonetheless, LR has limited applicability because it only produces a single value rather than a range. LR may also provide negative values—such as

TABLE XV
PERFORMANCE RESULTS OF MPORG AND LR FOR A SINGLE MANUFACTURING STAGE

Fabric Dataset	MPORG (Weaving)					LR (Weaving)				
	$\|E(C)\|$	$F(C)$	Y'	EB	I	$\|E(C)\|$	$F(C)$	Y'	EB	I
Microfiber	30	0.086	1.04	0.82	2	-	-	1.38	0.76	5
Upholstery	16	0.016	0.28	0.95	3	-	-	1.35	0.75	5
Pant	9	0.011	0.14	0.79	2	-	-	0.21	0.68	5
Lycra	6	0.075	1.75	0.75	2	-	-	1.06	0.85	5
Mean	-	-	-	0.83	-	-	-	-	0.76	-
STDEV	-	-	-	0.09	-	-	-	-	0.07	-

in the following equation for broken warp defects in microfiber manufacturing—but some parameters, such as weaving speed, do not have negative values.

$$\text{Broken Warp}_{\text{Microfiber}} = 0.03 + 0.0001(\text{Weft Density}) + 0.0002 \\ (\text{Weaving Shaft Quantity}) - 4.50 \times 10^{-5}(\text{Weaving Speed}) \\ + 2.90 \times 10^{-7}(\text{Beam Length}) - 0.0001(\text{Measure Wheel}).$$

IV. DISCUSSIONS

In general, our MPORG performed favorably and competitively with EBs of 0.88–0.89. Crucially, our MPORG method outputs an optimized range rather than a single value, allowing engineers to select a value according to their experience or to production machine tolerances.

Our MPORG outperformed the CART algorithm by approximately 25%; it also outperformed MR-CART and SBS-MR-CART on all datasets (see Tables XIII and XIV). In addition, compared with the MPORG method, LR is less useful because it may yield uninterpretable negative values.

In our sensitivity analysis, the merging of conditions for two defects yielded the best results (i.e., the highest EB). However, this was because most instances in the dataset had two types of defects (see Fig. 4). Thus, the number of defects to be used for merging can be based on the distribution of the number of types of defects across instances of the data. Our MPORG approach executed multistage optimization over only a few minutes (see Table V) on a midrange consumer desktop PC (specifically one with a six-core Intel Core i7-8700 CPU clocked at 3.20 GHz and with 64 GB of RAM). Thus, our method is suited to real-time defect prevention on a comprehensive dataset on all parameters for each manufacturing stage.

Our approach requires large data sets for numerous combinations of parameters to be tested. Specifically, our simulation results indicate that production data on approximately 2300 instances for at least a 4-year period is required for training. Moreover, the dataset should be cleaned.

Our approach is also limited by the fact that EB is not a comprehensive indicator of performance. Thus, we balanced EB and $|E(C)|$ in our performance evaluations. In any case, the union operator strikes a better balance between EB and $|E(C)|$ compared with the intersection operation. This is because the larger range from the union operation may result in a high number on $E(C)$ with better performance on EB. Conversely, the intersection operation yields smaller, and thus, potentially more informative, ranges. However, as indicated in Tables VI and IX, our MPORG approach does not always generate high-EB conditions that are also reliable. Thus, engineers may need to choose a condition with not only a high EB but also reliable $|E(C_m)|$.

V. Conclusion

At present, the I-Manufacturing dataset has no information on the manufacturing stage at which defects occur. Consequently, engineers cannot determine the manufacturing stages that should be targeted for optimization. Single-stage optimization may be useful for a specific production stage but are not useful for MMPs, which are common in fabric manufacturing. In MMPs, the parameters for all stages are closely related to each other and should not be optimized separately.

Our method prevents single-type or multiple-type defects in MMPs. In our simulations, our MPORG prevented approximately 88%–89% of defects and outperformed the CART algorithm, MR-CART method [31], and SBS-MR-CART method. Finally, this study opens the way to investigate the more complex MMPs further to expand the applicability range of our MPORG in future research. In addition, a decision support system can be used to help engineers choose conditions that have both sufficient reliability and a high EB.

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