Final Report

Optimising red meat supply chains using data and AI applications

Project code: P.PSH.1581

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Date published: 11 May 2026

PUBLISHED BY
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This is an MLA Donor Company funded project.

Meat & Livestock Australia acknowledges the matching funds provided by the Australian Government to support the research and development detailed in this publication.

Abstract

This project explored how improvements to beef supply chain performance could be achieved via improved utilisation of existing processing data by Völur's AI solutions. The project conducted a simulated analysis of the ways that artificial intelligence could digitise and support complex decisions in meat processing and identified a pathway to better value capture across meat value chains.

For the cube roll subprimal, the work first mapped the operational processes, key data sources and process decision points for the selected product lines used in the trial. It then tested the potential value of an automated approach to yield forecasting, allocation (batching), and scheduling functions by simulating a side-by-side comparison of cube roll production performance at an Australian red meat processing plant.

Based on the findings of this subprimal, the project explored the ways that Völur's AI solutions could improve the plant's bottom line via this simulated trial. The study also observed that the potential to maximise this uplift is dependent on both timely access to quality data and the plant's in-line operational adaptability to new data-driven insights.

This project delivered a preliminary use-case for estimating the potential benefits of digitised planning and optimisation in Australian meat processing plants, and established a theoretical foundation for scaling the adoption of data-enabled optimisation across the Australian red meat sector. This initiative aligns with Meat & Livestock Australia's wider objectives for increasing industry's digital capability to feed both forward and backward key product quality and yield intel and the evaluation and deployment of accurate and efficient objective measurement technologies and systems.

Executive summary

Background

This research aimed to address the question of how artificial intelligence (AI) and structured data optimisation can improve carcase allocation, production scheduling, and value recovery in beef processing operations. The work targeted a large-scale processor and supply chain stakeholder, where complex decision environments and carcase variability create measurable inefficiencies in yield performance and economic returns. The results are intended to inform future developments of an AI-enabled optimisation system and provide an evidence base for future research priorities across the red meat processing industry.

Objectives

The aims of the project were to:

- Establish a validated baseline of current sorting and allocation performance for one subprimal.
- Develop and test possible AI-driven allocation and optimisation algorithms under simulated commercial constraints.
- Quantify hypothetical economic uplift and operational improvements relative to existing practices.
- Define a pathway to further R&D, commercial commissioning and industry scale-up.

These objectives were achieved through successful baseline validation, simulation-based optimisation modelling, and quantified value assessment demonstrating measurable improvement potential.

Methodology

A phased methodology was implemented, including data consolidation, baseline performance analysis, predictive modelling, and simulation-based optimisation. Historical grading, yield, and order data were structured to enable economic allocation modelling under digitised plant constraints. Comparative scenario testing was undertaken to assess AI-driven scheduling performance against current manual planning systems for the cube roll product range.

Results/key findings

The project established a quantitative performance baseline and demonstrated validated optimisation opportunities through future AI-enabled allocation modelling. Simulation results showed improved sub-batch consistency, enhanced compliance with customer specifications, and measurable potential for increased carcase value recovery. Findings confirmed that improved data integrity and algorithmic decision support materially enhance production efficiency and economic performance.

Benefits to industry

The project provides the foundations of a scalable optimisation R&D framework which may be capable of improving carcase utilisation, scheduling accuracy, and value capture across processing operations. Adoption of such systems could reduce value leakage per head, strengthen processor–producer alignment through improved feedback mechanisms, and enhance overall supply chain competitiveness within the Australian red meat sector.

Future research and recommendations

The project uncovered a plethora of future applied R&D opportunities. This future work should prioritise further study into the three identified optimisation areas of yield prediction, dynamic batching, and optimised process scheduling, and aim to run full commercial testing and validation of the economic gains for each under live operating conditions. Expansion of optimisation coverage across additional primals is also advised to enable whole-of-carcase value optimisation. Continued investment in automated data capture and real-time analytics capability will also be critical to supporting industry-wide scalability and long-term impact.

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1. Background

1.1 Industry Problem

The Australian red meat processing sector operates within a complex production environment characterised by biological variability, fixed customer specifications, labour constraints, and narrow margins. Each beef carcase differs in weight, fat cover, muscling, and primal yield potential, yet processors must consistently meet tightly defined domestic and export order requirements.

This structural variability creates an inherent optimisation challenge to allocate carcases and primals in ways that maximises total carcase value and maintains throughput efficiency and specification compliance. When processing plants cannot meet these challenges, inefficiencies appear in the form of suboptimal cut plans, downgrade losses, and misalignment between supply and demand.

Although significant volumes of grading, yield, and production data are routinely collected within modern processing plants, decision-making remains experience-based and supported by legacy planning tools. So, a clear knowledge and implementation gap exists between the improved availability of data and the utilisation of validated and commercially deployable optimisation tools that operate within real plant constraints.

The project's processing partner had identified a desire for a solution to assist with these issues of complexity across their meat operations and continue driving their push for continuous improvement and optimal data-driven decision making across their business.

1.2 Opportunity to be explored & potential impact of results

Völur is a global software company headquartered in Norway that specialises in applying data science and artificial intelligence (AI) to optimise red meat supply chains. Its core focus is production planning and carcase allocation, using AI-driven algorithms to determine how individual carcases — based on their unique biological characteristics — should be sorted, cut, and directed to specific market segments to maximise overall value. This capability directly aligns with the segregation and allocation objectives of the current project, where optimal matching of carcase attributes to product specifications is critical to improving value capture.

Völur has established international experience in implementing AI-based optimisation systems within commercial meat processing environments. The company has worked extensively with major processors around the world, developing algorithms that leverage current and historically available datasets. This experience enables Völur to integrate advanced measurement systems with optimisation algorithms capable of generating actionable production recommendations.

The Völur platform uses integrated data sources and AI optimisation models to support decision making across sorting, cutting, and production planning processes. By combining supply data (e.g. carcase grading, yield estimates, inventory levels) with demand information (e.g. customer orders, product specs, bills of materials, and market prices), the system generates optimised cutting and allocation plans designed to maximise carcase value while maintaining service levels (see **Figure 1** below).

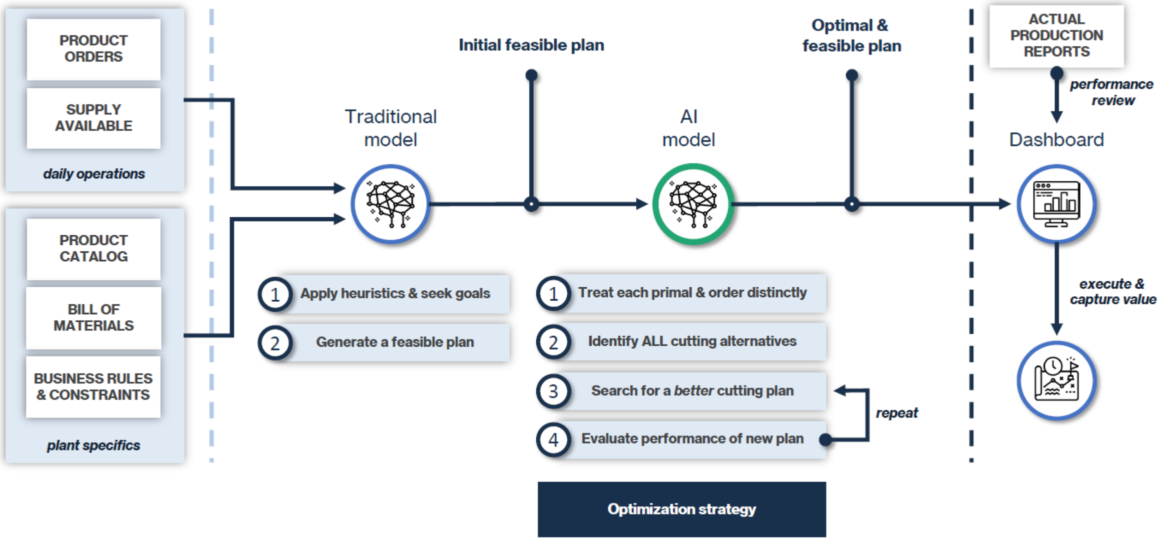

Figure 1: *Schematic of Völur's AI approach to optimising meat processing business decisions.*

Unlike traditional planning approaches which rely heavily on manual decision-making and experience-based assessments, AI-enabled production systems evaluate thousands of potential allocation combinations simultaneously. Under conventional methods, production plans are typically developed by balancing available carcase supply against confirmed customer orders, with plant teams executing these plans based on operational experience. While this approach can ensure order fulfilment, it does not systematically optimise carcase utilisation or total economic return. In contrast, AI-driven planning systems are designed to maximise carcase value while satisfying primary demand, effectively matching the right carcases to the right products under defined operational constraints. This results in a more balanced optimisation of profit and service levels.

The project proposed to design, simulate and evaluate an AI-driven data solution within an Australian commercial processing context. Outcomes from the pilot will inform the development of generalised guidelines for adoption and integration of AI-enabled data management systems across the Australian red meat industry, supporting scalable implementation and broader industry transformation.

2. Objectives

The overall objective of this project was to design, simulate and attempt to quantify the benefits of an AI-enabled data management and optimisation solution to improve carcase allocation, production planning, and value recovery within a commercial beef processing environment.

Specifically, the project sought to:

- Establish a validated baseline of current sorting, sub-batching, and allocation performance within the pilot processing facility for the cube roll subprimal.
- Consolidate and structure relevant production, grading, yield, and order data to support predictive and prescriptive analytics of this subprimal.
- Design and test preliminary optimisation models capable of generating optimised allocation and cutting plans under simulated operational constraints.

- Quantify potential improvements in carcase utilisation, specification compliance, and economic value relative to existing planning methods for cube rolls.
- Identify integration requirements for embedding the Völur platform within existing plant workflows and business data systems.

These objectives were addressed via staged milestone activities, phased development, and simulation-based validation within the processor's operating environment.

3. Methodology

The project adopted a phased methodology progressing from baseline diagnostics through to predictive modelling and optimisation simulation evaluation and reporting. The approach combined structured data consolidation, analytical modelling, and scenario-based optimisation to ensure technical robustness while remaining grounded in commercial operating conditions.

For simplicity, the scope of this trial was limited to the cube roll subprimal. This sub primal subset was chosen for analysis both due to its high value margins as well as operational variability.

Milestone 1 – Baseline Assessment and Data Consolidation
The first stage involved establishing a validated baseline of current carcase sorting, sub-batching, and production planning performance for cube rolls within the pilot facility. Historical grading, yield, and order fulfilment data were extracted from existing plant systems and consolidated into a structured analytical dataset. This process required data cleaning, reconciliation of inconsistencies, and alignment of production outputs with order specifications. This phase was successful in quantifying current-state allocation performance and identifying gaps in data consistency and measurement resolution.

Milestone 2 – Predictive Modelling and Yield Estimation
Using the consolidated dataset, basic predictive models were developed to estimate yield outcomes and carcase value potential based on objective measurement inputs (e.g. carcase weight, fat depth, grading data) for the cube roll product line. The datasets utilised and machine learning modelling techniques tested are outlined below in Sections 4 & 5. These models enabled the simulation of primal sales order prioritisation and optimisation for segregation of bodies.

Milestone 3 – AI-Enabled Allocation and Optimisation Simulation
Building on the predictive framework, AI-driven optimisation algorithms were applied to simulate economically optimised carcase allocation and cutting plans for cube rolls under defined operational constraints. Constraints incorporated into the modelling included order requirements, product specifications, sub-batching rules, throughput capacity, and sequencing considerations. Comparative scenario analysis was undertaken to evaluate AI-generated allocation strategies relative to existing heuristic-based planning methods.

Milestone 4 – Evaluation, On-site Validation Testing, and Reporting
The final stage focused on evaluation of modelling outputs, validation of assumptions with operational stakeholders, and documentation of findings. This included reviewing optimisation results against baseline performance metrics, assessing sensitivity to key input variables, and identifying practical considerations for future implementation. This included a trial whereby the processing team manually implemented a pre-packing weighing and batching experiment to test the

potential value of Völur's sorting optimisation solution in an Australian red meat processor application.

Overall, the methodology proved effective in progressing from diagnostic assessment to simulated optimisation modelling within a digitised plant context. The staged approach reduced implementation risk by testing assumptions at each phase prior to advancing to more complex modelling activities. Although integration into live plant workflows was not completed within this project stage, the analytical framework and validated performance improvements provide a solid foundation for future commissioning and scale-up.

4. Results

4.1 Overview of Results

This project used the cube roll subprimal to run a simulated evaluation of the application of structured data management, predictive modelling, and AI-enabled optimisation to improve carcase allocation and production planning within a commercial beef processing environment. The results presented below progress from baseline performance assessment through predictive yield modelling and optimisation simulation, alongside a theoretical economic impact assessment and documentation of future-stage R&D opportunities.

Across all modelling outputs, the AI-enabled optimisation framework demonstrated opportunities for improvements in allocation efficiency and estimated carcase value recovery compared with existing heuristic-based planning methods. While results are simulation-based and subject to live commissioning validation, findings confirm a sound technical feasibility and commercial potential.

4.2 Data Mapping, Process Baseline & Assessment

4.2.1 Cube Roll Process & Decision Trees

The first phase of analysis involved gaining a thorough comprehension, then digital recreation, of the existing processes and decision points used by the processing team in the production of cube roll products. This involved mapping of the flow of physical product, overlayed with a summary of key data points which are obtained along each key phase of processing.

Following this, a baseline analysis was undertaken to quantify existing carcase sorting, sub-batching, and allocation performance under current production planning methods. This confidential assessment was shared with the processor and informed model calibration activities and established the reference case against which optimisation scenarios were evaluated.

The analysis demonstrated variability in carcase utilisation outcomes and highlighted opportunities for improved alignment between carcase characteristics and product specifications.

4.2.2 Data Integrity and Measurement Assessment

Data extracted from plant systems was assessed for completeness, consistency, and suitability for predictive modelling. Variability was observed in yield measurement resolution and grading consistency across datasets. While sufficient for modelling purposes, the assessment identified that optimisation performance is linked to input data granularity and integrity. These findings informed later sensitivity testing.

4.3 Predictive Yield and Value Modelling Results

Basic predictive models were developed to estimate cube roll yield and carcase value potential using objective carcase measurements and grading inputs. Model performance was evaluated using standard statistical accuracy metrics.

The results demonstrated that available plant and carcass-level data can be used to generate yield forecasts with reasonable accuracy (≈90%), however the practical suitability of these models for prescriptive optimisation is dependent on both high-quality data inputs and sufficient product traceability of cuts through the processing chain. Sensitivity testing indicated improved performance could be achieved with higher-resolution yield inputs such as those delivered by upgraded yield systems such as the Frontmatec BCC-3.

4.3.1 Yield Prediction Model Components

The model operated in two key processing steps; raw carcase data features were combined to generate a set of characteristics for each carcase side, which would then be utilised in the cube roll yield prediction model. The features used included:

- HSCW (Hot Standard Carcase Weight)
- P8_FAT (fat depth in mm)
- MARBLE_SCORE (visual marble score)
- MSA_MARBLE_SCORE (MSA marble score)
- EYE_MUSCLE_AREA (cm^2)
- OSSIFICATION (score)
- HUMPHEIGHT (hump height - Bos indicus indicator)

4.3.2 Understanding Prediction Intervals

When the model predicted yields, it provided a range with calibrated uncertainty (e.g. predicted yield = 2.5%, and 90% interval = 2.2%-2.8%).

Table 4. Description of calibration qualities for model predictions.

Calibration State	What Happens
Well-calibrated	~90% of actual values fall within 90% intervals
Overconfident	Only 60-70% of actuals fall within (intervals too narrow)
Underconfident	99% of actuals fall within (intervals too wide, not useful)

4.3.3 Cube Roll Prediction Model Performance

The model generated in this trial achieves **87% coverage** (close to the 90% target), indicating well-calibrated uncertainty estimates and reasonable correlation across both side and batch-level data inputs.

Table 5. Evaluation metrics of project's yield model compared to batch-level averaging.

Metric	Yield Model	Existing Method	Improvement
Approach	ML on carcase features	Batch-level averages	—
Training data	69 batch-date observations	Historical production	—
Side-level RMSE	0.135%	0.198%	32% better
Batch-date RMSE	0.275% ± 0.049%	0.384%	28% better
MAE	0.207% ± 0.030%	0.300%	31% better
90% Coverage	86.8%	N/A (no uncertainty)	—

4.3.4 Simulated Business Value Uplift of Improved Predictions

If successfully implemented, yield forecasting enables improves processing decisions by reducing uncertainty about what incoming supply will produce by cut/spec. With tighter forecasts, plants can optimize the cut plan for margin and commitments, detect shortages or surpluses earlier, and rely less on buffers that drive overproduction and inventory. In practice, it helps teams choose the right mix, buy the right animals/lots, allocate scarce premium specs to the right customers sooner, and schedule labour/lines/packaging to match expected volumes.

When the project's models improvement in prediction quality are compared to rolling batch-level averages and evaluated for sensitivity in driving optimised business decisions (see Figure 2 below), it was observed that an improved AI yield forecasting tool can drive great business value. The PoC yield model from this trial could be extrapolated to deliver a possible ~$180K/year in added potential value of improved yield predictions for the cube roll subprimal.

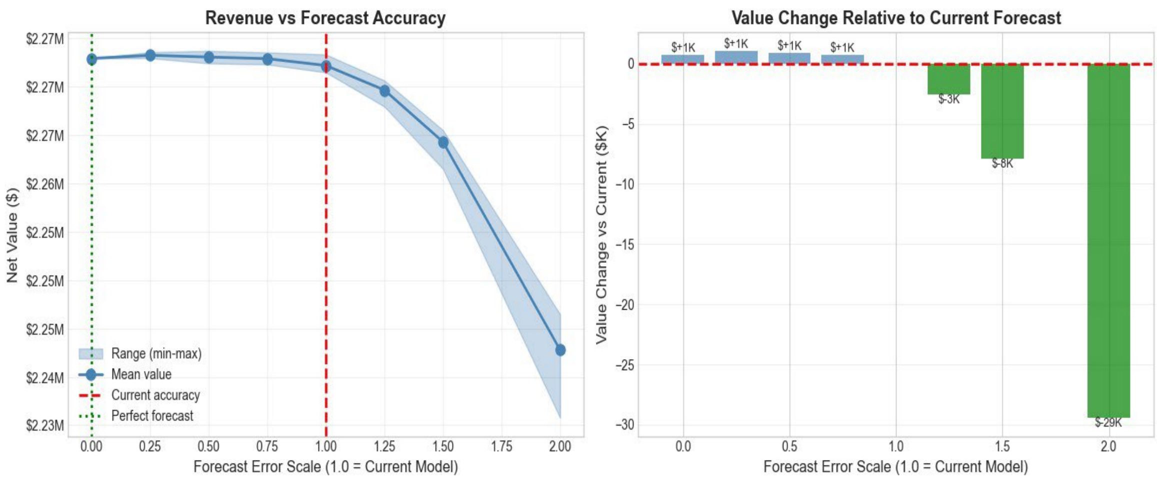

Figure 2: Charts mapping the sensitivity of revenues compared to yield forecast accuracy for the cube roll subprimal.

4.3.5 Current Limitations & Future R&D for Yield Prediction

In the process of designing and simulating this AI-powered yield prediction tool, a key enabling technology limitation was identified, whereby the prediction of individual carcase/primal yields alone is very difficult to translate directly into improved in-line classifications without advanced traceability mechanisms. Even if a highly accurate prediction yield model was developed, it requires a means to correctly recognise and assign individual cuts from their source carcase, which cannot currently be performed in the room at line speed.

Hence, it was observed that at this time, yield predictions could instead be more effectively utilised as an input into pre-boning allocation interventions (see Section 4.4 below), rather than as a standalone tool.

Alongside a pairing with future cut-level traceability tools, future R&D for this yield prediction modelling could also better understand the marginal costs and benefits of different sources of input data, to allow processors to better prioritise investment of new measurement tools across various stages of the processing chain. Preliminary discussions with MLA indicate this approach aligns with wider industry aspirations for exploring new objective measurement data integrations.

4.4 AI-Optimised Allocation Simulation Results

In the next work package, basic AI-driven optimisation algorithms were generated to test how optimised allocation and cutting plans may be deployed under defined operational constraints. Constraints incorporated into modelling included order requirements, product specifications, throughput limits, sequencing rules, and sub-batching requirements.

The Allocation Simulator was developed to evaluate how different allocation strategies impact value capture, order fulfilment, and downgrade risk. Using four weeks of production data for cube rolls, multiple allocation approaches were tested, ranging from simple rule-based methods to advanced optimisation techniques.

4.4.1 Optimised Allocation Scenarios

Four allocation strategies were tested: a Greedy approach which matches orders with supply on a first-come first-served basis, a priority-based approach, a cost optimisation strategy, and a revenue optimisation strategy designed to maximise net value after accounting for downgrade costs.

Table 6. Description of the four different allocation strategies evaluated.

Strategy	Description	Approach
Greedy	Allocates each cube roll to the first eligible order	Simple first-come, first served
Priority	Scores orders by margin × urgency + fill rate bonus	Allocates to highest-scoring eligible orders
Optimisation	Minimises total cost (downgrade + unfulfilled penalty)	Evaluates multiple downgrade paths
Revenue Optimisation	Batch-level greedy maximising net revenue	Considers FOB price minus downgrade costs

4.4.2 Simulation Process & Allocation Flow

The Allocation Simulator worked by orchestrating:

1. **Production Phase:**
   - Samples carcase sides based on production schedule
   - Predicts yields using ML models (NGBoost)
   - Creates cube roll objects with realized weights
2. **Allocation Phase:**
   - Applies chosen strategy to allocate cube rolls to orders
   - Handles downgrades and basic pack fallbacks
   - Tracks allocation outcomes and costs
3. **Metrics Collection:**
   - Daily production and allocation statistics
   - Order fulfilment rates
   - Downgrade costs and volumes

Subsequently, the logic used by the Allocation Simulator follows the derived sequence of cube roll product allocation, from priority customers through to basic pack stockpile.

4.4.3 Performance of Various Product Allocation Strategies

Across all simulations, the revenue optimisation strategy consistently delivered the highest economic performance, achieving 14–16% higher total value compared to baseline and simpler allocation approaches. Over the four-week analysis period this strategy generated the strongest overall net value while maintaining order fulfilment rates above 90%, highlighting the potential for improved allocation decisions to enhance profitability without compromising customer service.

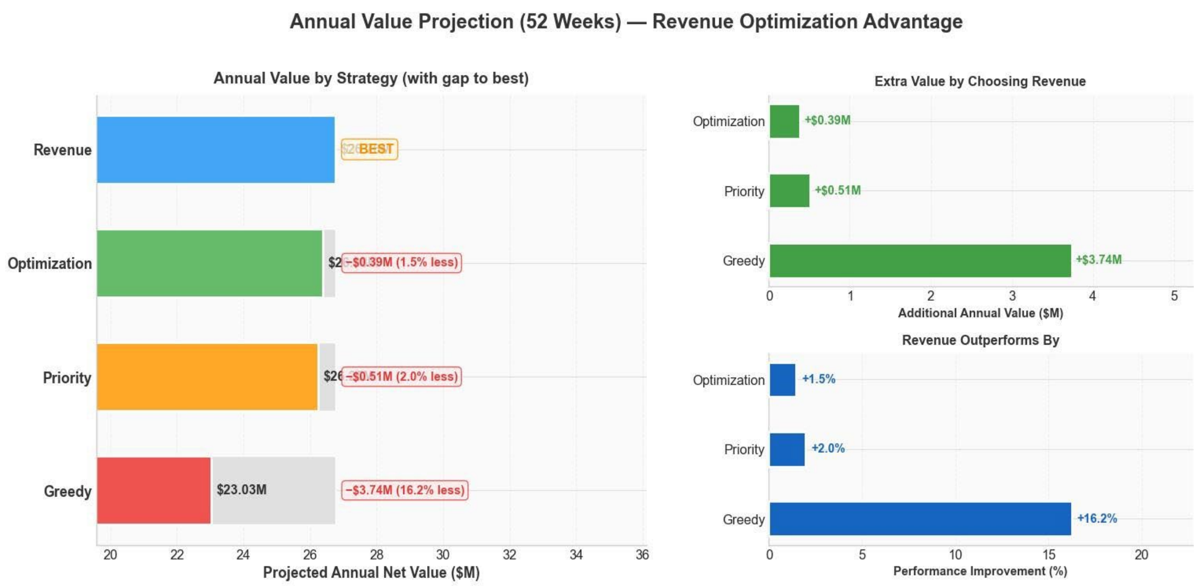

Figure 3: A projection of annual value projection differentials across the differing allocation strategies.

A key driver of this improvement was the reduction in downgrade costs. The optimisation-based strategies were able to minimise downgrade events where higher-grade product is redirected into lower-value orders, highlighting that a substantial portion of value uplift comes from avoiding inefficient allocation decisions rather than solely increasing production output.

Performance consistency was also observed across the analysis period. The relative ranking of strategies remained stable week-to-week, and the value advantage of the optimisation approach compounded over time. This indicates that the benefits of improved allocation are systematic and repeatable, rather than dependent on specific production conditions.

Overall, the allocation simulator results indicate that allocation decisions represent a high-leverage opportunity for AI value creation, with advanced optimisation approaches capable of delivering substantial and sustained financial benefits in the presence of sufficient quality and timely access to input data. Sufficient operational adaptability is also a key determinant of the real-world uplift able to be achieved by improved allocation tools, whereby plants will need to be able to respond dynamically to adjusted production plans on weekly and daily time horizons.

4.5 Sub-batching for Improved Product Consistency Results

The sub-batching analysis focused on evaluating the impact of dividing existing production batches into smaller, more homogeneous groups based on carcase characteristics, particularly fat content. The analysis focussed specifically on the Batch C production over the 4-week trial window.

4.5.1 Existing variability in key product codes

The current state analysis revealed significant variability within existing batches, with fat levels and carcase size varying by up to 12–14% within a single batch. Addressing this level of variability offers opportunities to improve product consistency and expands the ability to capture premium pricing in markets where uniformity is highly valued.

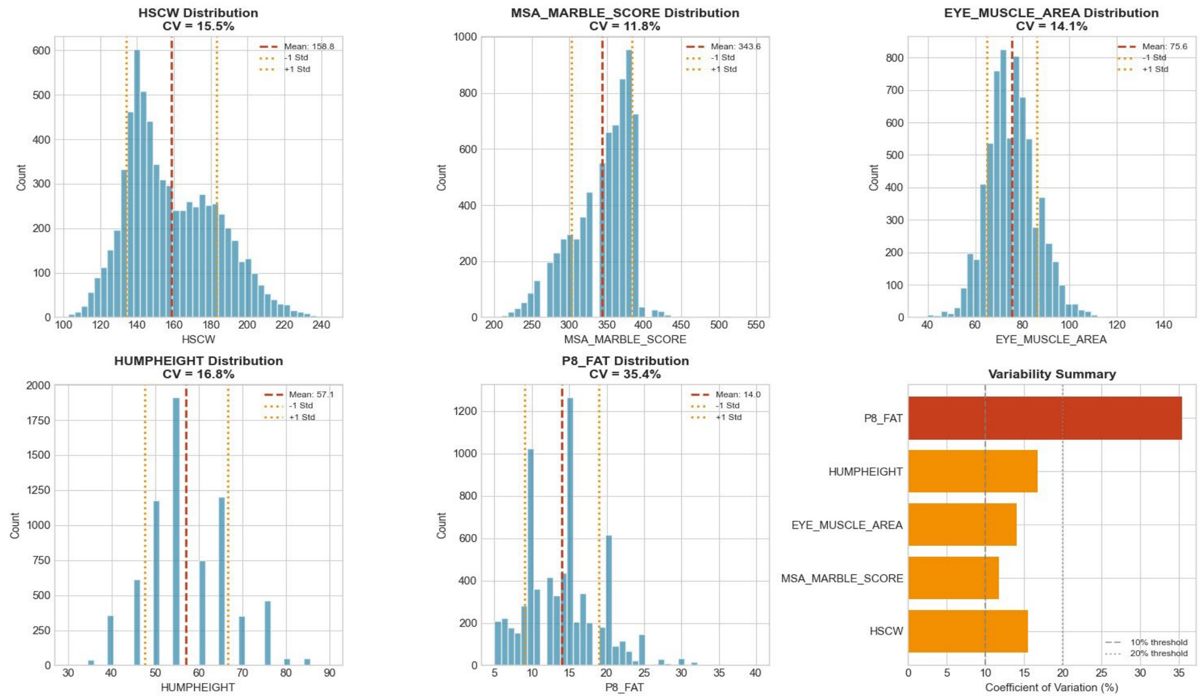

Figure 3: Visualisations of variance across key carcase features for the chosen Batch C carcases.

An analysis of variability across key carcase characteristics indicated that P8 fat scores were the most highly variable trait. So sub-batching trials focussing on this characteristic may uncover further opportunities for improved product consistency and value capture.

Table 9. Summary of the variability of key carcase characteristics observed.

Feature	Mean	Std Dev	CV%	Assessment
HSCW	158.8	24.6	15.5%	Moderate
MSA_MARBLE_SCORE	343.6	40.6	11.8%	Moderate
EYE_MUSCLE_AREA	75.6	10.6	14.1%	Moderate
HUMPHEIGHT	57.1	9.6	16.8%	Moderate
P8_FAT	14.0	5.0	**35.4%**	**High**

4.5.2 Evaluation of Possible Sub-Batching Strategies

The introduction of fat-based sub-batching strategies demonstrated a significant improvement in product homogeneity. By grouping carcases with similar fat characteristics, within-batch variability was reduced by more than 40%, resulting in tighter distributions of key quality attributes.

Table 10. Description of four different sub-batching strategies simulated for testing performance.

Strategy	Features Used	Target
Weight-Based	HSCW only	Simple, operationally easy
Quality-Based	MSA + HSCW	Better quality consistency
Multi-Feature	HSCW + HUMPHEIGHT	Alternative segmentation
Fat-Based	HSCW + P8_FAT	Targets highest CV feature

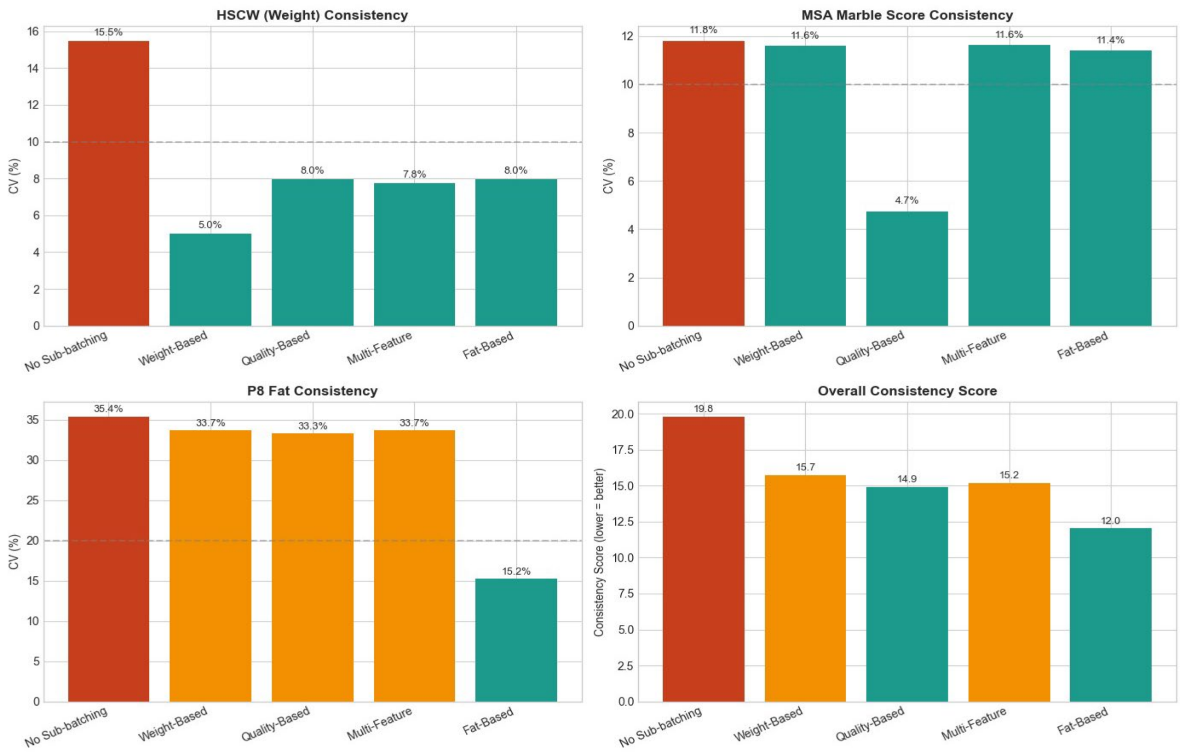

Figure 4: Analysis of the change in variability based on the proposed sub-batching strategies, including no sub-batching as the control.

This improved consistency enables processors to deliver more predictable products, which can enhance customer satisfaction, reduce claims or rejections, and support stronger positioning in high-value market segments.

4.5.3 Recommended Sub-Batch Structure

The recommended sub-batch structure for Batch C is based on a six-tier segmentation combining carcase weight (HSCW) and fat depth (P8_FAT), designed to balance product consistency, market alignment, and operational feasibility.

Specifically, carcases are first divided into two primary weight categories (≤160 kg and >160 kg), and then further segmented into three fat bands (low: 0–10 mm, medium: 10–16 mm, and high: >16 mm), resulting in six distinct sub-batches. Each sub-batch is aligned to a target market segment, ranging from premium lean products (low-fat categories, attracting ~5% price premiums) to standard domestic/export products (medium-fat, ~2% premium), and finally to manufacturing or commodity channels (high-fat, base pricing).

This structure enables more precise matching of product characteristics to customer requirements, improves consistency within each batch, and creates a clear pathway to capture value through differentiated pricing, while remaining sufficiently simple to support practical implementation on the processing floor.

4.5.5 Manual Weighing Trial Run to Validate Results on Site

A manual cube roll weighing and sorting trial was conducted over two production days to validate the feasibility and accuracy of implementing weight-based sub-batching in a live operational environment. Initial results from the first trial day (24th February) highlighted significant inconsistencies in classification, with a high proportion of incorrectly sorted product—most notably, over half of the sampled pieces in one category were misallocated relative to the 3.1 kg threshold. These errors were attributed to process challenges, including product already being redirected between programs and limitations in real-time decision-making on the floor.

However, results from the second trial day (25th February), which covered a full production run of over 300 bodies, showed a marked improvement in execution. Under controlled conditions, the manual weighing process demonstrated near-perfect classification accuracy, with no observed cases of heavier product being incorrectly allocated to lower-weight categories and only a small number of correctly identified edge cases. This improvement indicates that, when properly implemented, weight-based sub-batching is both operationally feasible and capable of delivering the level of precision required to support the proposed segmentation model.

Overall, the trial results provide strong practical validation of the sub-batching concept. While the initial trial highlighted the importance of clear process control and operational alignment, the subsequent results demonstrate that accurate sorting can be achieved at scale within a standard production shift. These findings support the conclusion that sub-batching is not only analytically sound but also implementable in practice, provided that appropriate procedures, training, and in-line measurement capabilities are established.

4.5.6 Key Findings & Next Steps of Improved Sub-Batching Recommendations

The findings of these results demonstrate that product consistency is not only a quality consideration but also a direct driver of financial performance. However, the implementation of sub-batching introduces several operational and technical requirements. Effective sub-batching depends on access to high-quality, carcase-level measurement data, including fat depth, weight, and grading characteristics. In addition, plants must have the capability to physically segregate and manage a larger number of batches, which may require changes to marshalling processes, floor layout, and workflow design.

The analysis also highlights that sub-batching increases operational complexity, as more granular sorting decisions must be executed in real time. As such, the successful adoption of sub-batching is contingent on the integration of data systems, optimisation tools, and operational processes. Importantly, the results suggest that sub-batching should not be applied uniformly across all production. Instead, the greatest value is realised when it is targeted toward high-value product streams, such as premium branded programs, where consistency commands a measurable price premium. This targeted approach allows processors to capture the benefits of improved consistency while managing the operational complexity associated with increased batch granularity.

5. Conclusion

This project identified multiple opportunities for AI-enabled data optimisation to improve carcase allocation, production planning accuracy, and value recovery within a commercial beef processing environment. While full commercial integration remains a future step, the modelling results confirm strong potential for scalable industry adoption and improved whole-of-supply-chain value capture.

5.1 Key findings

- A validated baseline of current carcase sorting, sub-batching, and production planning performance was established within the pilot processing facility.
- Historical grading, yield, and order data were successfully consolidated into a structured analytical dataset suitable for predictive and prescriptive modelling.
- Predictive models were developed to indicate an ability for future yield forecasts to be made using objective measurement inputs.
- AI-enabled optimisation simulations identified measurable opportunities to improve carcase allocation, sub-batch consistency, and alignment with customer specifications.
- Scenario modelling simulated quantifiable potential increases in carcase value recovery compared to existing heuristic-based planning methods.
- Sensitivity analysis also simulated that optimisation performance can improve with higher-resolution yield and grading data, highlighting the importance of data integrity and measurement accuracy.
- Practical implementation considerations and adoption guidelines were documented to support future commercial commissioning and broader industry scale-up.

5.2 Benefits to industry

The outcomes of this project indicate that AI-enabled data optimisation has the potential to materially improve carcase allocation, production planning accuracy, and value recovery within commercial beef processing operations. To maximise the opportunity for successful implementation of these features, processors are encouraged to invest in improved data capture, objective measurement technologies, and integrated planning platforms to enable economically optimised production scheduling under operational constraints.

For the wider red meat industry, the project uses this preliminary study focussed on the cube roll subprimal as a platform to expand our understanding of the potential benefits of applied AI across various processing phases. In the longer term, adoption of AI-driven optimisation platforms has the potential to improve whole-of-carcase value capture, strengthen international competitiveness, and support more sustainable utilisation of livestock resources across the Australian red meat sector.

6. Future research and recommendations

The project successfully simulated the technical feasibility and economic potential of AI-enabled optimisation for carcase allocation and production planning within a commercial beef processing environment. However, opportunities for improvement were identified in relation to data consistency, measurement resolution, and integration with the operational realities— highlighting that data quality and system readiness are critical enablers for successful deployment of AI tools.

6.1 Future R&D

In the process of sharing the results of this project with our industry stakeholders, Völur was able to clarify some of the key areas where future iterations of this work can begin delivering tangible value. Three points in the processing line were deemed ripe for further innovation, as demonstrated in the diagram below:

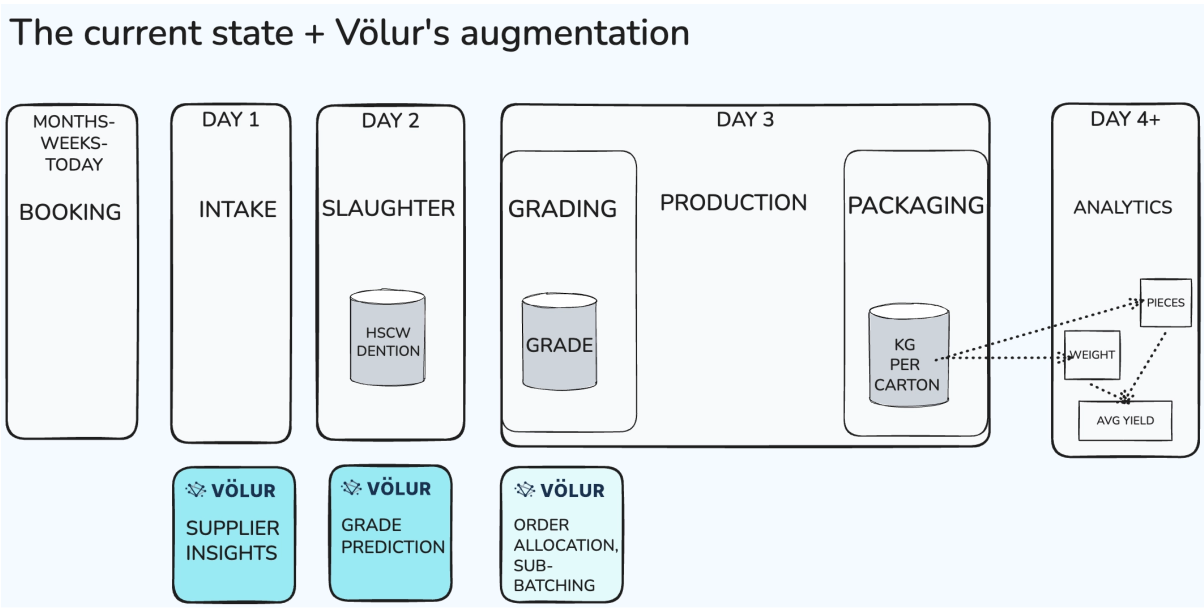

Figure 5: The future state of augmentation provided by Völur in the animal processing chain.

Here, there are three core elements which are presented as future areas for research and development in this collaborative partnership:

1. **Supplier Insights** focuses on building a supplier scoring and risk system to make sourcing more predictable and quality more consistent. It would rate farmers/feedlots using historical performance plus real-time inputs like IoT data, satellite signals, and weather, and generate predictions around reliability, volume, animal health, and seasonal variability. A key component is feedlot analytics (e.g., optimising days-on-feed and exit timing) to balance cost, yield, and grade while maintaining consistent standards across the year. Longer-term, it is positioned to use federated learning and incentives for data sharing, and to feed better upstream signals into grade prediction and downstream allocation into sub-batching.
2. **Grade Prediction** proposes layered AI models that get progressively more accurate from farm stage to arrival to post-chill confirmation, so planning and allocation decisions can happen earlier with confidence. It would combine signals like wearables/pedigree/feed, non-invasive arrival scans (e.g., hyperspectral/LiDAR), post-slaughter metrics and/or emerging hot grading technologies, producing probabilistic predictions rather than a single "certain" grade. That uncertainty-aware approach supports risk-managed decision-making (e.g., ensembles and simulation-style hedging). The expected impact is fewer grading bottlenecks and downgrades, and earlier identification/allocation of higher-grade animals to premium demand.
3. **Sub-batching** is about assigning individual carcases to the best possible customer orders as early as possible (post-arrival through post-chill) to maximise revenue, spec conformity, and efficiency. An optimisation engine would match carcases to orders using predicted grade and yield (and/or objectively measured hot carcass data), scoring assignments on value, risk/uncertainty, and sustainability, and allowing "hedging" (rerouting) if outcomes change. It is envisioned as a phased journey from rule-based matching to ML-driven, real-time allocation, potentially boosted by more direct measurement like scanning with devices such as the MEQ probe or alike. The target outcome is higher fulfilment reliability, less over/under-production, and meaningful margin uplift.

Each of these areas will be further ideated and refined between following the conclusion of this project, and each may present further significant steps forward in the digitisation and optimisation of Australia's meat industry.

6.2 Practical Application of Project Insights

More broadly, a key learning from the project is that processors should better understand the opportunities and costs of prioritising investment in structured data governance, standardised data capture protocols, and integration-ready digital infrastructure to support AI-enabled planning systems. Adoption of optimisation platforms should be staged, beginning with pilot implementations in defined production areas before broader plant-wide rollout. Clear change management strategies and training programs will be critical to embedding data-driven decision-making within operational teams.

6.3 Industry Development and Adoption Activities

Based on the experiences of this project, we observe that key industry bodies like MLA have an important role in the promotion of greater industry collaboration and knowledge sharing between processors, technology providers, regulators and other actors, so to enable the development of common goods for the digital transformation of Australia’s meat industry. Further, ongoing development of practical implementation guidelines, case studies, and demonstration pilots will support confidence and uptake across the sector. Continued co-investment in digital capability will also ensure that the red meat industry can achieve full value from AI-driven optimisation, and strengthen the long-term competitiveness of Australian meat on the global stage.