final report

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Prototype feedlot autonomous mobile robot for bunk calling

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Executive summary

A serialised campaign of adoption experiments for the prototype automatic bunk calling system (Bunk Scanner) was recently completed across three disparate feedlots through MLA project B.FLT.7009. These experiments demonstrated that under normal operating conditions the prototype Bunk Scanner predicted feed remaining in bunks accurately and repeatedly, outperforming human callers in both criteria.

The current investigation enabled development of a safe autonomous prototype mobile vehicle platform suitable for manoeuvring a new generation Bunk Scanner within a feedlot operation. With a view to reducing technical and schedule risks, we based our solution on an off-the-shelf unmanned ground vehicle robot to host the Bunk Scanner (aka 'BunkBot'). The robotic base was upgraded with additional critical functionalities including safety features and interlocks, and bespoke global and local navigation implementations. After completion of the solution's prototyping, we evaluated its performances against humans within a commercial feedlot environment.

We suggest this pursuit may deliver further value to feedlots than the light-vehicle-mounted format Bunk Scanner, based on possible additional productivity improvements. In the near-term we suggest that the autonomous mobile robot may at least complement, if not reallocate, a skilled resource by being available to operate unrestricted with overall higher performances. We also believe that longer-term benefits may be realised through increased bunk calling frequency with the mobile robot, possibly leading to increased carcase gains.

This report presents the outcomes of these experiments and demonstrates that under normal operating conditions, the BunkBot system predicted feed remaining in bunks accurately and repeatedly, once again outperforming human callers in both criteria, thereby representing a high-value outcome for the Australian red meat industry.

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1 Introduction

This final report describes the results of an experiment to evaluate a prototype autonomous system to estimate feed remaining in bunks of feedlot cattle.

1.1 Project intent

Assessment of feed remaining in bunks (calling) is a critically important job at a beef feedlot. This activity is currently only completed by humans, and the callers' assessments directly determine feed intake (bunk management) and the carcase gain of the cattle. Enabled by levy-funds, we recently delivered a prototype automatic bunk calling system (MLA B.FLT.0166), and through a series of scientific experiments (B.FLT.7009) demonstrated that the prototype's feed remaining predictions were more precise and accurate than human callers. The intention of this investigation was to advance the light vehicle-mounted prototype automatic bunk calling system by transferring the technology to an appropriate autonomous mobile robot platform that we have developed, delivered, and validated.

We suggest that this project may deliver value to feedlotters in at least two ways, both based on productivity improvements. In the near-term we expect that at least one labour unit at a feedlot dedicated to bunk calling may be reallocated, as the autonomous mobile robot will be able to replace this skilled resource by being available to operate unrestricted with overall higher performances. Longer-term benefits may be realised through increased bunk calling frequency with the mobile robot, ultimately leading to increased carcase gains. Additionally, by demonstrating that autonomous vehicles can operate in the feedlot environment, the platform may be used as a mounting point for future technologies.

2 Project objectives

The overall project objective that was agreed in the agreement is as follows,

1. Develop a prototype feedlot autonomous mobile robot for bunk calling.
2. Determine the precision, accuracy, and speed of result of the prototype to predict feed remaining for finisher diet.
3. Determine the precision, accuracy, and speed of humans to predict feed remaining for finisher diet.

3 Methodology

Our investigation sought to explore the feasibility and performance of an autonomous mobile robot for bunk calling, through delivery of a fit-for-purpose and safe platform for the prototype automatic bunk calling system provided in MLA project B.FLT.0166.

Our engineering design process has been underpinned by strong rigour for safety considerations, and these were guided by a preliminary risk assessment workshop with stakeholders to determine and document potential operability and automation hazards and their likelihoods, as well as suggested appropriate control methodologies. The output was a ranked list of key risks, and derivative benefits included a useful discussion about the control environment, risk appetite, and risk tolerances with a longer-term view for the industry.

The following sub-sections include a high-level summary of the engineering and validation experiment strategies. Project management activities performed throughout the project included provision of regular verbal and email updates to MLA and the host site so that all stakeholders were aware of project statuses, milestones, and interface and resourcing requirements.

3.1 Engineering

With a view to expedite delivery of an autonomous platform with minimal technical or commercial risk, we specified and procured an off-the-shelf mobile platform that was subsequently upgraded consistent with the controls agreed in the risk management process. Our prototype was based on the Clearpath Robotics' (Toronto, Canada) Warthog unmanned ground vehicle robot as indicated in Fig. 1. This platform is an OEM version of a commercially available remotely controlled recreational and off-road machine, that has been upgraded for research and development unmanned guided-vehicle (UGV) pursuits.

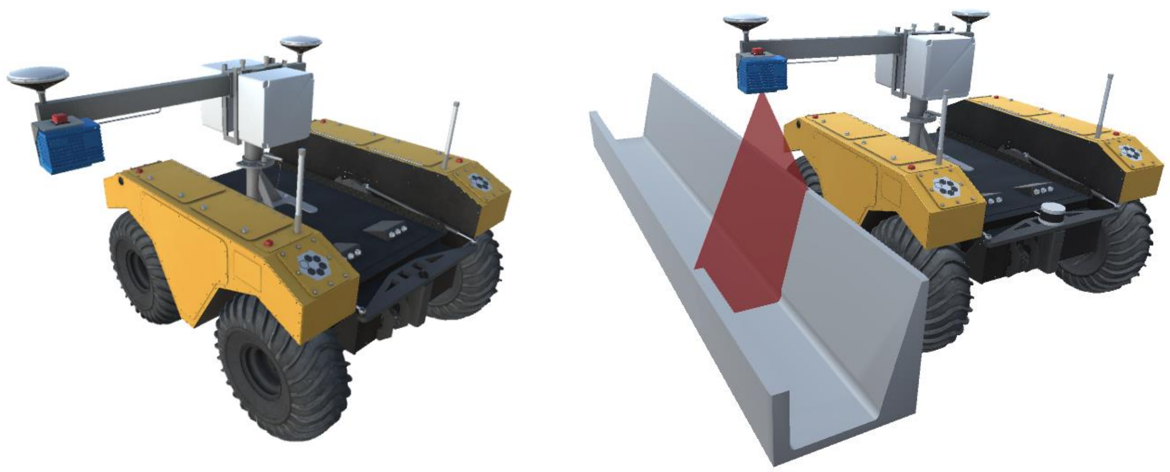

Fig. 1: Schematic of prototype feedlot autonomous mobile robot for bunk scanning's physical arrangement (left), and alongside nominal feed bunk representation.

The robot has been monikered 'BunkBot', and it provides a very technically and environmentally robust platform suitable for difficult operating environments. The vehicle was supplied with robotic operating system (ROS), with a view to simplifying and de-risking the development and customisation of the mobile robot. We found that despite basic software libraries being available for integration, significant customisation and development was required for appropriate and robust control of BunkBot. In summary, critical system features have been provided and include the following,

1. Localisation, that is, the robot's ability to determine its own position with appropriate degrees of freedom in world frame of reference (DOF FOR) and then to plan a path towards target locations. Inputs to this requirement are provided by a dedicated RTK GNSS heading rover (4DOF FOR).
2. Navigation, to enable the robot to traverse its environment, according to prescribed global planned paths, and reactive approaches and bunk-following implementations.
3. Navigation execution, including vehicle control interfaces, such as steering, directional, and speed and acceleration controllers.

4. Wirelessly transmitted emergency stop button with a limited range; the emergency stop also contains a heartbeat, so on out-of-range or communications failure event will activate.
5. Anti-collision system (ACS), to reduce the likelihood of the robot colliding with bunks, other vehicles, escapee livestock. The ACS has been enabled by a forward-facing multi-layer lidar with appropriate temporal and spatial performances.
6. Self-diagnostics and alarms, and abnormal operating conditions controls.
7. Central server databasing, historian, and user interfaces.

All project engineering and factory testing was completed in Brisbane, Queensland. Significant field developments and site testing were completed at the nominal experiment host site, as discussed in the next sub-section.

3.2 Experiment

The site activities utilised MLA's existing RTK GNSS base station capital asset, and Manabotix provided a new generation Bunk Scanner in-kind. After satisfactory confidence in the BunkBot system was established with all stakeholders, a validation experiment was undertaken at the host site, to assess the precision, accuracy, and reliability of the prototype autonomous mobile robot to estimate feed remaining for finisher diet against weighed-back mass observations.

The validation experiment targeted 100 observations of finisher diet, and appropriate environmental characteristics for the host site are included in Table 1. The predictions provided by BunkBot and human bunk callers were generated in-field and in 'real-time' and were later assessed against manually weighed-back mass observations.

Table 1: Characteristics of experiment host site

Standard cattle units (SCUs)	**Pens**	**Overall pen extents**	**Environmental conditions** (weather conditions are included later)
9,800	55	0.3km x 1.3km	Roads were in good condition: rows 1 to 3 were bitumen, and rows 4 to 12 were compacted fine base aggregate. Bunks in rows 1 to 3 were new slip-form concrete and were uniform. Bunks in rows 4 to 10 had mixed geometries and were very non-uniform, even within a single pen's extents.

3.2.1 Preliminaries

The GNSS RTK reference (base) station receiver (contained in weatherproof enclosure) previously supplied for project B.FLT.0166 was transferred, installed, and reconfigured at the host site, with bespoke ad hoc antenna and support infrastructure arrangements provided. A temporary ad hoc UHF transceiver arrangement was also provided to enable RTK correction communications, and these were achieved with 100% reliability across the site.

A new generation Bunk Scanner was installed on the BunkBot during the factory preparations and testing. Based on the activities of B.FLT.0166, the start and end positions of all pens had already been georeferenced, i.e. located in global coordinates based on GNSS measurements from the rover, to enable automatic localisation within the feedlot during the experiment. The baseline geometry for all feedlot bunks was then remeasured with the new arrangement. This was completed by following the front-end loaders with bunk sweeper attachment, and all feed bunks were scanned and databased.

The platform scale (CAS BW-L60, Brisbane, Q; ±0.01 kg readability), paddock vacuum (Greystone Maxi Vac), tarpaulins, and collection/weigh-back buckets provided during the previous experimental activities (B.FLT.0166) were also transferred in preparation for the experiment's commencement at that site.

3.2.2 Experiment protocol

The following experimental protocol was exercised for this project,

1. A daily dedicated bunk caller and BunkBot predicted feed remaining independently for a random selection of pens prior to feeding; this usually started at 0600h each day.
    a. The light vehicle for the human calling was operated at a maximum speed of 10kmh^{-1}.
    b. The peak forward travel speed of the BunkBot for the 100 observations was 10.0kmh^{-1} (2.78ms^{-1}) this speed was achieved for most of the bunk lengths, in-between acceleration and deceleration events (each nominally 2.00ms^{-2}).
    c. Human predictions were recorded manually, and BunkBot volume predictions were automatically stored to file onboard its processor's storage device. All predictions were also automatically pushed to a cloud server as backup (and when internet coverage was available).
    d. Livestock were pushed back from the feed so that it was not consumed before collection.
2. Feed was collected in buckets and vacuumed from each bunk, and the recovered masses were measured immediately on the platform scale in situ (i.e. within the pen roads) and returned to the appropriate pen bunks. Humans were kept blind from feed recovery and weigh-back activities.
3. Steps 1 through 2 were repeated until the feed trucks commenced the morning deliveries.
4. Feed density for the experiment was determined from a quotient calculated from significant known feed mass delivered (usually Rotomix 920-18; Dodge City, KS, USA) and its scale-head (Digistar EZ indicator; Fort Atkinson, WI, USA; ±5 kg readability) divided by the predicted volume, averaged over three bunks. The quotient was multiplied by scanned volume to determine predicted feed remaining.

The following section summarises the result and analyses outputs for the experiment.

4 Results

The following section describes the statistical analyses employed to assess the outputs of the evaluations, followed by presentation of the experimental results.

4.1 Statistical analyses

Several statistical analyses have been undertaken with a view to objectively assessing the performances of the prototype system and human bunk callers.

Observed feed remaining has been regressed on predicted feed remaining for both BunkBot and human bunk callers. The coefficient of determination (r^2) has been calculated on the line of regression as a measure of the observed and predicted feed remaining relationship strength.

Evaluation of the model's precision has been enabled through employment of several commonly used measures of deviance, including mean absolute error (MAE), mean square prediction error (MSPE), and root mean square error (RMSPE). Shah and Murphy (2006) defined MSPE as: $\Sigma (Oi - Pi)^2/n$, where n = number of paired observed (O) and predicted (P) feed remaining values being compared. The MAE is defined as: $(\Sigma|Oi - Pi|)/n$.

Furthermore, the MSPE can be decomposed to assess sources of variation, viz, (1) variation in central tendency (mean bias), (2) variation resulting from regression (systematic bias or line bias), and (3) random variation.

Variation resulting from mean bias has been calculated by squaring the mean bias of the prediction. Systematic bias has been calculated as the product of predicted feed remaining variance and the square of the deviation from 1 of the regression of observed on predicted gradient. Random variation was calculated as the product of the variance of observed data and the deviation from 1 of the coefficient of determination of the regression of observed on predicted data. Shah and Murphy (2006) noted that mean bias is useful to test the robustness of the model, whereas line bias can be used to test inadequacy in model structure. Mean proportional bias has been calculated as the slope of the regression of the predicted data on observed data with an intercept of 0 (Shah and Murphy, 2006). Over the range of observed values, a value of mean proportional bias less than one (< 1) denotes underprediction, whereas a value more than one (> 1) denotes overprediction.

In addition, mean and linear biases were calculated by regression of residuals (observed minus predicted feed remaining) on mean-centred predicted feed remaining (St-Pierre, 2003). St-Pierre (2003) noted that by centering predicted feed remaining to the mean value, the intercept of the linear model is estimated at the mean value of the independent variable rather than a value of zero.

The intercept term at the mean value is a measure of the mean prediction bias, and a t-test on the estimate of the intercept has been used to determine the statistical significance of this bias. The slope of this mean-centred regression is an estimate of the linear prediction bias, and a t-test has been used again to test significance. When the linear prediction bias has been found to be significant ($P < 0.10$), the magnitude of the bias within the range of predicted values was determined by calculating the bias at the minimum and maximum data points of the predicted values (St-Pierre, 2003).

4.2 Results

The following section contains a summary of experimental data analyses, employed for the BunkBot and human callers. Graphical charts of the results have also been provided.

4.2.1 Summary of regressions

Three human bunk callers and one diet (tempered barley grain finisher ration) were used during the experiment. Fig. 2 demonstrates the composition of feed remaining masses observed during the feedlot experiment, and then as a function of pen head count respectively.

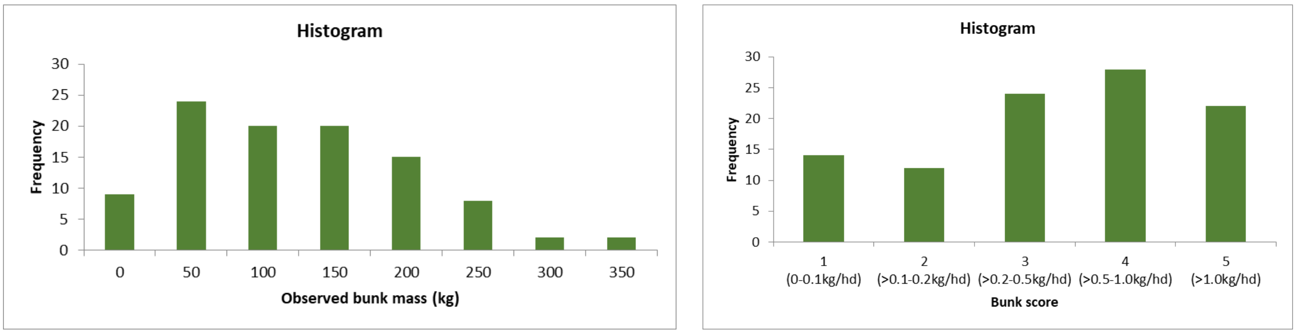

Fig. 2: Histogram of observed feed remaining masses (left), and these masses normalised over head count for nominal bunk scores for experiment.

Weather conditions for the experiment's duration are included in Table 2 below, sourced from the on-site digital weather station (MEA Feedlot Weather Station, Magill, SA).

Table 2: Significant weather conditions at host site during experiment in August and September 2019, with no measurements completed on 'greyed-out' days. The weather station was out-of-service from 20 to 27 August inclusive for regular service; no data were available for 3 September.

Day	**26/08**	**27/08**	**29/08**	**30/08**	**03/09**	**04/09**	**05/09**	**06/09**	**08/09**	**09/09**	**10/09**	**17/09**	**18/09**	**19/09**
Max. temp. (°C)			17.4	19.4		27.1	30.2	31.5	21.5	19.9	17.4	29.6	30.3	23.3
Min.temp. (°C)	N/A	N/A	10.8	1.8	N/A	5.8	6.5	7.1	6.8	8.0	5.6	9.5	6.2	
Rainfall (mm)			0.0	0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Results of the regression of observed on predicted feed remaining are shown in Table 3. Mean and linear biases are also reported, determined from the regression of residuals on mean-centred predicted feed remaining.

Table 3: Evaluation statistics of feed remaining predictions for human and machine (BunkBot), 100 observations from slick to 324kg. Mean and linear biases calculated using St-Pierre (2003) techniques.

Item	**Human**	**Machine**
Mean bias, kg	-2.59	1.60
P-value	0.35	0.07
Linear bias	-0.13	0.00
P-value	< 0.01	-
r^2, regression of observed on predicted feed remaining	0.88	0.99
RMSPE, kg	29.52	8.83
MSPE, kg^2	871.40	77.94
MAE, kg	20.86	6.85
Mean proportional bias	1.02	0.99
Decomposition of MSPE		
Mean bias, %	1%	3%
Systematic bias, %	13%	0%
Random bias, %	86%	97%
Bias at minimum predicted value, kg	10.76	-
Bias at maximum predicted value, kg	-33.94	-

It can be seen from Table 3 that BunkBot accurately and precisely predicted feed remaining in bunks, outperforming human callers in both criteria. BunkBot had a very small amount of mean bias (P-value 0.07), underpredicting feed remaining by 1.60kg. BunkBot had no linear bias to be tested with statistical significance, and this is reinforced by visual interpretation of its bias being consistent over the full range of feed remaining in the bunk, and so it follows that minimum and maximum biases have not been calculated. Precision of the prototype was excellent during the experiment (r^2 = 0.99). Mean absolute error for BunkBot was 6.85kg, and the RMSPE was 8.83kg.

Human performance was variable and less accurate. The reported mean bias was not significant (P-value = 0.35); that is, predictions were equally over and under observed masses, as reflected by the high random bias contribution (86%) to the MSPE. Humans had moderate precision (r^2 = 0.88). Significant linear bias (P-value = -0.13) was reported, with magnitude much larger than the BunkBot (10.76 to -33.94kg). Mean absolute error for the human caller was 20.86kg, and the RMSPE was 29.52kg. These results are improved from the previous experiment outcomes, which is particularly relevant as the dominant human caller was the same participant as B.FLT.7009, though it still demonstrates performance deficiencies against absolute metrics.

4.2.2 Chart results

The total experiment observed on predicted feed remaining for humans and the BunkBot (machine) are represented graphically below in Fig. 3.

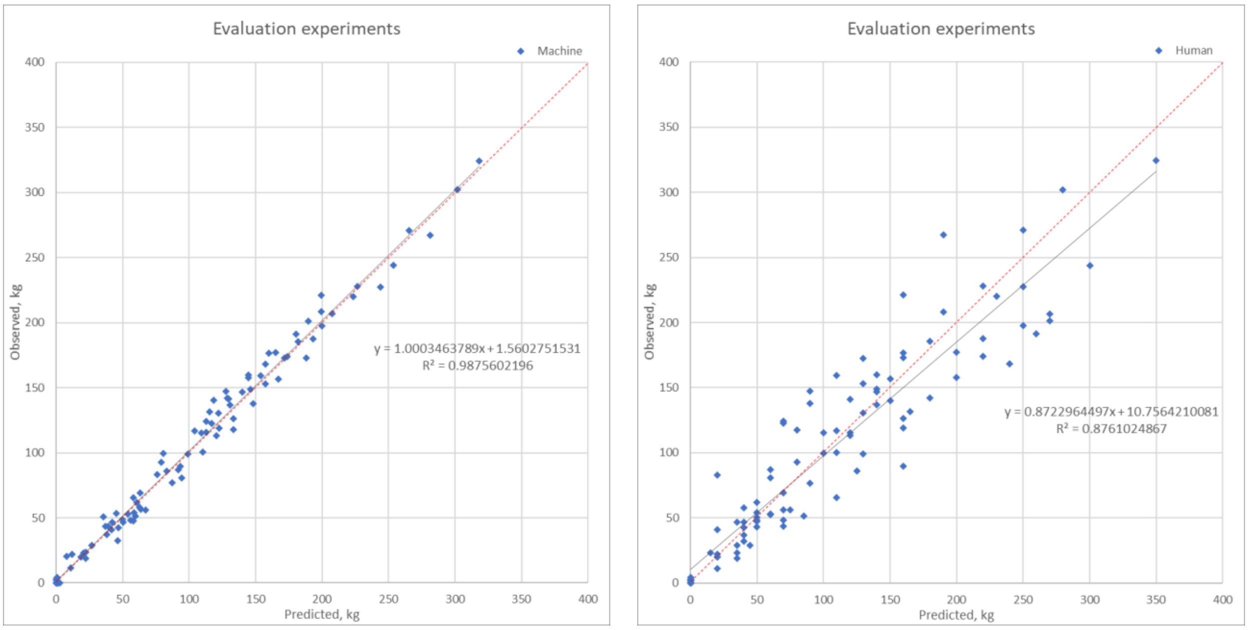

Fig. 3: Observed on predicted feed remaining masses for BunkBot (machine, left), and human caller, for Feedlot C experiment.

Sources of errors for the total experiment for human and the BunkBot (machine) are represented graphically below in Fig. 4, i.e. the residuals (errors, observations minus predictions) over mean-centred predictions. It can be seen again from BunkBot's error decomposition that a small mean bias exists (y-offset = 1.60kg), with very limited linear bias (gradient near zero), and a very low level of variability (precision). Conversely, the human plot further reinforces the insignificance of the very low mean bias (imprecision around y-intercept at -2.59kg), linear bias (moderate negative gradient as masses increase), as well as overall lack of precision. The human caller tended to overpredict as the feed remaining masses increased, and this behaviour is not consistent with the significant underpredictions with increasing masses observed during previous experiments.

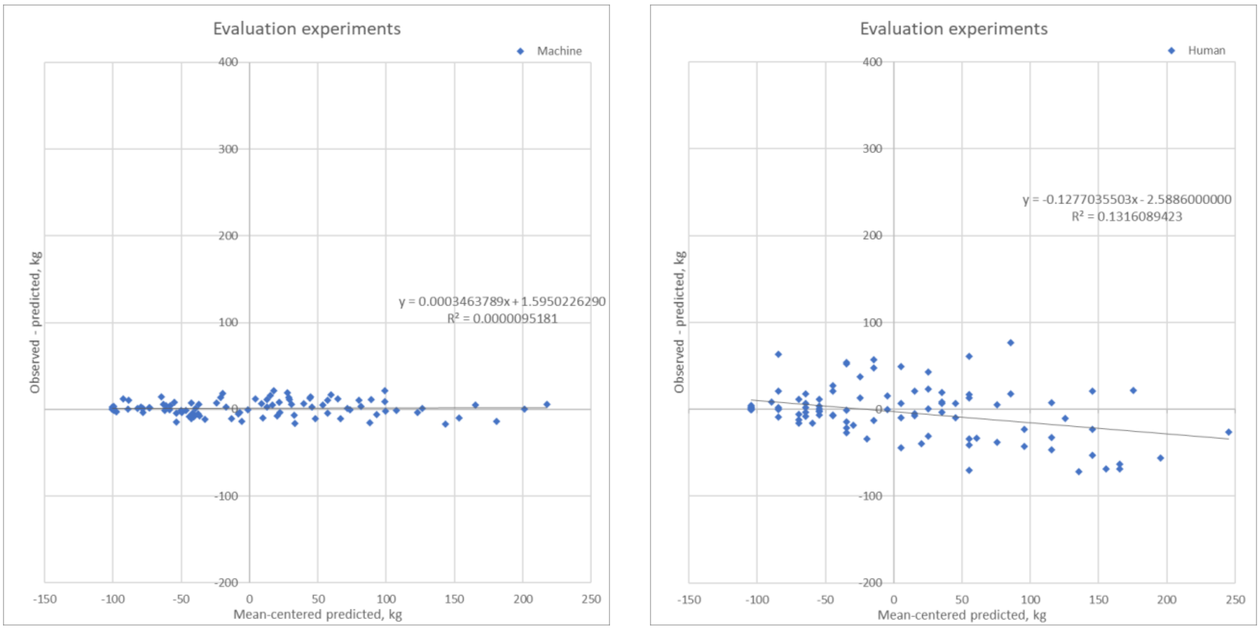

Fig. 4: Experiment residuals over mean-centred predictions for assessing sources of error in prediction models for experiment.

4.2.3 Impact of prediction errors on bunk scores during experiment

Table 4 summarises the potential impact of incorrect human bunk calls for the pens observed through the course of the experiment.

Table 4: Success table when applying bunk scores for humans and BunkBot.

Bunk scores	1	2	3	4	5
	(0-0.1kg)	(>0.1-0.2kg/hd)	(>0.2-0.5kg/hd)	(>0.5-1.0kg/hd)	(>1.0kg/hd)
Observations	14	12	24	28	22
Machine	14	12	23	27	19
	100.0%	100.0%	95.8%	96.4%	86.4%
Humans	14	11	20	20	15
	100.0%	91.7%	83.3%	71.4%	68.2%

These data can also be represented with graphical charts, as shown in Fig. 5.

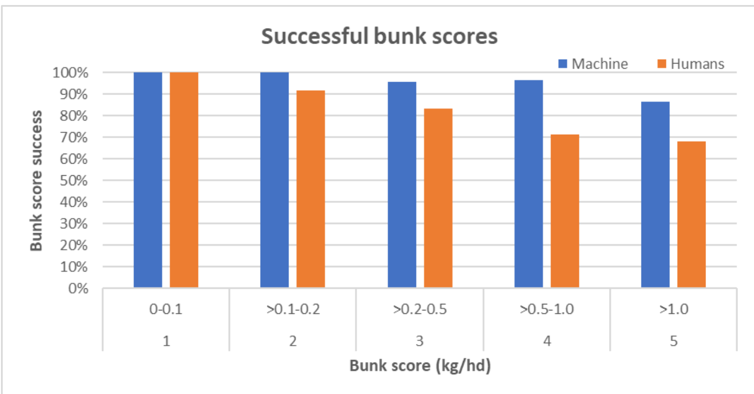

Fig. 5: Success chart when applying bunk scores for humans and BunkBot.

From this table, human callers had a higher number of prediction errors, especially as the feed remaining masses increased, and this is consistent with the previous experimental results. BunkBot had less errors (five total), and on review all were within 17kg of the observed mass, so very near the cusps of the nominal correct scores, and so may be attributed to rounding issues to achieve these discrete scores.

5 Discussion

Against the results presented in this report, the BunkBot system has been demonstrated to be highly repeatable (precise) and accurate for predicting feed remaining in bunks within a commercial feedlot. Human callers predicted feed remaining in bunks with less accuracy and precision, and these errors are more evident at higher masses.

It should be noted that the overall results achieved at each host site during this experiment are marginally improved from the feedlot validation experiment completed during the prototype Bunk Scanner's validation experiments (300 observations completed in August 2018, results published in final report of project B.FLT.7009).

6 Conclusions/recommendations

Against the results presented in this report, the prototype autonomous bunk calling system, BunkBot, provided highly repeatable (precise) and accurate feed remaining predictions during the validation experiment in a commercial feedlot environment. In contrast, the human callers provide less accurate and precise feed remaining predictions, and this is most evident with higher masses. Their performances with lesser feed remaining masses are probably acceptable for normal operating requirements.

A statistical methodology has been exercised with a view to assess feed remaining predictions provided by BunkBot and human callers. The methodology has provided very clear and objective support for BunkBot's precision and accuracy.

7 Key messages

We are very excited about the potential benefits that the red meat industry should garner through our technology solutions partnership. We have been very pleased with the relationship between ourselves and MLA, and our ability to respond effectively to this opportunity through the prompt supply of the working prototype system.

With MLA's support, we have delivered a prototype autonomous bunk calling system that has demonstrated significant potential benefit to the red meat industry. We suggest that a commercially viable product should be available in the near-term based on the successful outcomes of this project.

8 Bibliography

The following literature was cited in this report.

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