Hierarchical decision making for proactive quality control: system development for defect reduction in automotive coating operations

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Abstract

Product quality control (QC) in manufacturing usually relies solely on inspection. Once a quality problem is found, a solution is sought usually based on experience, which is basically ad hoc. A new generation of QC requires the integration of both quality prediction and inspection. Automotive coating is a typical example. In the paint shop of an automotive assembly plant, topcoat filmbuild quality on vehicle surface has been a major concern. In production, defects are frequently generated in the very thin coating layers, which can degrade severely both coating appearance and durability. Trial and error in troubleshooting is a usual practice.

In this paper, we introduce a proactive QC approach by resorting to artificial intelligence and engineering fundamentals. The approach is developed for solving a class of engineering problems for which conventional reactive QC approaches are feeble due to system complexity and uncertainties, such as that in paint applications. The main focus of the approach is on-process, rather than post-process. Thus, the domain knowledge about a process is fully explored and correlation of the process to product quality is established in a systematic way. In this approach the knowledge is expressed either symbolically or numerically, and structured in a hierarchy as reasoning progresses. Decision making is performed by a fuzzy MIN–MAX algorithm for heuristic knowledge and optimization for fundamental knowledge. To demonstrate the efficacy of the methodology, an application to QC of automotive topcoat is illustrated through developing an intelligent decision support system. This system is capable of evaluating process performance, and providing various valuable decision supports for defect prevention in different stages of a topcoat application process.

Keywords: Quality control; Intelligent decision support; Artificial intelligence; Fuzzy logic; Automotive coating

1. Introduction

Most quality control (QC) techniques used in the manufacturing industries today are post-process based (Kane, 1989). In plants, QC engineers and process verification engineers inspect final products. The identified quality problems are usually statistically analyzed, and solutions are then derived frequently based on experience. Process engineers are responsible for taking actions, such as fixing equipment, re-adjusting operational parameters, educating operators for good operational practice, and reworking on the returned products. Methodologically, inspection-based QC techniques are reactive to the product quality, since the premise of applying them is the generation of quality problems. Note that in some manufacturing industries, such as automotive painting and electroplating industries, once a quality problem is identified on a final product, it has already appeared on many other products. Even if a correct action is immediately taken at one stage of a multi-stage process, there will be still a certain number of products coming out with the same problem because those products have already been manufactured in the process after that stage. On the other hand, experience-based solution identification is not systematic and always consistent. For the same type of quality problem, engineers in different shifts may have different views and thus take different actions. Conceivably, the effectiveness of QC can be very different.

Due to increasing economic pressure and more stringent environmental regulations, the product quality standard becomes much higher, and process operation...
much more difficult. Traditional inspection-based QC alone is no longer sufficient. Nearly a decade ago, Wu et al. (1989) introduced a new QC concept called New Generation Quality Control. The focal point of the concept is process control. Needless to say, if product quality can be appropriately modeled into a process control scheme, then product quality can be significantly improved. Nevertheless, in the automotive coating industry, for example, such a QC approach is yet to be developed at the both theoretical and practical levels.

Recently, Lou and Huang (2001) introduced a process control-optimization-based, proactive QC approach for enhanced automotive coating. They suggested adding quality-bearing process optimization to the conventional regulatory control. This permits the adjustment of process operational settings when a quality improvement is justified. The approach can be generalized as a hierarchical process control scenario for proactive QC in any manufacturing processes. As shown in Fig. 1, the lower layer is for both the servo control and the regulatory control. The former is to allow the system to track set point changes. The later is to ensure smooth operations through rejecting disturbances. In this regard, the feedforward control is for rejecting more effectively measurable disturbances, while the feedback control is mainly for unpredictable disturbances. Usually, this control system is already implemented in plants. The newly introduced upper layer is designed for quality-bearing process optimization that consists of four components:

(a) A quality analyzer that evaluates the information about the final product. It transmits the quality information to the component, quality controller, when the product is found out of specification.

(b) A quality controller that identifies the root cause(s). If a quality problem is caused by improper process settings, relevant process parameter(s) will be identified and sent to the component, process optimizer. If it is due to equipment malfunction or failure, management or operator’s impropperness, or other than process setting related reasons, then the quality controller will send the information to engineers for off-line treatment.

(c) A quality predictor that predicts product quality using process information. This information may come from different operational stages in the process. The correlation between a set of process variables and a set of quality variables will be the key for the predictability of this component.

(d) A process optimizer that optimizes process operation so that product quality can be ensured. Optimization decisions will be made based on the information from the quality predictor and the quality controller.

While the hierarchical process control promises quality assurance using both process and post-process information, the effectiveness of the proactive QC is determined by the functionality of components and their integration. The development of these four components requires the use of all types of acquirable knowledge and available information that can be either numerical or symbolic, and either structured or unstructured. This renders the use of different modeling and decision-making techniques, depending on the type of industrial problem to be investigated.

This paper focuses on hierarchical decision making for proactive QC in the manufacturing industries. A specific application is for the defect prevention of vehicle coatings during automotive paint spray and drying operations. Due to process complexity and information uncertainties, adequate domain knowledge and pertinent data need be fully utilized. This requires the knowledge to be represented either symbolically or numerically, and structured in a hierarchy. A hybrid decision-making method is also introduced to derive the best possible problem-solving solutions. These developments are resorted to artificial intelligence, engineering fundamentals, and optimization techniques. The developed approach is adopted as the core of an intelligent decision support system for defect reduction in automotive coating operations. This system is capable of evaluating process performance and providing various valuable decision supports for defect prevention in different stages of a paint application process.

2. Automotive coating operation and quality concern

2.1. Process

A typical flowsheet of an automotive paint shop is depicted in Fig. 2. In the shop, vehicles one by one on a conveyor move through about 20 processes where five layers of thin coatings, such as phosphate, e-coat,
powder, basecoat, and clearcoat, are developed on vehicle surface. Usually, it takes about 8h for each vehicle to go through the shop at a conveyor line speed of about 10–14 ft/min (Cohen and Gutoff, 1992). The topcoat (i.e., basecoat and clearcoat) application process (the fourth line in the figure) consists of basecoat spray, oven baking or ambient flash, clearcoat spray, and oven drying/curing operations. This is most critical for coating quality.

Fig. 3 illustrates a general topcoat spray process, which consists of two sub-processes, one for interior spray by robots, and the other for exterior spray by spray bells. Each sub-process can have two passes of robot spray and/or two passes of bell spray, although the figure shows only one each. The coating quality is mainly referred to exterior coating. In a spray booth, bells are mounted on the top and two sides, from which emulsified paint droplets are delivered onto the different panels of moving vehicles. For instance, Bells B1–B3 are for horizontal panel spray (i.e., hoods, roofs, and lift gates), and other bells (B4–B9) for vertical panel spray on the left and right sides of vehicle bodies.

After spray, the vehicles covering wet film on surface will then be moved to an oven. The oven can be as long as 500 ft. It is usually divided into 6–7 zones, each of which has its own heating mechanism and operational setting. In the oven, three types of interdependent phenomena occur in the film. As shown in Fig. 4, they are: (i) heat transfer on vehicle panels due to radiation, convection, and conduction in the coating layers, (ii) mass transfer of solvents through diffusion and evaporation that leads to the change of moisture content.
and film coatings, and (iii) cross-linking reactions in each of the clearcoat and basecoat that form a 3D molecular network in the film. Note that before clearcoat is applied onto the vehicle surface, the basecoat is already dried and cross-linking reaction in this layer is finished. In the process, physical drying and chemical polymerization take place simultaneously. Operational modes directly influence the physical, chemical, and mechanical properties of the coating.

2.2. Process-focused defect analysis

A main quality concern in the automotive paint shop is the appearance of various defects on vehicle coating, such as sags, runs, solvent popping, craters, orange peels, and blister. In a plant with the production rate of 300 vehicles per shift, for example, an identification of 200–300 defects during operation and over 100 defects on the final products in a shift is common. Although many defects can be eliminated relatively easily by sanding, polishing, repainting, etc., many others may require several steps of reprocessing that is time consuming and costly. Needless to say, defects must be prevented, or at least reduced, wherever possible.

Equipment malfunction, process variation, and improper process operation can lead to the generation of a variety of defects on vehicle coating (Koleske, 1995). For instance, a very low fluid delivery can occur due to improper process setting. This can generate solvent pop and inter-coat adhesion failure. If the fluid delivery is set too high, other defects, such as mottling and craters, may occur. If a film-drying rate in an oven is too high, solvent removal from the film will be too fast, which can cause popping and orange peels. An overbaked film can deteriorate physical properties and give poor adhesion and coating strength. The formation of blisters, crinkling, and bubbling is another example of process variation. These defects are all caused by the exposure of the film in a high temperature environment for an improperly long time. If the temperature exceeds the solvent boiling point, bubbles appear. When they burst, blisters form. Crinkling is also caused by the bubbles that pucker the surface. If the temperature is too high, it can even raise the skin up. On the other hand, if the temperature is too low, the crosslinking reaction will be incomplete (Gutoff and Cohen, 1995).

A great emphasis should be made on the operational status of facilities and operational procedures. Industrial practice has shown that it is impossible to maintain a high film quality if any facility malfunction exists or the operation fluctuates. Very often, when a facility problem (e.g., a humidifier problem in a spray booth) is detected, it may not be scheduled to fix immediately until the production line is shut down. In this case, operational parameters (e.g., spray bell fluid delivery and shaping air) should be reset as a response to the changing environment; otherwise, filmbuild problems will persist. Certainly, a systematic approach is needed for preventing defects in this regard.

Paint properties, such as viscosity and solid level, play a critical role in filmbuild (Gutoff and Cohen, 1995). Nevertheless, it is still not very clear how these properties affect coat appearance. It is also unknown how spray booth air (e.g., temperature, humidity, and air down-draft) should be optimally set as paint properties change. Precise, fundamental correlation between process variables and quality variables is too difficult to derive. Experimental data and operational experience may be fully explored to establish the best possible correlation.

3. Decision-making hierarchy for QC

The defect-focused QC can be realized in a hierarchy as shown in Fig. 5. This hierarchy follows a general logic: when a solution is to be searched, it is always preferred to narrow down the solution space as much as possible, as the information becomes more available. In most manufacturing operations, once a quality problem is identified, the responsible processes should be identified first. In a responsible process or sub-process, the operational status of process facilities must be evaluated before any action on process operational settings is taken. Otherwise, if a process operational setting is readjusted without fixing the facility problem first, then a quality problem may be temporarily handled at best. However, other quality problems may occur that makes QC more complicated. As to the information required for decision making at the different levels of the hierarchy, the information needed for the first level (i.e., Process Analysis) is the least, while that for the last level (i.e., Operational Improvement) is the most.

The effectiveness of solution identification relies on the decision-making process. This process encompasses the search of decision tree and knowledge manipulation.
In automotive coating, for example, each of the 20 processes consists of a number of sub-processes, each sub-process contains various facilities, and each facility has some operational parameters. Therefore, the cause-effect mapping between processes and defects need be carefully determined. The concept of the mapping is depicted in Fig. 6(a). A process \((P_i)\) may be related to a number of defects \((D_j)\). Likewise, a defect may be caused by operational problems in more than one process.

Fig. 6(b) demonstrates two reasoning mechanisms: forward (from process to quality) and backward chaining (from quality to process).

Note that each mapping is, in fact, a knowledge application. All mappings form a knowledge tree. The knowledge tree consists of a variety of nodes and links. Each node is designated for an event, while each link between two nodes reflects a cause. In a partial tree structure shown in Fig. 7, node \(n_a\) is called an ancestor of node \(n_b\), if \(n_a\) appears anywhere on the path from the initial node \(n_0\) to node \(n_b\). Naturally, node \(n_b\) is called the descendent of \(n_a\). Node \(n_c\) is called a parent of node \(n_d\) if \(n_d\) emanates directly from \(n_c\), and \(n_d\) is called a child of \(n_c\) (Yager, 1985).

Following the knowledge tree concept, a decision tree for defect analysis can be constructed. It can be either event driven (e.g., from defects to process parameters) or data driven (e.g., from process parameters to defects). Fig. 7 is an event-driven decision analysis tree. An evaluation of a decision tree is a process of computing a series of mappings between every two adjacent layers in the tree. The figure shows the following three types of mappings in the four layer tree:

(i) Mapping between the defect layer and the process layer. Each mapping can be expressed as \(M(D_i, P_j)\).
(ii) Mapping between the process layer and the sub-process layer. It can be expressed as \( M(P_i, S_{ij})\in [0, 1] \).

(iii) Mapping between the sub-process layer and the process variable (parameter) layer. Each mapping can be expressed as \( M(S_{ij}, V_{ij,k})\in [0, 1] \).

Note that any mapping is quantified as a possibility. For instance, the values of “0” and “1” of an \( M(P_i, S_{ij}) \) function indicate, respectively, no relation and exact relation between process \( P_i \) and sub-process \( S_{ij} \), while a value in between shows how possible a relation exists. It is known that a possibility is different from probability, although both have a value between 0 and 1. Mathematically, probability \( (P(i)) \) follows the following relationship:

\[
\sum_{i=1}^{M} P(i) = 1.
\]

By contrast, possibility \( (\text{Poss}(j)) \), or mapping \( M(i, j) \) in this case, has the following relationship:

\[
\sum_{j=1}^{N} \text{Poss}(j) = \sum_{j=1}^{N} M(i, j)\in [0, N].
\]

This indicates that, to the extreme, a relationship between node \( i \) and node \( j \) \((1, 2, ..., N)\) either does not exist \( (M(i, j) = 0) \) or perfectly exists \( (M(i, j) = 1) \). Any value between 0 and 1 signifies a vague relationship. This is reasonable in defect analysis. A defect occurrence may be surely related to some processes (“1” is assigned for the mappings), vaguely related to some others (some nonzero values smaller than “1” are assigned), and have no relationship with the remaining (“0” is assigned).

4. Hybrid modeling for quality

To permit the evaluation of the mappings and decision making, the defect-relevant factors, such as the status of equipment, operating conditions, and operators’ practice, must be fully characterized. This characterization can be accomplished through process modeling. Since the available knowledge and information are both numerical and symbolical, structured and unstructured, and precise and imprecise, multiple modeling techniques need be used.

4.1. Fuzzy modeling

The defects due to mechanical malfunction and improper operational practice can be modeled using fuzzy logic. Usually, those quality problems can be identified and solved based on experience. Thus, the knowledge is basically expressed linguistically. Fuzzy logic is much more alike the way of human logic approach than conventional crisp (or Boolean) logic conclusion (Zimmermann, 1991). Crisp logic attempts to be precise, and gives clearly true or false. By contrast, fuzzy logic permits the vagueness in real life. It uses rigorous mathematics to complete imprecise information. This information can be either symbolic or numeric (Takagi and Sugeno, 1985; Huang and Fan, 1993; Luo and Huang, 1997; Lou and Huang 2000a).

The defect models related to mechanical and operational problems are in fact a large number of hierarchically structured fuzzy rules \( \{R_i | i = 1, 2, ..., P \} \) each of which has one of the following two structures:

Type I \( R_i ^1 \) : \( \text{IF } \{x_j \in A^i_j | j \in R^n\} \text{, THEN } \{y_k \in B^i_k | k \in R^n\} \).

\[
\text{(3)}
\]

Type II \( R_i ^2 \) : \( \text{IF } \{x_j \in A^i_j | j \in R^n\} \text{, THEN } \{y_k = b_{k,0} + \sum_{j=1}^{m} b_{k,j} x_j | k \in R^n\} \).

where \( A^i_j \) is the fuzzy set defined for variable \( x_j \) in rule \( R_i ^1 \); \( B^i_k \) the fuzzy set defined for variables \( y_k \) in rule \( R_i ^2 \); \( b_{k,j} \) the coefficient in the numerical expression relating output variable \( y_j \) to input variable \( x_k \) in rule \( R_i ^1 \).

Type I rules are used for modeling defect generation when only experience is available while Type II rules are for the modeling when both experience and experimental data (incomplete imprecise and/or uncertain) are available. The use of these two types of rules can capture both heuristic knowledge and vague information to the maximum extent. The rules are structured in a three-layer hierarchy shown in Fig. 5. There are the layers for identify: (i) responsible processes and subprocesses (ii) mechanical problems associated with facilities and solutions and (iii) optimal process settings. Type I rules are used for all the layers while Type II rules are for the last layer where an improper operating condition exists (reflected by undesirable parameters).

4.2. Fundamental modeling

Lou and Huang (2000b) developed an integrated, fundamental model for an oven where the vehicle topcoat is baked. The model characterizes various heat and mass transfer phenomena and polymerization reaction occurring in the curing operation. It can reveal the dynamic behavior of the film on vehicle surface that includes panel temperature profiles, solvent removal progress, film thickness changes, and cross-linking completeness in any zones of an oven at any time. This model greatly facilitates the identification of a number of defects that can be generated in the oven, such as solvent popping and orange peels as described in a
previous section. It is also an integral part for process operational improvement as shown in Fig. 5 (Level 3). In real-time closed-loop control, this model can provide the key information for the process optimizer in the system shown in Fig. 1.

4.3. Neural network (NN) modeling

Neural network techniques have been widely used to model complex systems for which fundamental models can be hardly developed, or they are too complicated to use in real settings. Automotive paint spray is a typical case where it is infeasible to develop, or they are too complicated to be modeled accurately. Such complex systems for which fundamental models cannot be developed, or they are too complicated to be accurately modeled, are typical target area for neural network techniques.

Unique feature of the modeling is the use of limited data as it is restricted by measurement insufficiency and sensor unavailability. The developed model establishes reliable correlation between spray parameters and film performance variables. Extensive model-based simulations have revealed process behavior under various operating conditions (Lou, 2001). This greatly facilitates a thorough analysis of spray operations and an identification of effective ways for coating quality improvement. This modeling approach is general for a variety of problems where the data source is unsatisfactory.

5. Decision making

A decision-making process is essentially an optimization process. In QC-related decision making, if different modeling techniques are used, different optimization techniques should be correspondingly employed for the highest efficiency.

5.1. Fuzzy decision making

For those quality problems characterized by fuzzy rules, traditional mathematical optimization techniques cannot be used. For the Type I rules, the following fuzzy MIN–MAX reasoning algorithm is highly desirable (Zimmermann, 1985).

\[ \mu_j(x) = \max_{i \in I} \left\{ \min_{k \in K} \{ \mu_{i,k}(x_k) \} \right\}, \]  

where \( \mu_j(x) \) and \( \mu_{i,k}(x_k) \) are the fuzzy membership functions of variables \( x \) and \( x_k \), respectively; subscript \( i \) and \( j \) denote, respectively, the rule number and the layer of the rule lies in.

The MIN–MAX algorithm is computed in two stages. In the first stage, the truth value of the rule can be evaluated by calculating all the membership functions in its IF part using the MIN operation, i.e.,

\[ \tau_i = \min_{k \in K} \{ \mu_{i,k}(x_k) \} \]  

In the second stage, the most appropriate rule will be selected by performing the MAX operation on all the rules, i.e.,

\[ \tau = \max \{ \tau_i \mid i = 1, 2, \ldots, I \} \]  

Based on the results of the preceding levels, this operation continues in the succeeding layers of a decision tree.

Note that in a Type-I rule, the THEN part has only linguistic terms. By contrast, in a Type-II rule, the THEN part has a numerical expression. Thus, for the Type II rules, decisions can be made using the following formula (Huang et al., 2000):

\[ \hat{y}_j = \sum_{i=1}^{p} \omega^i \hat{y}^i_j, \]  

where \( \hat{y}^i_j \) is the estimation of the \( j \)th output variable in the \( i \)th layer, based on the known input, \( X = \{ x_1^*, x_2^*, \ldots, x_m^* \} \). The weight, \( \omega^i \), has the following expression:

\[ \omega^i = \frac{w^i}{\sum_{i=1}^{p} w^i}, \]  

where \( A^i(x_j^*) \) is the membership function value for the given input \( x_j^* \). Apparently,

\[ \sum_{i=1}^{p} \omega^i = 1. \]  

Note that the estimated output variable, \( \hat{y}_j \), is determined by the estimated values by all rules in the \( j \)th layer. This computation can give the best possible solution very quickly.

5.2. Mathematical optimization

For the operations that are modeled using first principles and/or neural network techniques, the system characterizations are all numerical. Thus, a variety of mathematical optimization methods can be used, such as linear programming, nonlinear programming, and dynamic programming (Edgar et al., 2001). Lou (2001) used a nonlinear programming technique to optimize an oven operation in an automotive paint shop. The optimization simultaneously realized energy reduction (2.5%) and filmbuild improvement (particularly cross-linking quality of the topcoat). The same technique was used to optimize a clearcoat spray operation what was characterized by an integrated NN model (Lou, 2001; Lou and Huang, 2001). The optimization is particularly
effective to improve the film thickness and uniformity by 25%.

The mathematical programming technique can be naturally used to reduce or even eliminate various defects. In an optimization model, the defect prevention can be expressed a number of operational constraints, such as the upper limit of a panel heating rate (to prevent solvent popping), the lower and upper limit of the fluid delivery and shaping air of spray bells (to prevent sags, runs, etc.), and the lower and upper limit of spray booth air temperature (to prevent off-color, runs, dry spray, etc.) (Lou, 2001).

6. DRACO—An intelligent decision support system

The decision analysis and decision-making methodology described in the previous sections has been used to develop an intelligent decision support system for defecte reduction in automotive coating operations (DRACO). This system is designed to evaluate process performance, and provide valuable decision supports for defect reduction in various stages of a topcoat application process. It is particularly useful for process engineers, process verification engineers, and QC engineers to conduct comprehensive and quick process analyses and to identify the most desirable solutions in different capacities.

6.1. System structure

As shown in Fig. 8, the system consists of four key components: a knowledge base, a database, an inference engine and a user interface. A user can input knowledge and data to the system, and check the knowledge base and database via the interface where decision-making algorithms are embedded.

Knowledge base: The knowledge base contains fuzzy rules, NN models, and mathematical models. They serve for different purposes, such as for identifying defects, locating facility malfunctions, correleting defect problems with process operational practice, etc.

If defects occur while no equipment malfunction is found, or if equipment problems are not severe and cannot be fixed immediately, then operational parameters of robots and bells, paint, booth air conditions, oven operating conditions, flash time, etc., need be adjusted.

Database: The database contains various data that can be classified into the following categories: (i) process design data—process flowsheet, equipment status, nominal operational settings of equipment and facilities, such as zone and oven settings, booth air temperature, humidity, and downdraft, (ii) paint data—paint viscosity, temperature, solid level, resistivity, etc., (iii) production and quality data—autospect data, oven panel temperatures, quality information, such as filmbuild thickness and defect data, (iv) process verification data—yard audit results and recommendations, and (v) QC management data—the status of QC procedural implementation. There are many intermediate values generated during computation. The data are expressed as numerical values, string, array, compound and boolean.

6.2. System development and operation

The system resides in the intelligent system development tool, LEVEL 5 Object, on a PC. In this tool, a high-level, object-oriented multi-paradigm language, PRL, which is similar to natural English, is used for programming. The system has a user-friendly Graphical User Interface (GUI), through which vivid displays, tables, pushbuttons, radios, pictures, hyperregions, etc., can be designed to facilitate the easy use. Also, it is easy to access all common database formats, external programs, and text files. This makes the data management quite efficient.

Several window snapshots are demonstrated here. The title window is shown in Fig. 9. A user can click the OVERVIEW pushbutton at the bottom of the window to view the introduction of DRACO. Activating the CONTINUE pushbutton can let the system move on to the DEFECT AND TOPCOAT COLOR INFORMATION window, which is shown in Fig. 10.

In the upper left corner of this new window, the user can select a defect type from the Defects list by clicking the DEFECT SELECTION pushbutton. Immediately, a corresponding defect picture will be popped up below the list. The Color Selection list is in the upper right corner, while the Vehicle Type is listed in the lower right part of the window. The user can select the vehicle type and topcoat color from these lists.

By clicking the CONTINUE pushbutton, the next window, DEFECT LOCATION AND SEVERITY
INFORMATION, will be open (Fig. 11). In this window, the user can input defect information by following the steps below:

1. Highlight one of the vehicle panels (i.e., left, right, or horizontal panel) in the table entitled "Panel". In the figure, for example, a Horizontal/Rear panel is selected.
2. Click the pushbutton, CLICK HERE to activate a panel picture shown on the right-hand side of this pushbutton. The panel is divided into a number of regions; each region is assigned a number.
3. Identify the region numbers from the panel picture where defects exist. For example, there are some defects in the middle front part of the roof. This region is numbered H.2.4.
4. Highlight a region label (e.g., H.2.4) from a table entitled Location Index.
5. Click the ADD pushbutton, to add a selected region (e.g., H.2.4) to the table entitled Identified Locations. Note that if the user add mistakenly a region into the Identified Location Table, (s)he can use the DELETE pushbutton to delete this wrong information.

Fig. 9. Title window of DRACO.

Fig. 10. Defect and topcoat color information window.
(6) Select a coating layer from the table entitled “Layer” where the defect may occur. If the user is not sure which layer the defect lays, then just select the option, Not Sure.

(7) Select a severity level for the identified defect from the table, Severity. In this case, the level Severe is selected.

(8) Click the CONTINUE pushbutton, the system will activate the PROCESS RELEVANCY IDENTIFICATION window (Fig. 12).

In this new window, all major processes relevant to the identified defect are automatically identified, which are listed in the table entitled Main Processes. To get more detailed process information, the user needs to highlight one of the major processes to which (s)he wants to investigate further. In the figure, the Main Color process is highlighted. Then, by clicking the SEARCH RELEVENT SUBPROCESSES pushbutton, the system searches the knowledge base and lists all the relevant sub-processes in the table entitled Main Subprocesses. In this case, three subprocesses are identified, and the Clearcoat Spray Operation is highlighted. By clicking the CONTINUE pushbutton, a detailed analysis for the highlighted sub-process will show up (Fig. 13).

At the top part of Fig. 13, all relevant spray facilities in different operational zones are identified. All the possible mechanical problems for the spray facilities are shown under MECHANICAL PROBLEM CHECK LIST. The user can check if there exist any of those problems. If so, handle these mechanical problems first. If the facilities run well, or some minor mechanical problems cannot be eliminated until during the break down time, then a process parameter adjustment in relevant booths should be considered. This can be done by clicking the CONTINUE pushbutton to activate a new window.

In the PROCESS DIAGNOSIS window in Fig. 14, the type of defect, the responsible booth zone and bell/gun and trigger zone are listed in the top part. To conduct a process diagnosis, the user needs to input process data in the table entitled Process Data Input. The data are classified into three groups: Booth and Vehicle, Bell or Gun, and Paint. All the process data is filled into the entries. After that, by clicking the ANALYSIS AND DECISION pushbutton, the system will pop up the ANALYSIS AND DECISION Window. Recommended process parameter adjustments are the reference for the decision makers.

6.3. Application studies

DRACO has been used to conduct a variety of studies on defect reduction in automotive paint shops. In this section, an application for reducing sags and runs is presented in detail. For simplicity, the defect and process information shown in Figs. 10–14 is used for solution identification. The vehicle type of interest is a navy blue sedan.

Example 1—Identification of mechanical malfunctions: As stated previously, when a type of defect occurs, the first troubleshooting action is to check and fix mechanical problems. In production, different defects are always associated with different types of mechanical malfunctions. For example, Figs. 10 and 11 show three sags and runs on the roof (Location Index No. H.2.4).

![Fig. 11. Defect location and severity information window.](image)
The system identifies the following possible mechanical malfunctions (see, Fig. 13).

1. The regulators of relevant guns and bells in specific zones. Note that the air pressure coming out from a compressor is generally higher than needed, thus a regulator is used to control air pressure and to adjust the fluid flow. If sags and runs are detected at a specific panel location, the regulator of the corresponding bells should be checked. In this case, bells C-7-b-c.2 in the first pass and C-7-b-d.2 in the second pass are responsible for the defects at H_2.4. The regulators of these two bells should be checked.

2. The trigger on time of the bells in specific zones for horizontal panel spray. Note that bells should be triggered on time. In this example, the index of relevant trigger zones of both bells C-7-b-c.2 and C-7-b-d.2 are 4. Thus, the trigger time of trigger zone 4 of both bells need be examined.

3. Downdraft facility in specific zones. Note that downdraft facilities blow away the overspray drift and dirt entry. If the downdraft is too strong, it is easy to get sags and runs. In this case, since sags and
runs were found on the clearcoat and the clearcoat spray is in zone 7, the downdraft facility in zone 7 must be checked.

(4) The working conditions of spray bell for lift gate. Under similar operating conditions, it is easy to get sags and runs on the lift gate. If sags and runs are detected, the regulator, pattern adjusting valve, and the bell air cap of the spray bell for the lift gate shall also be carefully examined. Since panel index H.24 does not belong to the lift gate, this checking item can be neglected. Note that the MECHANICAL PROBLEM CHECK LIST in Fig. 13 is general for any panel of a vehicle. Thus, this suggested check is still included.

Example 2—Adjustment of process parameters: When no mechanical malfunction is found, the reoccurrence of this defect can be eliminated by adjusting process operational parameters. As shown in Fig. 13, bells C-7-b-c.2 and C-7-b-d.2 are responsible for the sags and runs. Thus, we need to check their process settings.

The PROCESS DIAGNOSIS Window of bell C-7-b-c.2 is shown in Fig. 14. After the user inputs the process operation conditions and clicks the pushbutton,
ANALYSIS AND DECISION, the system will provide the process change recommendation as shown in Fig. 15.

The system found that the fluid delivery of 144 cc is too high; it is better to lower it by 19 cc. The shaping air pressure of 24 pm is also slightly high; it is suggested to reduce by 1 pm. The distance between the spray bell and the target panel is 12 ft, which is acceptable. Analysis of the booth and vehicle operating conditions through the Inference Engine shows that the booth temperature of 82°C/14°F is somewhat high; it should be controlled at 80°C/14°F. The booth downdraft should be reduced by 3 fpm. The paint viscosity, however, is reasonable. Although not shown in this figure (need be scrolled down on the screen), the voltage and turbine speed of the bell are also acceptable. The same procedure can be followed to generate a list of recommendation for the change of process settings related to bell C-7-b-d.

Example 3—Improvement of management: Another equally important measure in QC is the reinforcement of maintenance and management procedures. As indicated in Fig. 12, Main Color, Paint Mixing and Miscellaneous Processes are the three main processes relevant to the generation of sags and runs. Under the major process of Main Color, the relevant sub-processes are Basecoat Spray Operation, Clearcoat Spray Operation and Maintenance and Management. It is better to check the quality management status of the relevant sub-processes one by one. If the user wants to check the sub-process of Maintenance and Management, (s)he can highlight this option and click the pushbutton, CONTINUE. Fig. 16 shows the QC requirements for this sub-process, where the last two of the six check points are listed. Among the six, three checks are failed. Based on the importance weights assigned to the checks, about 67% of possibility is identified for appearance of the dry spray defect.

7. Concluding remarks

Proactive QC is becoming more and more attractive in the manufacturing industries due to increased economic and environmental pressure. Effectiveness of the proactive QC requires the appropriate use of available knowledge and information as much as possible. This suggests the adoption of different process modeling and decision-making techniques. In this paper, process control-optimization-based proactive QC is introduced. Hybrid modeling and hierarchical decision making are described in detail. The efficacy of the methodology is demonstrated through illustrating an intelligent hierarchical decision support tool, namely DRACO, for the defect reduction in automotive coating operations. The proactive QC methodology is general and thus is, in principle, applicable to any manufacturing processes.

Note that the most effective proactive QC is to realize a two-layered closed-loop control. As shown Fig. 1, optimized process parameter setting need be sent to controllers as set points. The open-loop QC presented in the paper is the first step of the overall proactive QC paradigm. Once the optimized process setting has been proven always optimal, a complete closed-loop QC can be realized.

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