High-throughput Simulation and Machine Learning Approaches for Can Body Design

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1 Introduction

Novelis is a world leader in aluminium flat rolled products and a major supplier to the beverage can-making industry. As such, Novelis is deeply involved in supporting the can-making industry to help shaping a more sustainable future together. Reducing the amount of metal used for each beverage can is a major driver for improving sustainability of the beverage can packaging, thus Novelis is actively investigating and developing state of the art modelling tools and approaches to support further optimization of the beverage can.
In this work, a proof of concept for applying machine learning approaches to the field of can body analysis and optimization is investigated. The aim of the work is to determine the feasibility of training a machine learning system on a data-set of can body forming and performance simulations to carry out real-time predictions of can performance and formability indicators. Leveraging a set of previously developed Novelis' finite element models of the can body forming and performance testing processes, the full set of relevant can body geometry, forming process and material properties is parametrized in order to facilitate automated model generation. With this set of parametrized models, a large number of finite element model simulations is carried out by varying the parameters within a reasonably large range to generate a data-set of approximately 1500 unique can simulation variants. Finally, a machine learning model is trained on the data and used as a surrogate model to provide predictions of can performance. The quality of the fit is evaluated, and a limited number of predictions are validated against un-seen data. Validation is carried out against real-world can body performance data and a comparison between the test data, FEA simulation data and machine learning predictions is carried out.

2 Training data generation

Training data is generated by running parametric variations of finite element simulations of the can body forming process and can body performance test. These simulations represent the relevant stages of the can body forming process and select performance test which were of interest in this work. The forming stages considered here include:

- Cup drawing
- Re-draw and bottom forming,
- Re-forming,

and the performance tests:

- Dome reversal pressure,
- Axial buckle load.

These models are collected in an automated simulation workflow, schematically shown in Fig. 1.

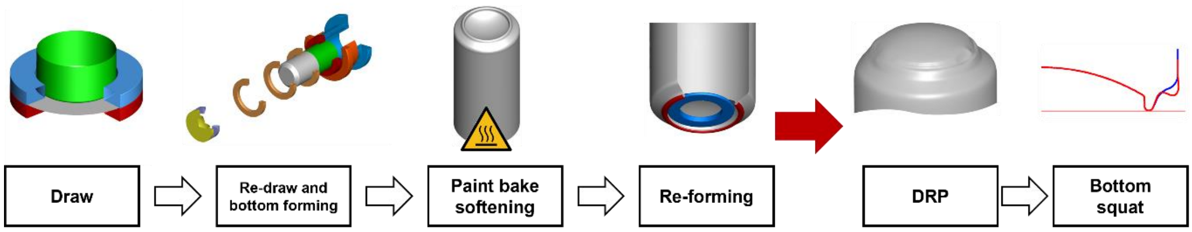


Fig.1: Can forming and performance simulation workflow.

2.1 Forming process

Cup drawing is a cylindrical deep drawing operation, in which a circular blank is cut out of a sheet of metal, held between a die and a blank holder, and a cylindrical punch draws a cup in a single downwards stroke.
In the second operation, the cup is re-drawn to a smaller diameter, representing the diameter of the final can body, and the bottom of the can is formed against the bottom forming tooling in a single stroke. The cup is held by a re-draw sleeve against a re-draw die in the initial stage and a cylindrical punch draws the material through the tooling. In the real-life process, the side-wall of the cup is extended in the axial direction by passing the material through several ironing rings, reducing its thickness against the punch and elongating the side-wall. This step is omitted in the simulation as it was found to have little influence on the final performance of the bottom of the can. Finally, at the bottom of the stroke, the dome and outer chime of the can body are formed.
Following the re-draw step, the cans undergo an internal lacquering process and an external decoration process, followed by a washing process. The internal lacquer serves as a barrier layer between the beverage and the aluminium can material whereas the external lacquer mostly serves decorative purposes. In order to cure the applied coatings and dry the cans after the washer, the cans undergo several thermal cycles at temperatures exceeding 200°C. This causes work hardening recovery in the highly cold-worked metal and reduces the yield strength of the material by a significant amount.
Re-forming is an additional forming operation used to improve the pressurization performance of the bottom of the can body. It is an incremental roll-forming operation where a roller, or a set of rollers, rotate eccentrically to further re-form the legs of the centre dome towards a concave shape, which is otherwise not possible in the drawing operation. The final cross-section shape of the bottom of the can is shown on Fig. 2 below:

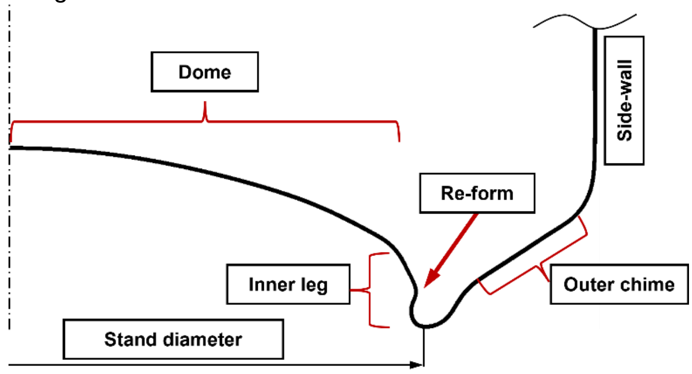


Fig.2: Can bottom geometry and nomenclature.

2.2 Performance evaluation

The can body has to withstand several different loading conditions to be considered fit-for-purpose. Particularly for carbonated beverages, the pressure stability of the can is of utmost importance, this is in turn evaluated by the dome reversal test, where the finished can body is internally pressurized until the dome at the bottom of can reverses (Fig. 3). A typical internal pressure requirement for a beverage can body is 6.2 bar (90 psi).

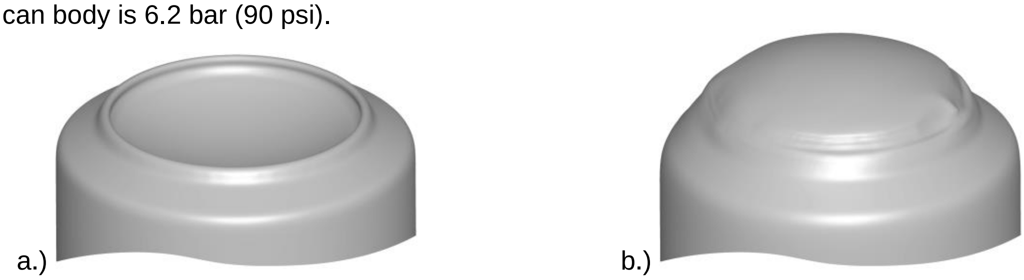


Fig.3: Can body bottom a.) before, and b.) after dome reversal (simulation).

Several forming processes (not discussed in this work), vertical stacking of un-filled can bodies and the filling process itself require the can to withstand significant axial load. A typical requirement for axial load is 1 kN. The test involves placing the can body between two rigid plates and applying a compressive load along the axial direction until the can buckles. The peak load is considered the axial buckle load of the can body. The can body exhibits two distinct modes of axial buckle:

- Side-wall buckle,
- Bottom squat.

In side-wall buckle, the cylindrical wall of the can buckles in a stochastic manner, making it a highly perturbation dependant phenomenon. Bottom squat occurs if the side-wall is sufficiently strong to shift the buckling mechanism onto the bottom of the can body, which then buckles axi-symmetrically. In this work, only the bottom squat failure mode is considered (Fig. 4).


a.)

b.)

Fig.4: Bottom squat failure mode.

2.3 Modelling approach

An axisymmetric modelling approach is adopted to accelerate calculation time. The can body geometry is nominally axisymmetric, excluding any material anisotropy effects or process variations, which are neglected in this work.

In all cases, the forming tools are considered rigid and a penalty contact is prescribed between the tools and the can body. Fully integrated axisymmetric volume weighted elements are used (shell element type 15, number of integration points equal to 4) for the deformable can body. Five elements through the thickness and an average element size of approximately 0.25 mm in the radial direction are used. The rigid tools are modelled using volume weighted 2D axisymmetric shell elements (beam element type 8).

Fig. 5 shows the 2D axisymmetric cup forming simulation. The draw die is fixed in space and a constant load is applied to the draw-holder. The punch has a prescribed motion boundary condition.

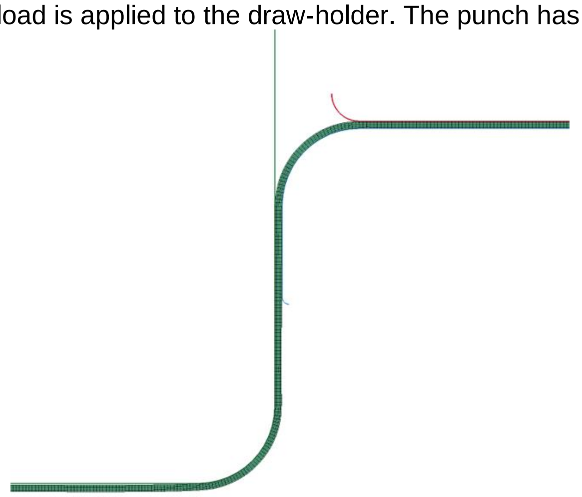


Fig.5: Close-up view of the cup forming simulation during the downward stroke.

The results from one forming stage simulation are transferred to the subsequent step by using a ***INTERFACE_SPRINGBACK_LSDYNA** keyword and by including the resulting dynain fine in the input deck.
The re-draw simulation is shown in Fig. 6-a.) below, the re-draw die and the dome plug are fixed in space, and the re-draw sleeve is assigned a constant clamping load. The punch has a prescribed motion boundary condition. The outer retainer is assigned a constant load in the upwards direction, and is held in place using the ***CONSTRAINED_RIGID_BODY_STOPPERS** keyword.
The re-forming simulation (Fig. 6-b.)) consists of a receptacle, fixed in space and a re-form wheel which moves radially by prescribed motion to simulate eccentric motion of the real-life process. Nodes on the top of the can side-wall are prescribed a constant load, to prevent the can body from moving in the receptacle.

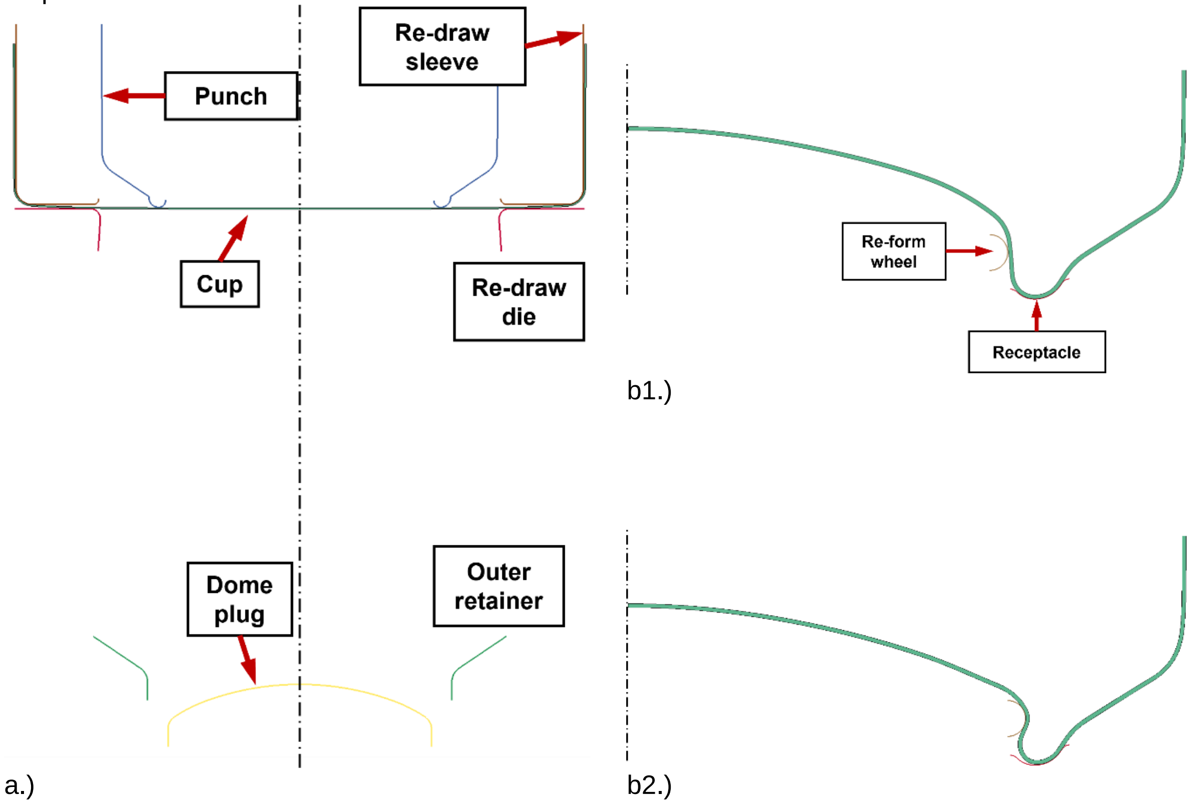


Fig.6: FEA simulation models of a.) the re-draw and bottom forming simulation and b.) re-forming process.

2.4 Constitutive model and hardening law

In order to ensure consistent material properties between the 2D axisymmetric and 3D shell element models, the Von Mises yield locus is used. The hardening behaviour of the aluminium alloy is described using an exponential equation:

$$\sigma_Y(\varepsilon_{pl}) = B + (A + K \cdot \varepsilon_{pl})\left[1 - e^{-\frac{c}{A}\varepsilon_{pl}}\right], \quad (1)$$

where:
A … amount of hardening
B … initial yield stress
K … slope of linear region
c … shape coefficient

This has been found to represent the stress-strain behaviour of can body material well and gives good results in the simulations.
To simulate the softening of the material during recovery in the thermal processing of the can body, two separate flow curves are defined, one for the as-rolled material and one of the material after thermal exposure (Fig. 7). The material properties are changed in the spring-back simulation step following the re-draw simulation. This is a crude approximation of the material properties evolution from a

metallurgical standpoint, but it captures the reduction of the mechanical properties of the can body sufficiently well.

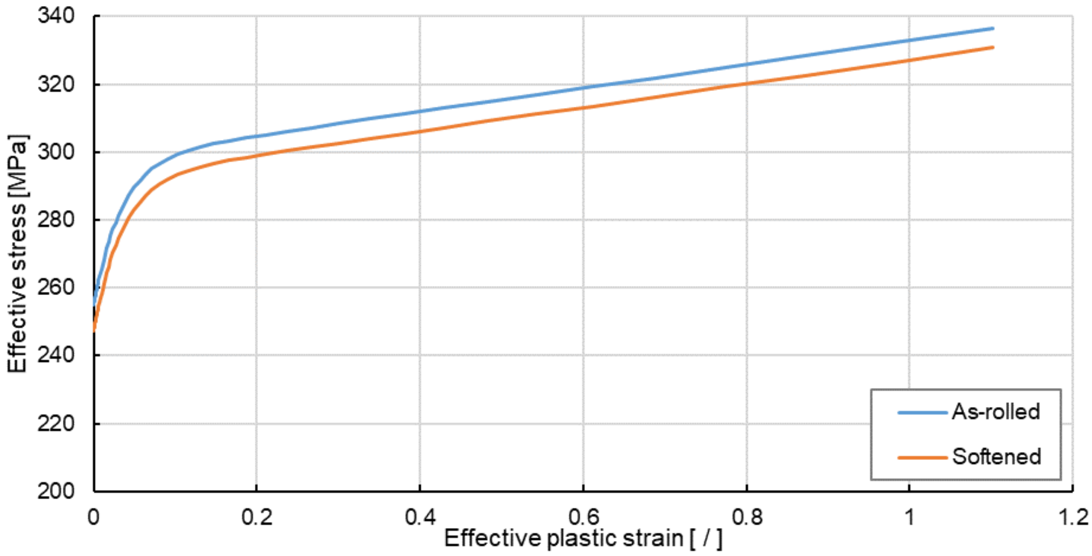


Fig.7: Flow curves of the as-rolled and softened material.

2.5 Parametric decomposition of the FEA model

In order to enable automated generation of the can body forming models and an automated workflow execution, a fully parametric description of the can body forming process is established. This includes parametric descriptions of the:

- Forming tool geometries,
- Process parameters,
- Material properties.

It is important for the performance of the machine learning model that all the parameters are fully independent of each other and that they describe the entire process uniquely. This is particularly true of the tooling geometries, which, in turn, determine the final can body geometry. An example of one such decomposition is shown on Fig. 8 for the dome plug, the re-draw punch, the outer retainer and the re-forming tooling.
Using the exponential equation described in chapter 2.4, the material properties can be fully described by:

- Yield stress,
- Ultimate tensile strength,
- Uniform elongation,
- Slope of the hardening curve,
- Amount of softening during thermal treatment.

Process parameters include:

- Dome depth,
- Re-form diameter,
- Re-form height,

In total, the entire can body forming process is described by 26 variable parameters.

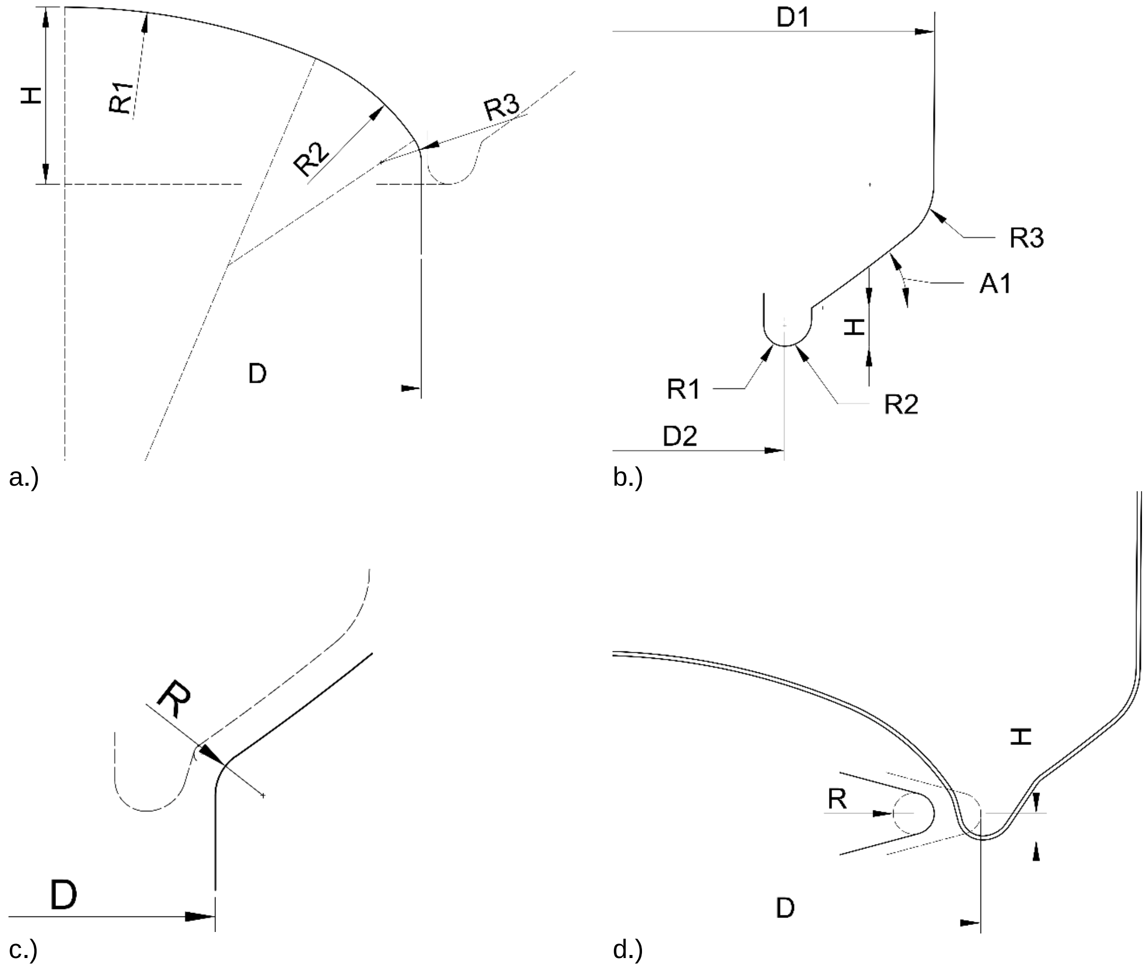


Fig.8: Parametric description of the can forming tooling geometry, a.) dome plug, b.) re-draw punch, c.) outer retainer and d.) re-draw looing.

2.6 Dataset generation

The data-set is generated by varying all the input parameters in a random manner between a minimum and maximum value. Approximately 1500 unique sets of parameters were evaluated. The entire set of forming and performance models is executed for each parameter set. A subset of the minimum and maximum bounds assigned to the parameters is shown in Table 1.

Parameter	Min.	Max.
Gauge [mm]	0.200	0.300
Yield strength [MPa]	240.0	320.0
Can outer diameter [mm]	55.0	70.0
Can stand diameter [mm]	42.0	54.0
Dome Depth [mm]	8.0	15.0

Table 1: Select data-set minimum and maximum parameter bounds.

An automated post processing routine is established, which evaluates 7 performance metrics:

- Dome reversal pressure before re-forming,
- Dome reversal pressure after re-forming,
- Axial buckle load (bottom squat),
- Metal mass,
- Liquid volume,
- Maximum thinning before re-forming,
- Maximum thinning after re-forming.

Metal mass and liquid volume are calculated to a height of 15 mm above the lowest point of the can body, to provide a consistent means of comparing different bottom geometries.
From the point of view of the machine learning model, the input parameters represent the features, and the performance parameters represent the targets.

3 Machine learning model

The machine learning model used is a Gradient boosting regressor. It is trained on the 7 performance metrics from the simulation process and the 26 input parameters. The dataset was split into a train set and a test set with a 75:25 split ratio.
The machine learning model training shows good results with all mean average error within acceptable bounds (Fig. 9). A level of over-fitting is present, however, the prediction accuracy is acceptable.

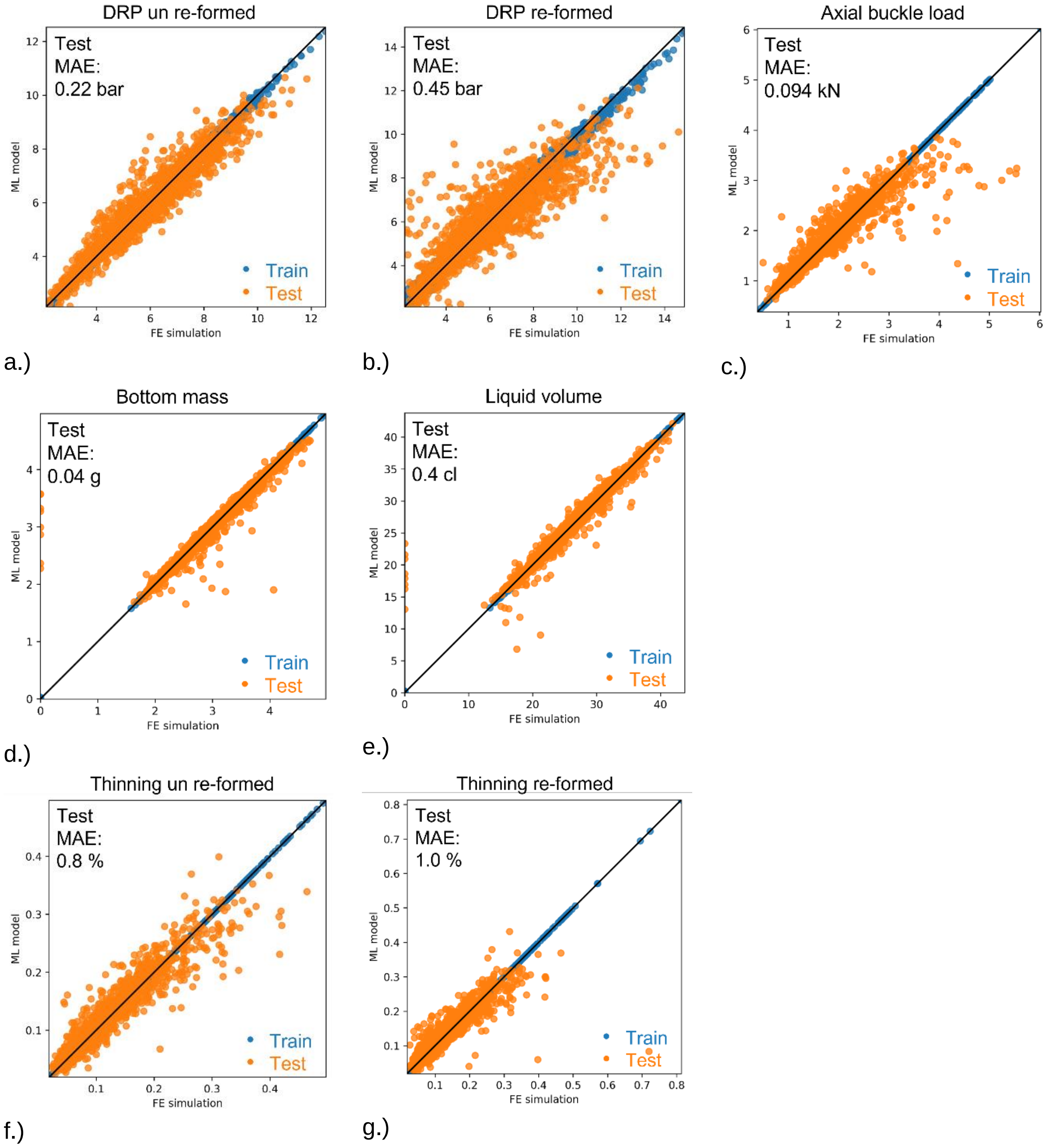


Fig.9: Correlation plots between FEA simulation results and the machine learning predictions for the train and test data-sets, a.) dome reversal pressure before re-forming, b.) dome reversal pressure after re-forming, c.) axial buckle load, d.) metal mass, e.) liquid volume, f.) thinning before re-forming, and g.) thinning after re-forming.

4 Results and validation

To validate the machine learning results, validations tests were carried out at the Novelis Global R&D Centre, Kennesaw, GA, USA. Different can body design were formed on a laboratory scale can production line with variating settings of the reformer and dome depth. In this initial validation stage, only the dome reversal pressure tests were carried out. The forming was varied in such a way, as to achieve variations of the final can body geometry in the following parameters (Fig 10.):

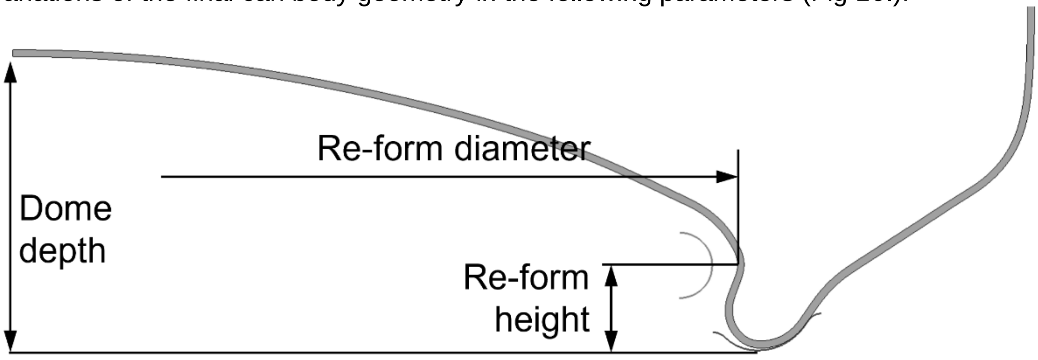


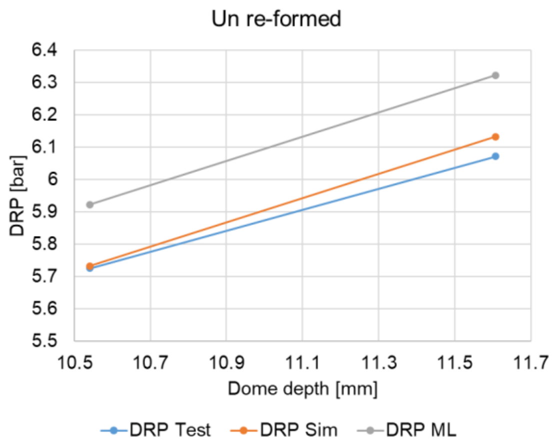
Fig.10: Can bottom geometrical parameters.

The forming parameters used in the validation are shown in Table 2, along with their minimum and maximum bounds where applicable:

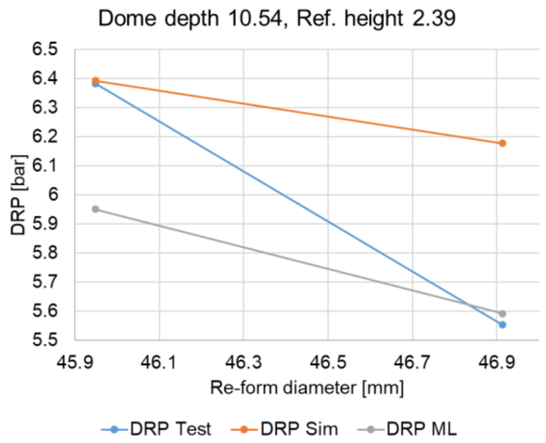
Parameter	Min.	Max.
Dome Depth [mm]	10.54	11.61
Reform Diameter [mm]	45.95	47.14
Reform Height [mm]	2.18	2.39
Gauge [mm]	0.260	
Yield strength [MPa]	253.7	

Table 2: Validation test forming parameters.

The results of the machine learning model predictions, compared to the finite element model simulation results and the physical test data for various combinations of dome depth and re-forming set-up are shown in Fig. 11 and 12 below.



a.)



b.)

Fig.11: FEA simulation and machine learning predictions of dome reversal pressure for a.) an un re-formed can body at different dome depts and b.) different re-formed diameters at a dome depth 10.54 mm and a re-form height of 2.39 mm.

Fig. 11-a.) shows the comparison of dome reversal pressure results for an un re-formed can body at two different dome depths. The machine learning model captures the relative performance change well, however, it over-predicts the absolute measured value by between 3.4 and 4.2 %.

Fig. 11-b.) shows the dome reversal pressure results for a re-formed can body at a dome depth of 10.54 mm with a re-from height of 2.39 mm. In this case, the machine learning model under-predicts the dome

reversal pressure significantly, by 6.8 % at the lower re-form diameter. The finite element model itself show a poor agreement with the results and the machine learning model follows that trend at a lower absolute level.

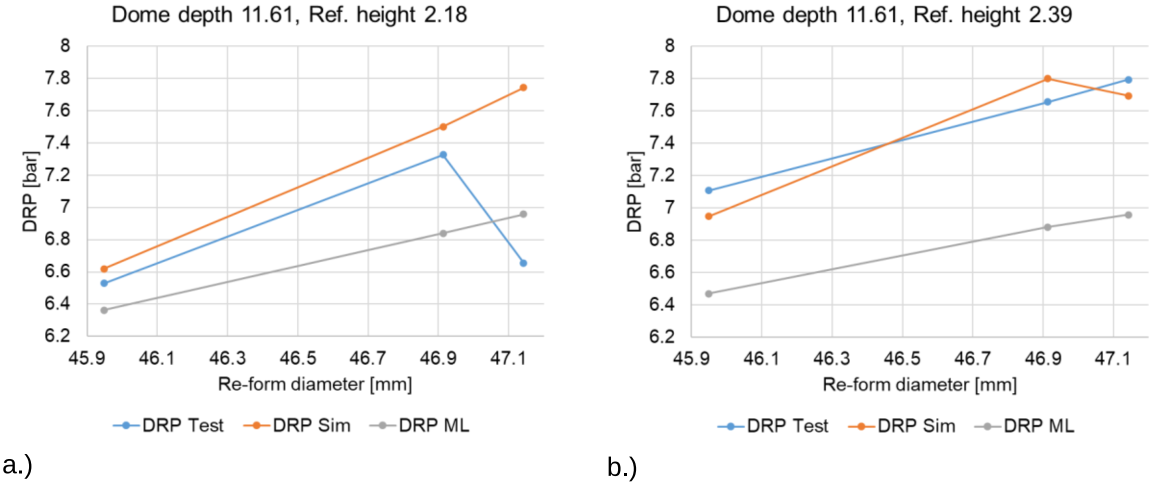


Fig.12: FEA simulation and machine learning predictions of dome reversal pressure for a re-formed can body at a dome depth of 11.61 mm and a.) a re-form height of 2.18 mm, b.) a re-form height of 2.39 mm.

Fig. 12 shows the dome reversal pressure results at a dome depth of 11.61 mm for two different re-form heights as a function of re-from diameter. In both cases, the machine learning model follows the trends of the finite element model better than those of the physical experiment, particularly at the higher re-from diameters, and significantly under-predicts the dome reversal pressure. The error rises with re-from diameter and is at its highest at approximately 6.9 % on Fig. 12-a.) at a re-from diameter of 47.14 mm. The shortcomings of the finite element model are also visible and follow the trend shown in Fig. 11-b.).
Possibly, there are physical phenomena present in the forming process at higher re-from diameters, which the underlying finite element model does not capture with sufficient accuracy. The machine learning model predictions diverge most from the finite element simulation results at higher re-from diameters, indicating that those effects might be captured better at other points in the data-set.

5 Summary

A methodology was developed for predicting performance parameters of a formed beverage can body using a machine learning approach. The can body forming process has been parametrized and a set of finite element models developed to simulate the can body forming and performance testing. These models have been used in a high-throughput simulation approach, to generate a large training data-set to train a gradient boosting regressor machine learning model. The machine model is in-turn used to provide real-time predictions of can body performance.
The machine learning model has been validated in a limited way on predictions of dome reversal pressure performance and has shown acceptable accuracy to provide useful data for engineering applications. The relative error of the machine learning predictions is below approximately 7 %, however, the trends observed in the physical experiment are preserved, i.e. the relative change in performance from one variant to another is captured well by the machine learning model, in some cases even better so than the finite element simulation by itself.
In its current state, the accuracy of the machine learning model is sufficient to perform non-critical analyses, such as initial screening of test variants, design space exploration or on-site troubleshooting, where the speed of prediction is more relevant than the absolute accuracy of the results.
In further work, the size of the data-set will be continuously grown to provide more training data for the machine learning model. Additionally, the inaccuracies of the finite element model at high re-form diameters need to be addressed.