

INCORPORATION OF SUSTAINABILITY METRICS IN PAINT FORMULATION OPTIMIZATION USING MACHINE LEARNING

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application claims the benefit of U.S. Provisional Application Serial No. 63/513,443 filed July 13, 2023, the contents of which are incorporated in their entirety herein.

TECHNICAL FIELD

[0002] The present specification relates to paint formulations, and more particularly, to incorporation of sustainability metrics in paint formulation optimization using machine learning.

BACKGROUND

[0003] Paint formulations can include a variety of ingredients in different concentrations that can be combined to manufacture a particular paint product.

SUMMARY

[0004] In one embodiment, a method may include receiving a first paint formulation comprising a plurality of ingredients, receiving a maximum allowable deviation for each of the ingredients of the first paint formulation indicating a maximum amount to vary each of the ingredients in candidate paint formulations, receiving one or more constraints comprising minimum threshold values of one or more performance metrics associated with the paint formulation, determining a plurality of candidate paint formulations, each candidate paint formulation having a modified list of ingredients with an amount of each ingredient being within the maximum allowable deviation, inputting the plurality of candidate paint formulations into a trained model, wherein the trained model outputs performance metrics associated with an input paint formulation, determining values of the one or more performance metrics associated with each of the candidate paint formulations based on an output of the trained model, selecting a subset of the candidate paint formulations having values of the performance metrics greater than or equal to the minimum threshold values based on the output of the trained model, determining a sustainability metric of each candidate paint formulation among the subset of the candidate paint formulations, and selecting the candidate paint formulation having the highest sustainability

metric among the subset of the candidate paint formulations as an optimal paint formulation.

[0005] In another embodiment, an apparatus may include a controller programmed to receive a first paint formulation comprising a plurality of ingredients, receive a maximum allowable deviation for each of the ingredients of the first paint formulation indicating a maximum amount to vary each of the ingredients in candidate paint formulations, receive one or more constraints comprising minimum threshold values of one or more performance metrics associated with the paint formulation, determine a plurality of candidate paint formulations, each candidate paint formulation having a modified list of ingredients with an amount of each ingredient being within the maximum allowable deviation, input the plurality of candidate paint formulations into a trained model, wherein the trained model outputs performance metrics associated with an input paint formulation, determine values of the one or more performance metrics associated with each of the candidate paint formulations based on an output of the trained model, select a subset of the candidate paint formulations having values of the performance metrics greater than or equal to the minimum threshold values based on the output of the trained model, determine a sustainability metric of each candidate paint formulation among the subset of the candidate paint formulations, and select the candidate paint formulation having the highest sustainability metric among the subset of the candidate paint formulations as an optimal paint formulation

BRIEF DESCRIPTION OF THE DRAWINGS

[0006] The embodiments set forth in the drawings are illustrative and exemplary in nature and not intended to limit the disclosure. The following detailed description of the illustrative embodiments can be understood when read in conjunction with the following drawings, where like structure is indicated with like reference numerals and in which:

[0007] FIG. 1 depicts a schematic diagram of a computing device for incorporating sustainability metrics into paint formulation optimization, according to one or more embodiments shown and described herein;

[0008] FIG. 2 schematically depicts a plurality of memory modules of the computing device of FIG. 1, according to one or more embodiments shown and described herein;

[0009] FIG. 3 depicts a flowchart of an example method for operating the computing device of FIG. 1, according to one or more embodiments shown and described herein; and

[0010] FIG. 4 depicts a flowchart of an example method for training the model maintained by the computing device of FIG. 1, according to one or more embodiments shown and described herein.

DETAILED DESCRIPTION

[0011] Paint formulations may be modified to optimize various criteria such as cost and/or performance metrics. In particular, a paint formulation may be optimized to incorporate multiple objectives to ensure the maintenance of critical properties while maximizing or minimizing selected target material behaviors.

[0012] Paint formulation optimization may focus on product performance characteristics. A major challenge of the 21st century is the transformation of our economy towards a sustainable one, including minimizing environmental impacts while maintaining performance advancements of materials critical to daily life. As such, there is a growing consumer demand for products produced sustainably, such as with lower emissions, reduced waste, less use of hazardous materials, and the like. As such, a need exists for methods of incorporating sustainability metrics into the assessment and optimization of paint formulations.

[0013] The embodiments disclosed herein describe methods and apparatus for incorporating sustainability metrics in paint formulation optimization using machine learning. In embodiments, a paint formulation may be analyzed and modified using a machine learning model to improve one or more sustainability metrics associated with the paint formulation while maintaining certain minimum performance metrics, as disclosed herein. In particular, a machine learning model may receive information about an existing paint formulation and certain user specified criteria relating to allowable modifications to the formulation and minimum performance metrics. The machine learning model may then output a modified paint formulation having one or more improved sustainability metrics. That is, the machine learning model may output a modified paint formulation that is more environmentally friendly than the original paint formulation, while maintaining minimum performance levels. As such, paint manufacturers may utilize the embodiments disclosed herein to improve the environmental impact of their paint formulations while maintaining paint quality.

[0014] Turning now to the figures, FIG. 1 schematically depicts an example configuration of a computing device 100, according to the embodiments disclosed herein. The computing device

100 may comprise a variety of different types of devices (e.g., a local computing system, a cloud computing system, and the like). The computing device 100 may perform the operations of the embodiments disclosed herein. In particular, the computing device 100 may train and maintain a machine learning model used to determine optimal paint formulations, as disclosed herein. In the illustrated example, the computing device 100 includes one or more processors 102, a communication path 104, one or more memory modules 106, a data storage component 108, and network interface hardware 110, the details of which will be set forth in the following paragraphs.

[0015] Each of the one or more processors 102 may be any device capable of executing machine readable and executable instructions. Accordingly, each of the one or more processors 102 may be a controller, an integrated circuit, a microchip, a computer, or any other physical or cloud-based computing device. The one or more processors 102 are coupled to a communication path 104 that provides signal interconnectivity between various modules of the computing device 100. Accordingly, the communication path 104 may communicatively couple any number of processors 102 with one another, and allow the modules coupled to the communication path 104 to operate in a distributed computing environment. Specifically, each of the modules may operate as a node that may send and/or receive data. As used herein, the term “communicatively coupled” means that coupled components are capable of exchanging data signals with one another such as, for example, electrical signals via conductive medium, electromagnetic signals via air, optical signals via optical waveguides, and the like.

[0016] Accordingly, the communication path 104 may be formed from any medium that is capable of transmitting a signal such as, for example, conductive wires, conductive traces, optical waveguides, or the like. In some embodiments, the communication path 104 may facilitate the transmission of wireless signals, such as WiFi, Bluetooth®, Near Field Communication (NFC) and the like. Moreover, the communication path 104 may be formed from a combination of mediums capable of transmitting signals. In one embodiment, the communication path 104 comprises a combination of conductive traces, conductive wires, connectors, and buses that cooperate to permit the transmission of electrical data signals to components such as processors, memories, sensors, input devices, output devices, and communication devices. Additionally, it is noted that the term "signal" means a waveform (e.g., electrical, optical, magnetic, mechanical or electromagnetic), such as DC, AC, sinusoidal-wave, triangular-wave, square-wave, vibration, and the like, capable of traveling through a medium.

[0017] The computing device 100 includes one or more memory modules 106 coupled to the communication path 104. The one or more memory modules 106 may comprise RAM, ROM, flash memories, hard drives, or any device capable of storing machine readable and executable instructions such that the machine readable and executable instructions can be accessed by the one or more processors 102. The machine readable and executable instructions may comprise logic or algorithm(s) written in any programming language of any generation (e.g., 1GL, 2GL, 3GL, 4GL, or 5GL) such as, for example, machine language that may be directly executed by the processor, or assembly language, object-oriented programming (OOP), scripting languages, microcode, etc., that may be compiled or assembled into machine readable and executable instructions and stored on the one or more memory modules 106. Alternatively, the machine readable and executable instructions may be written in a hardware description language (HDL), such as logic implemented via either a field-programmable gate array (FPGA) configuration or an application-specific integrated circuit (ASIC), or their equivalents. Accordingly, the methods described herein may be implemented in any conventional computer programming language, as pre-programmed hardware elements, or as a combination of hardware and software components. The memory modules 106 are discussed in more detail below in connection with FIG. 2.

[0018] Referring still to FIG. 1, the example computing device 100 includes a data storage component 108. The data storage component 108 may store data used by the computing device 100, such as parameters of the machine learning model maintained by the computing device 100, training data used to train the model, and the like, as disclosed herein. The data storage component 108 may also store other data used by the various components of the computing device 100.

[0019] Still referring to FIG. 1, the computing device 100 comprises network interface hardware 110 for communicatively coupling the computing device 100 to external computing devices, such as computing devices that store training data. As such, the network interface hardware 110 may send data to and/or receive data from various external computing devices. The network interface hardware 110 may comprise a wired and/or wireless connection to one or more external computing devices. In other examples, the network interface hardware 110 may be send data to and/or receive data from other computing devices.

[0020] The network interface hardware 110 can be communicatively coupled to the communication path 104 and can be any device capable of transmitting and/or receiving data via a network. Accordingly, the network interface hardware 110 can include a communication

transceiver for sending and/or receiving any wired or wireless communication. For example, the network interface hardware 110 may include an antenna, a modem, LAN port, Wi-Fi card, WiMax card, mobile communications hardware, near-field communication hardware, satellite communication hardware and/or any wired or wireless hardware for communicating with external computing devices.

[0021] Referring now to FIG. 2, the one or more memory modules 106 of the computing device 100 include a paint formulation reception module 200, a constraint reception module 202, a candidate formulation determination module 204, a performance metric determination module 206, a performance metric comparison module 208, a sustainability metric determination module 210, a paint formulation selection module 212, a training data reception module 214, and a model training module 216. Each of the a paint formulation reception module 200, the constraint reception module 202, the candidate formulation determination module 204, the performance metric determination module 206, the performance metric comparison module 208, the sustainability metric determination module 210, the paint formulation selection module 212, the training data reception module 214, and the model training module 216 may be a program module in the form of operating systems, application program modules, and other program modules stored in one or more memory modules 106. Such a program module may include, but is not limited to, routines, subroutines, programs, objects, components, data structures and the like for performing specific tasks or executing specific data types as will be described below.

[0022] The paint formulation reception module 200 may receive a paint formulation. As used herein, a paint formulation comprises information about the composition of a particular paint product. In embodiments, the paint formulation reception module 200 may receive a paint formulation for an existing paint product. As discussed above, the computing device 100 may be used to improve the environmental impact of paint formulations. Thus, the paint formulation reception module 200 may receive an existing paint formulation to be modified.

[0023] In some examples, a paint formulation may include a list of ingredients and a concentration of each ingredient. In some examples, a paint formulation may include different categories and a class of ingredients in each category. For example, categories may include binder and extender, and classes may refer to different binders and extenders that may be used in a paint formulation. In some examples, a paint formulation may include a particle size of each class of ingredients in each category. By inputting classes of ingredients within different categories, users

may utilize the disclosed embodiments without inputting specific details of paint formulations, which may be desirable in order to protect trade secrets and other proprietary information.

[0024] In some examples, the computing device 100 may display a user interface that a user may utilize to enter information about a paint formulation. For example, the user interface may display different categories and different classes of ingredients within each category that a user may select. The user interface may also allow a user to enter other information about a paint formulation such as concentrations or particle sizes of ingredients.

[0025] After the paint formulation reception module 200 receives a paint formulation, the components of the received paint formulation may be stored in the data storage component 108. The computing device 100 may then determine a modified paint formulation based on the received paint formulation, as disclosed herein.

[0026] The constraint reception module 202 may receive one or more user specified constraints, as disclosed herein. In some examples, the constraints may indicate a maximum allowable deviation of each ingredient or class of ingredients in a paint formulation. That is, a user may specify a maximum amount to vary each of the ingredients of a specified paint formulation in a modified paint formulation. As discussed above, the computing device 100 receives an existing paint formulation and determines a modified paint formulation having improved sustainability metrics. By specifying a maximum allowable deviation for one or more ingredients, a user may ensure that the modified paint formulation generated by the computing device 100 does not vary any of the original ingredients by more than a specified amount.

[0027] In some examples, the constraint reception module 202 may receive a maximum deviation percentage of a particular ingredient. For example, a user may specify that a particular binder amount may not be modified by more than 5%. In other examples, the constraint reception module 202 may receive a maximum deviation mass of a particular ingredient. For example, a user may specify that a particular extender amount may not be modified by more than 1 gram. In some examples, the constraint may receive a maximum amount that a ratio of two particular ingredients may be modified. For example, a user may specify that the ratio between ingredients A and B should not be modified by more than 10%.

[0028] In addition to receiving maximum allowable deviations of ingredients, the constraint reception module 202 may also receive minimum threshold values of one or more

performance metrics associated with the paint formulation. This may allow a user to specify a minimum quality of paint associated with a modified paint formulation determined by the computing device 100. In some examples, the constraint reception module 202 may receive minimum threshold values of gloss and scattering. However, in other examples, the constraint reception module 202 may receive minimum threshold values of other performance metrics.

[0029] The candidate formulation determination module 204 may determine one or more candidate paint formulations. In particular, each such candidate paint formulation may comprise a paint formulation having a modified list of ingredients compared to the user specified paint formulation, with an amount of each ingredient being within the maximum allowable deviation received by the constraint reception module 202. In some examples, candidate paint formulations generated by the candidate formulation determination module 204 may include the same ingredients as the paint formulation received by the paint formulation reception module 200, with certain ingredients having different concentrations and/or particle sizes. In other examples, candidate paint formulations generated by the candidate formulation determination module 204 may include different ingredients than the paint formulation received by the paint formulation reception module 200. For example, certain amounts of one or more ingredients in the original paint formulation may be replaced by one or more other ingredients in candidate formulations.

[0030] In some examples, the candidate formulation determination module 204 may follow a set of rules to generate candidate paint formulations. In particular, one or more rules may specify certain ingredients that can be swapped for other ingredients. For example, a rule may indicate that one particular ingredient may be replaced with another ingredient that has a lower cost or better sustainability metric without significantly degrading the quality of the paint formulation. These rules may also have more complicated relationships. For example, a rule may indicate that one ingredient can be swapped for multiple ingredients, or multiple ingredients in combination may be swapped for a different combination of ingredients. These rules may ensure that quality standards of the paint formulation are maintained. In embodiments, these rules may be stored by the data storage component 108 and utilized by the candidate formulation determination module 204 to generate candidate paint formulations. In some examples, the candidate formulation determination module 204 may utilize a search algorithm to generate candidate paint formulations. In some examples, certain constraints, such as an amount of water or an amount of filler are held constant in order to keep the candidate formulations in the same class as the received paint formulation.

[0031] The performance metric determination module 206 may determine one or more performance metrics of the candidate paint formulations generated by the candidate formulation determination module 204. In particular, the performance metric determination module 206 may input each of the candidate paint formulations into a trained machine learning model, which outputs one or more performance metrics based on an input paint formulation. The machine learning model may be trained as discussed in further detail below. In the illustrated example, the machine learning model comprises a neural network. However, in other examples, the model may comprise an equation, genetic programming, or other model frameworks.

[0032] As discussed above, a user may specify an existing paint formulations to be modified, and one or more minimum performance metrics to be maintained in any such modified formulations. As such, after the candidate formulation determination module 204 determines candidate formulations, the performance metric determination module 206 may predict performance metrics of the candidate paint formulations in order to determine whether each candidate paint formulation meets the user specified minimum performance metrics.

[0033] In order to determine the performance metrics of a candidate paint formulation, the performance metric determination module 206 utilizes a model that has been trained to predict performance metrics of a paint formulation based on the composition of the paint formulation. In particular, the model may be a machine learning model trained based on historical data, as discussed in further detail below. Once the model has been trained, a paint formulation may be input into the model, and the model may output one or more predicted performance metrics of the paint formulation. This may allow a large number of candidate paint formulations to be analyzed to determine their performance metrics without needing to actually manufacture and test each such formulation. In embodiments, the performance metrics may include gloss and scattering. However, in some examples, other performance metrics may be specified as well such as scrub, durability, stain, and the like.

[0034] The performance metric comparison module 208 may compare the performance metrics of each candidate paint formulation, as determined by the performance metric determination module 206, to the minimum performance metrics received by the constraint reception module 202. As such, the performance metric comparison module 208 may determine which of the candidate paint formulations have acceptable performance for the user. In embodiments, the candidate formulations having performance metrics that do not meet the

minimum specified performance metrics may be discarded, while the candidate formulations meeting the minimum specified performance metrics may be further analyzed, as disclosed below.

[0035] The sustainability metric determination module 210 may determine one or more sustainability metrics associated with a paint formulation. The sustainability metrics determined by the sustainability metric determination module 210 may comprise metrics that indicate the environmental impact of the manufacture and/or use of paint having the specified formulation. For example, sustainability metrics may include a carbon footprint associated with a paint formulation, an amount of greenhouse gasses emitted during the manufacture of the ingredients of a paint formulation, and the like.

[0036] In some examples, the sustainability metric determination module 210 may access a database that indicates sustainability metrics of a variety of materials and combinations of materials. The sustainability metric determination module 210 may then utilize this database to determine the sustainability metrics of each ingredient or combination of ingredients in a paint formulation and sum the values of the sustainability metrics of each ingredient or combination of ingredients to determine the sustainability metrics of the paint formulation as a whole.

[0037] The paint formulation selection module 212 may select a particular candidate paint formulation among the candidate paint formulations generated by the candidate formulation determination module 204 and present the selected paint formulation to a user. In one example, the paint formulation selection module 212 may select the candidate formulation having the highest value of a particular sustainability metric (e.g., lowest carbon footprint) among the candidate formulations that meet the minimum performance metrics received by the constraint reception module 202. As such, the paint formulation selection module 212 may select the most environmentally friendly paint formulation that meets the performance characteristics specified by a user.

[0038] In some examples, the paint formulation selection module 212 may select a particular candidate paint formulation based on a combination of sustainability and cost, as disclosed herein. In these examples, the constraint reception module 202 may receive weight values, specified by a user, indicating how much sustainability should be weighted as compared to how much cost should be weighted. For example, the constraint reception module 202 may receive a first weight associated with sustainability and a second weight associated with cost. This

may allow a user to specify how much they care about sustainability and how much they care about cost. In some examples, a user may utilize a graphical user interface with a slider to indicate how much to weight cost versus sustainability. The weights for cost and sustainability may then be determined based on where the user sets the slider.

[0039] In these examples, the paint formulation selection module 212 may determine a cost of each candidate paint formulation. For example, the paint formulation selection module 212 may access a database indicating a cost of each ingredient in each candidate paint formulation, and the paint formulation selection module 212 may determine the cost of each candidate paint formulation based on the cost, and amount of each ingredient in a paint formulation. The paint formulation selection module 212 may then determine a value of an objective function for each candidate paint formulation based on the first weight indicating how much sustainability should be weighted, a second weight indicating how much cost should be weighted, a sustainability metric associated with each candidate formulation, and the cost of each formulation. The paint formulation selection module 212 may then select the candidate paint formulation having the highest value of this objective function. In some examples, the paint formulation selection module 212 may select the candidate paint formulation having the highest value of the objective function by solving a multi-objective optimization.

[0040] The training data reception module 214 may receive training data to be used to train the model maintained by the computing device 100 to receive a paint formulation and predict one or more performance metrics of the paint formulation, as disclosed herein. As discussed above, the computing device 100 may utilize a trained machine learning model to predict performance metrics of candidate paint formulations. In particular, the computing device 100 may utilize supervised learning techniques and training data to train appropriately train the model, as disclosed herein.

[0041] In embodiments, the training data received by the training data reception module 214 may comprise a plurality of training examples, wherein each training example comprises a paint formulation and ground truth values of one or more performance metrics. The ground truth values may be determined experimentally, such as by taking measurements of values of various performance metrics for paint with known formulations. Performance metrics may be measured for a large number of paint formulations in order to generate a robust set of training data. The

training data may then be received by the training data reception module 214 and stored in the data storage component 108 to be used to train the model, as disclosed herein.

[0042] The model training module 216 may train the model maintained by the computing device 100 to predict one or more performance metrics for a paint formulation based on the training data received by the training data reception module 214, as disclosed herein. In the illustrated example, the model maintained by the computing device 100 is a machine learning model (e.g., a neural network), and the model training module 216 uses supervised learning techniques to train the model based on the received training data. In particular, the model training module 216 may learn parameters of the model that minimize a loss function between the values of the performance metrics predicted by the model and the ground truth values of the performance metrics across the set of training data. However, in other examples, the model maintained by the computing device 100 may be another type of model, such as a hybrid model or a first principle model.

[0043] Once the model training module 216 trains the model, the learned parameters may be stored in the data storage component 108. The trained model may then be used by the performance metric determination module 206 to predict performance metrics of candidate paint formulations, as disclosed above.

[0044] FIG. 3 depicts a flowchart of an example method of determining a modified paint formulation, which may be performed by the computing device 100 according to the embodiments disclosed herein. At step 300, the paint formulation reception module 200 receives a paint formulation specified by a user. As discussed above, the received paint formulation may comprise ingredients and concentrations of a paint formulation to be modified to be more environmentally friendly. In some examples, the paint formulation may include classes of ingredients in different categories, rather than a specific ingredient list.

[0045] At step 302, the constraint reception module 202 receives maximum allowable deviations of ingredients and/or ratios of ingredients specified by the user. As discussed above, these maximum allowable deviations may indicate a maximum amount that the user is willing to have particular ingredients or particular ratios of ingredients changed from the specified paint formulation in a modified paint formulation.

[0046] At step 304, the constraint reception module 202 receives minimum performance metrics specified by the user. In particular, the minimum performance metrics comprise threshold values of one or more performance metrics that any modified paint formulation must satisfy. In some examples, the constraint reception module 202 may receive a maximum allowable deviation of one or more performance metrics specified by the user. For example, the user may specify that scattering should not vary by more than 3% from the user specified paint formulation. This may ensure that any modified paint formulation closely matches the performance of the user specified paint formulation.

[0047] At step 306, the candidate formulation determination module 204 determines a plurality of candidate paint formulations based on the paint formulation received by the paint formulation reception module 200 and the maximum deviations received by the constraint reception module 202. That is, the candidate formulation determination module 204 may determine a plurality of candidate formulation, in which each candidate formulation is modified from the original paint formulation within the limits of the maximum allowable deviations specified by the user. For example, a candidate formulation may replace some amount of TiO_2 in the user specified paint formulation with opaque polymer.

[0048] At step 308, the performance metric determination module 206 determines one or more performance metric for each candidate paint formulations generated by the candidate formulation determination module 204. In particular, the performance metric determination module 206 may input each candidate paint formulation into the model maintained by the computing device 100, and the model may output one or more predicted performance metrics associated with each input candidate paint formulation.

[0049] At step 310, the performance metric comparison module 208 compares the predicted performance metrics associated with each candidate paint formulation to the minimum performance metrics specified by the user. The performance metric comparison module 208 then eliminates from consideration each candidate paint formulation that does not need the specified minimum performance metrics, thereby reducing the candidate paint formulations under consideration for the optimal paint formulation.

[0050] At step 312, the sustainability metric determination module 210 determines a sustainability metric for each candidate paint formulation that was not eliminated from

consideration by the performance metric comparison module 208. The sustainability metric may be a carbon footprint associated with a candidate paint formulation, an amount of greenhouse gasses emitted during the manufacture of the components of a candidate paint formulation, or another metric related to environmental sustainability. Then, at step 314, the paint formulation selection module 212 selects the candidate paint formulation having the highest sustainability metric as the optimal paint formulation. The optimal paint formulation may then be presented to a user.

[0051] FIG. 4 depicts a flowchart of an example method of training the model maintained by the computing device 100. At step 400, the training data reception module 214 receives training data comprising a plurality of paint formulations and ground truth performance metrics associated with each paint formulation. Then, at step 402, the model training module 216 utilizes supervised learning techniques to train the model to predict one or more performance metrics of an input paint formulation based on the received training data.

[0052] It should now be understood that embodiments described herein are directed to incorporation of sustainability metrics in paint formulation optimization using machine learning. In particular, a user may specify a paint formulation, and a computing device may determine a modified paint formulation that is more environmentally sustainable while meeting certain user specified performance characteristics. This may allow users to improve the sustainability of paint formulations while maintaining minimum quality standards

[0053] It is noted that the terms "substantially" and "about" may be utilized herein to represent the inherent degree of uncertainty that may be attributed to any quantitative comparison, value, measurement, or other representation. These terms are also utilized herein to represent the degree by which a quantitative representation may vary from a stated reference without resulting in a change in the basic function of the subject matter at issue.

[0054] While particular embodiments have been illustrated and described herein, it should be understood that various other changes and modifications may be made without departing from the spirit and scope of the claimed subject matter. Moreover, although various aspects of the claimed subject matter have been described herein, such aspects need not be utilized in combination. It is therefore intended that the appended claims cover all such changes and modifications that are within the scope of the claimed subject matter.

CLAIMS

1. A method comprising:
 - receiving a first paint formulation comprising a plurality of ingredients;
 - receiving a maximum allowable deviation for one or more of the ingredients of the first paint formulation indicating a maximum amount to vary one or more of the ingredients in candidate paint formulations;
 - receiving one or more constraints comprising minimum threshold values of one or more performance metrics associated with the first paint formulation;
 - determining a plurality of candidate paint formulations, each candidate paint formulation having a modified list of ingredients with an amount of each ingredient being within the maximum allowable deviation;
 - inputting the plurality of candidate paint formulations into a trained model, wherein the trained model outputs performance metrics associated with an input paint formulation;
 - determining values of the one or more performance metrics associated with each of the candidate paint formulations based on an output of the trained model;
 - selecting a subset of the candidate paint formulations having values of the performance metrics greater than or equal to the minimum threshold values based on the output of the trained model;
 - determining a sustainability metric of each candidate paint formulation among the subset of the candidate paint formulations; and
 - selecting the candidate paint formulation having the highest sustainability metric among the subset of the candidate paint formulations as an optimal paint formulation.
2. The method of claim 1, wherein at least one of the performance metrics comprises gloss.
3. The method of claim 1, wherein at least one of the performance metrics comprises scattering.
4. The method of claim 1, wherein the sustainability metric is based on a carbon footprint associated with a paint formulation.

5. The method of claim 1, wherein the sustainability metric is based on an amount of greenhouse gasses emitted during manufacture of the ingredients of a paint formulation.
6. The method of claim 1, wherein the first paint formulation comprises a class of ingredients in each of a plurality of categories.
7. The method of claim 6, wherein the first paint formulation comprises an amount of each class of ingredients in each of the plurality of categories.
8. The method of claim 6, wherein the first paint formulation comprises a particle size of each class of ingredients in each of the plurality of categories.
9. The method of claim 1, further comprising:
 - receiving a first weight associated with sustainability and a second weight associated with cost;
 - determining a cost of each candidate paint formulation among the subset of the candidate paint formulations;
 - determining a value of an objective function for each candidate paint formulation based on the first weight, the second weight, the sustainability metric of each candidate paint formulation, and the cost of each paint formulation; and
 - selecting the candidate paint formulation having the highest objective function value as the optimal paint formulation.
10. The method of claim 9, further comprising determining the value of the objective function by solving a multi-objective optimization.
11. The method of claim 1, further comprising:
 - receiving training data comprising a plurality of sample paint formulations and measured values of the performance metrics for each sample paint formulation; and
 - training the model to predict the performance metrics of the input paint formulation based on the training data.
12. An apparatus comprising a controller programmed to:

receive a first paint formulation comprising a plurality of ingredients;

receive a maximum allowable deviation for one or more of the ingredients of the first paint formulation indicating a maximum amount to vary one or more of the ingredients in candidate paint formulations;

receive one or more constraints comprising minimum threshold values of one or more performance metrics associated with the first paint formulation;

determine a plurality of candidate paint formulations, each candidate paint formulation having a modified list of ingredients with an amount of each ingredient being within the maximum allowable deviation;

input the plurality of candidate paint formulations into a trained model, wherein the trained model outputs performance metrics associated with an input paint formulation;

determine values of the one or more performance metrics associated with each of the candidate paint formulations based on an output of the trained model;

select a subset of the candidate paint formulations having values of the performance metrics greater than or equal to the minimum threshold values based on the output of the trained model;

determine a sustainability metric of each candidate paint formulation among the subset of the candidate paint formulations; and

select the candidate paint formulation having the highest sustainability metric among the subset of the candidate paint formulations as an optimal paint formulation.

13. The apparatus of claim 12, wherein the sustainability metric is based on a carbon footprint associated with a paint formulation.

14. The apparatus of claim 12, wherein the sustainability metric is based on an amount of greenhouse gasses emitted during manufacture of the ingredients of a paint formulation.

15. The apparatus of claim 12, wherein the first paint formulation comprises a class of ingredients in each of a plurality of categories.

16. The apparatus of claim 15, wherein the first paint formulation comprises an amount of each class of ingredients in each of the plurality of categories.

17. The apparatus of claim 15, wherein the first paint formulation comprises a particle size of each class of ingredients in each of the plurality of categories.
18. The apparatus of claim 12, wherein the controller is further programmed to:
- receive a first weight associated with sustainability and a second weight associated with cost;
 - determine a cost of each candidate paint formulation among the subset of the candidate paint formulations;
 - determine a value of an objective function for each candidate paint formulation based on the first weight, the second weight, the sustainability metric of each candidate paint formulation, and the cost of each paint formulation; and
 - select the candidate paint formulation having the highest objective function value as the optimal paint formulation.
19. The apparatus of claim 18, wherein the controller is further programmed to determine the value of the objective function by solving a multi-objective optimization.
20. The apparatus of claim 12, wherein the controller is further programmed to:
- receive training data comprising a plurality of sample paint formulations and measured values of the performance metrics for each sample paint formulation; and
 - train the model to predict the performance metrics of the input paint formulation based on the training data.