Operational evaluation of an optical sensor for the automatic in-line estimation of total mixed ration fibre length and particle size in a mixing wagon

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Abstract

The optimal management of cattle nutrition promotes animal health and welfare, increases livestock farms' productivity and competitiveness, and enhances environmental sustainability practices. Animal feeding operations play a crucial role as many factors can drive the theoretical ration formulated by nutritionists far from the one the animals ingest. Precision feeding technologies (*e.g.*, NIR sensors on the milling cutter of the chopper-mixer wagon; computer vision systems installed in the mixing tank) may allow for accurate and real-time analysis of the chemical and physical properties of total mixed ration (TMR) ingredients, reducing errors during its preparation and distribution. This work compares the physical quality and the length of the fibre of the TMR resulting from the chopping-mixing process of a conventional mixing wagon, one machine-learning-assisted mixing wagon and an automatic feeding system under actual operating conditions. Between October 2021 and November 2022, TMR sampling occurred on four dairy farms and one fattening bulls farm in Northern Italy, specifically in the Brescia, Cremona, and Mantua districts. TMR samples underwent particle size analysis using the Penn State Particle Separator (PSPS) method and, once in the laboratory, moisture analysis and fibre length measurement. Concerning TMR particle size analysis, the PSPS method revealed that the machine learning-assisted mixing wagon provided TMR with physical features comparable to that from ordinarily run mixing wagons. At the same time, the automatic feeding system resulted in TMR with finer particle size, following the farmers' choice not to use long-stemmed forages. Regarding fibre length, only the TMR resulting from the operator-based mixing wagon aligned with the targeted fibre length of 5 cm, while the AFS and the ML-assisted mixing resulted in higher fibre lengths. Overall, the use of computer vision (CV) systems is helpful for the consistency of the TMR and represents a valuable solution for animal farming, particularly when employing low- or inexperienced operators. Further studies are, however, needed to improve the training of the with elements that can replicate the operator experience.

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Introduction

Cattle farming has undergone significant market demand-driven changes, which have resulted in a rise in production, fewer but larger farms with higher livestock populations, and more specialised workers (Istituto Nazionale di Statistica, 2022). The dairy sector is adopting digitalisation by investing in automation, robots, and sensor technologies to ensure proper animal management and improve animal welfare and production quality monitoring (Berckmans, 2017). Precision feeding is a key part of this approach: it provides tailored and controlled rations that meet the specific nutritional needs of various cattle groups, helping to maximise animal welfare and productivity (González *et al*., 2018).

In the 1960s, the total mixed ration (TMR) method was developed alongside mechanised farming (McCoy *et al*., 1966). In the TMR, all ingredients in cattle feed are weighed, chopped (when necessary) and mixed to provide cows with a balanced ration; however, errors or inaccuracies in TMR preparation result in differences between the designed ration, the feed given, and what the cows consume, affecting feed digestion and animal productivity (Sova *et al*., 2013). Buckmaster (2009) outlines several factors contributing to the variance between designed and administered TMR, including i) operator-related errors, *e.g.* the order of ingre-

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dient loading, weighing, chopping-mixing time, and unloading in the feeding area; ii) the mixer wagon efficiency and maintenance level, *e.g*. the knife sharpness in the chopping-mixing chamber; iii) ingredient composition variability due to seasonal changes. In addition, Miller-Cushon and DeVries (2017) outline the role of animals' preference for the TMR's most palatable components.

Automated feeding systems (AFS) with robotic technology have been gaining importance due to rising demands on performance-related feeding of cows and animal welfare. These systems automate tasks like high-frequency filling, mixing, and distributing feed, ensuring cows receive a high-quality, consistent diet that meets their nutritional needs. AFS helps reduce the variability associated with manual ration preparation and distribution, leading to better cow health and milk production and fostering dairy farming competitiveness (Da Borso *et al*., 2017; Tangorra and Calcante, 2018). Aside from TMR variations influenced by human factors, fluctuations in the chemical composition, particularly the dry matter (DM) content, inevitably occur in forage – particularly silages - and other ration ingredients throughout the day (Cherney *et al*., 2021). Consequently, real-time monitoring of the qualitative and quantitative aspects of the TMR fed to animals becomes crucial, ensuring the distributed ration meets the nutritional requirements of the cow's metabolism in relation to their physiological state. Various sensor solutions facilitate the chemical and physical characterisation of the nutritional profile of TMR ingredients. For instance, near-infrared spectroscopy (NIR) utilises the interaction between matter and light radiation to non-destructively analyse the nutritional composition of the loaded ingredients and allow real-time weighing adjustments to reduce the gap between the planned and the administered rations (Büscher *et al*., 2014; Yakubu *et al*., 2022). Computer vision (CV) systems are increasingly prominent in precision feeding technologies: when placed within mixer wagons, they enable visual analysis of the mixture homogeneity and average fibre length during chopping (Rahkonen, 2017). These sensors capture multiple ration images during the mixing and employ artificial intelligence (AI) or machine learning (ML) algorithms to extract, process, and interpret data. CV has been expanded into vast field areas, from recording raw data to extracting image patterns and information interpretation (Patel *et al*., 2012). It combines different concepts, including digital image processing, machine learning and pattern recognition. The benefits of these technologies are as follows: ration homogeneity (more consistent blending of the ingredients), optimised chopping-mixing time, reduced risk of over- or under-mixing, potential savings in time and energy consumption, and the possibility of hiring low-experienced operators. However, to the authors' best knowledge, there appears to be a gap in the scientific literature regarding studies that specifically focus on applying CV systems in ordinary operational conditions. This study aims to evaluate the functional operability of an optical sensor for the real-time estimation of the homogeneity of the ration and the average length of the fibre in ordinary conditions of the mixing wagon filling, making a comparison with the physical quality of a ration prepared using the same mixing wagon without the use of this device and the ration resulting from the use of an AFS.

Materials and Methods

Optical sensor's description, installation, and operation

The tested sensor (Dinamica Generale, Poggio Rusco, MN, Italy) adopts CV technology. The system is installed on the lateral back side of the mixing chamber (Figure 1). It operates a digital 8-megapixel sensor backlit camera that captures digital images of the TMR during the mixing process at 1080p resolution with a frequency of 30 frames per second. The process of determining the fiber length starts with the segmentation of the image through binarisation to separate the TMR from its background and facilitate the measurement of the length between any two points within the object to consider. Homogeneity assessment calculates the homogeneity factor of an image based on its grey and colour value distribution. Statistical calculations of the standard deviation of each pixel from the mean grey value indicate low-variating pixel standard deviations for high homogeneity (Gonzalez and Woods, 2008). Calibrating the measured pixels to a metric unit or to a reference standard pattern (*i.e.*, comparing the image measurements with the farmers' accepted standards) is necessary for ML software proper performance (Dormann, 2020). The manufacturer calibrated the sensor and the software following the farmer's indications for fibre length (5 cm) and TMR uniformity before the beginning of the study. After loading the ingredients, the operator switches the device on and the image acquisition and processing start. Using

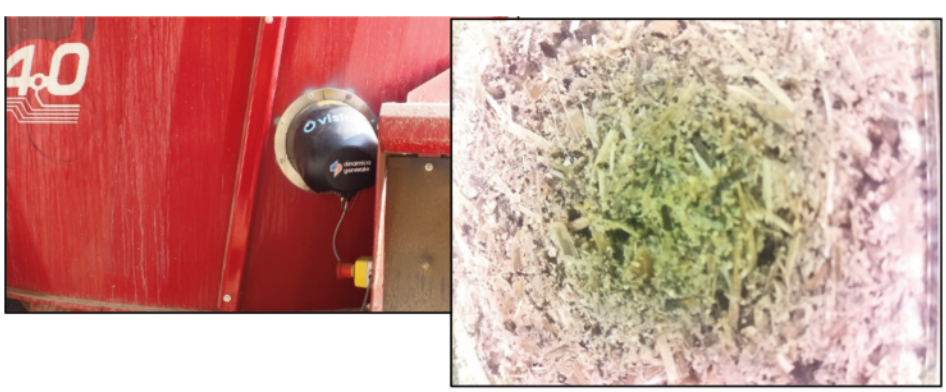

Figure 1. Details of the sensor installation for fibre length and TMR homogeneity assessment (on the left) and a screenshot of the captured image (on the right).

a Wi-Fi connection, the appliance sends data to a remote server that analyses and compares the acquired frames to assess the TMR uniformity and fibre length and check that these meet the farmer's established requirements. When the ML software detects the reaching of the targeted parameters, it indicates the stopping of the mixing.

Description of the monitored farms

Between October 2021 and November 2022, TMR sampling occurred on four dairy farms and one fattening bulls farm in Northern Italy, specifically in the Brescia, Cremona, and Mantua districts known for their specialised animal farming. All the animals in these farms were housed freely. The sampling followed all applicable animal welfare and biosafety codes and regulations. Table 1 summarises the characteristics of the monitored farms and the used machinery. Farms operating mixing wagons fed the TMR twice daily, typically between 5:00 and 6:00 AM and 4:00 and 5:00 PM. In contrast, farms with AFS continuously fed TMR throughout the day, with frequencies up to twelve distributions a day. The loading sequence for farms using mixing wagons was long-stemmed hay requiring extended processing, grains or premixes, pre-processed forages (*e.g.* silages), minerals and vitamins, and finally, water and other liquid ingredients. Farmers relied on their experience to assess the mixing-chopping time required (when asked about it, they provided mixing-chopping times ranging from 10 to 12 minutes); however, when operating the mixing of the TMR, the mixing time was measured with a digital chronometer.

In farm 1, the trial considered the TMR resulting only from the 32 m^3 mixing wagon (Table 1) run both ordinarily and using the optical sensor calibrated according to the farmers' standard (ML-assisted procedure). The farmers with the AFS followed the same loading sequence during automatic filling; however, they did not use long-stemmed forage and based their TMR on silages and concentrated feed. For the AFS, the farmers set the mixing time to five minutes per wagon after the last loaded ingredient and before moving to ration administering.

TMR sampling and analysis

Fresh TMR dry matter content and particle size distribution in each farm were evaluated by sampling five representative TMR samples (500 $g_{f.w.}$ each) immediately after delivery along the feed bunks every 5 m of distance. For each sample, a fisrt subsample of approximately 300 $g_{f.w.}$ underwent particle size analysis on-site using a Penn State Particle Separator with screens of 19, 8, and 1.18 mm, following the manual shaking procedure that Heinrichs (2013) outlined to determine the particle size of the administered TMR. Particle size distribution (%) resulted from equation 1:

$$P_{i,j} = \frac{W_{i,j}}{\sum_{i=1}^{4} W_{i,j}} x\ 100 \qquad \text{(Eq. 1)}$$

where $P_{i,j}$ is the percentage weight of the particles that each separator screen retained and $W_{i,j}$ is the amount of TMR fraction that the 19, 8, and 1.18 mm screens (i = 1, 2, and 3) and the bottom pan (i = 4) intercepted for each j^{th} sampling site along the feed bunk (j = 1, 2, 3, 4 and 5).

A second subsample (approximately 200 $g_{f.w.}$), promptly taken to the CREA laboratory in Treviglio for analysis, underwent dry matter measurement by drying it in a forced-air oven at 60°C until constant weight. The results of this measurement have been expressed as a percentage of wet-based dry matter content ($DM_{w.b.}$, eq. 2):

$$DM_{w.b.} = \frac{W_{d.s.}}{W_{f.s.}} x\ 100 \qquad \text{(Eq. 2)}$$

where $W_{f.s.}$ and $W_{d.s.}$ are the fresh and dry weights of the TMR subsample. Subsequently, to ascertain the length of the fibres retained by the 19 mm sieve, 50 randomly sampled fibres per sub-sample were measured with a millimetre ruler.

Table 1. A brief description of the monitored farms.

Farm	Lactating animals (no.)	TMR preparation and delivery system	Feed pushing technology
Farm 1	1300	24, 27 and 32 m^3 self-propelled cutter mixing wagons (Rover Jumbo Up 24, Italmix Srl, Ghedi, BS, Italy; SelfLine 500+ and Selfline 100+, Siloking, Tittmoning, Germany) with vertical augers. The 32 m^3 mixing wagon hosts the optical sensor for TMR homogeneity and fibre length assessment.	The operators run a self-propelled feed pusher with 5 hydraulically controlled rotating reels equipped with brushes (Motobrush, Storti SpA, Belfiore, VR, Italy).
Farm 2	120	The operator runs a trailed 20 m^3 cutter mixing wagon with horizontal augers (Samurai5, Seko Industries Srl, Curtarolo, PD, Italy)	The operator runs a small tractor with a front-mounted rubber-coated metal mould to push feed leftovers back into the feed bunk.
Farm 3	300	Operators run one self-propelled 20 m^3 cutter mixing wagon with a vertical auger (Dobermann SW 220 evo, Storti S.p.A., Belfiore, VR, Italy)	An automatic self-moving drum-pushing system (Ranger 2, Boumatic, Madison, WI, USA) pushes feed leftovers back into the feed bunk.
Farm 4	400	One self-propelled and self-loading automatic feeding system (Vector, Lely, Maassluis, The Netherlands) with two 2 m^3 wagons with a vertical auger provides for TMR preparation and distribution.	When not delivering the feed, the AFS wagons act as drum-pushing systems.
Farm 5	1100*	One self-propelled and self-loading automatic feeding system (Vector, Lely, Maassluis, The Netherlands) with two 2 m^3 wagons with a vertical auger provides for TMR preparation and distribution.	When not delivering the feed, the AFS wagons act as drum-pushing systems.

TMR, total mixed rations; *housed fattening bulls.

Data processing

Data underwent statistical processing with Minitab 17 statistical software (Minitab Inc., 2010). Specifically, the Levene test (p<0.05) assessed the equality of variances within the dataset (Levene, 1960), and the Kolmogorov-Smirnov test (Massey, 1951) checked the assumption of normality distribution of the data. Next, an analysis of variance (ANOVA) was employed by using the generalised linear model (GLM) multivariate procedure (Hastie and Pregibon, 1992) followed by the Tukey *post-hoc* test (p<0.05) (Keselman and Rogan, 1977). The farms, PSPS screens (19, 8, and 1.18 mm, bottom pan, labelled S1 to S4), and the presence or absence of ML-assisted technology during TMR preparation were considered as fixed factors, while the weight percentage that each separator screen retained (Si) served as the dependent variable in the study.

Fibre length underwent analysis of the distribution for each TMR preparation and delivery system, reporting the minimum and maximum recorded lengths and calculating the average and the median values, the interquartile range (IQR), the skewness, and the kurtosis of a whole of 1750 replicates. Additionally, using the same software, TMR fibre lengths underwent the one-sample t-test (Ross and Willson, 2017) to compare the sample mean of each TMR preparation system to the 5.00 cm targeted fibre length value and examine whether the means resulting from the measurements are statistically different from it (p<0.05).

Results and Discussion

The TMR processing combines materials into animal feed proportionally, involving several steps and unit machines. Table 2 reports the average dry matter content of the rations freshly administered to animals. Such moistures range from 35.3 % for *Farm 5* to 52.7 % for *Farm 1*.

The reason for these differences may rely on the use of long-stemmed forages, which require adding water or other liquid ingredients to the bulk of TMR to reduce the feed sorting activity (Heinrichs *et al*., 1999; Kudrna, 2003; Sova *et al*., 2014), while *Farm 4* and *Farm 5* do not use long-stemmed forages. All the recorded moistures are, however, in line with the optimised TMR moisture content between 60% and 50% (Havekes *et al*., 2020; Leonardi *et al*., 2005; Leonardi and Armentano, 2003; Miller-Cushon and DeVries, 2009).

Figure 2 reports the results of the GLM processing on the weight percentage distribution of the particles in the freshly administered TMR. The processing pointed out that the farm was not a significant factor. However, the interaction between the PSPS screens and TMR preparation technology was significant. When preparing the TMR with the AFS and the conventional mixing wagon without the optical sensor, the 8 mm screen (S_2) intercepted the highest quantity of particles. In contrast, the TMR resulting from the mixing wagon with ML-assisted procedure resulted in

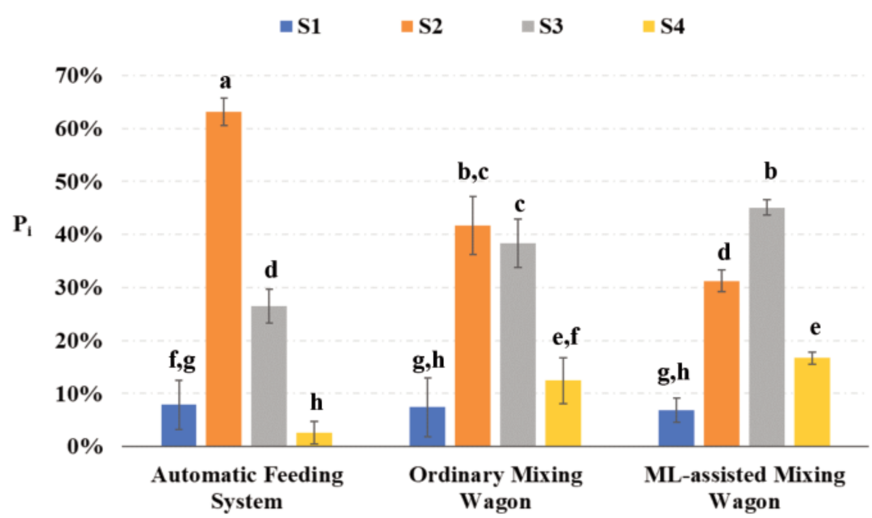

Figure 2. Weight per cent distribution of the freshly administered TMR fractions retained by the PSPS screens at varying TMR preparation and delivery technology. The means not sharing a letter differ significantly (p<0.05). TMR, total mixed ration; PSPS, Penn State Particle Separator; ML, machine learning.

Table 2. Dry matter content of the freshly administered total mixed rations in each monitored farm (mean ±SD). The means not sharing a letter differ significantly (p< 0.05).

Farm	DMw.b. (%)	Min	Max
Farm 1	52.7±0.88^a	51.2	54.3
Farm 2	52.0±3.22^a	50.7	53.4
Farm 3	43.0±0.97^b	42.1	44.1
Farm 4	40.9±1.22^b	39.4	42.0
Farm 5	35.3±3.06^c	31.2	39.5

Table 3. The results of the analysis of the length distribution (cm) of the total mixed ration fibres intercepted by the 19 mm sieve of the PSPS.

TMR preparation and delivery system	Min.	Max.	Mean	Median	Skewness	Kurtosis
AFS	1.00	14.7	5.60	5.20	0.76	0.64
Conventional mixing wagon	0.60	16.4	4.81	4.60	0.85	1.65
ML-assisted mixing wagon	0.70	15.3	5.70	5.50	0.77	0.56

PSPS, Penn State Particle Separator; TMR, total mixed ration; AFS, Automated feeding systems; ML, machine learning.

Table 4. The results of 1 sample *t*-test.

TMR preparation and delivery system	SD (cm)	95% Confidence interval (cm)	T	*p*
AFS	0.0723	5.46-5.74	8.33	0.00
Conventional mixing wagon	0.108	4.59-5.02	-1.76	0.078
ML-assisted mixing wagon	2.694	5.32- 6.09	3.60	0.00

TMR, total mixed ration; AFS, Automated feeding systems; ML, machine learning.

having the highest quantity of particles retained by the 1.18 mm screen (S_3), meaning that the monitoring action of the image analysis software caused feed particles to undergo considerable size reduction as the weights of the fines fractions increased significantly compared to the outcomes of ordinary mixing wagon and AFS. The TMR mixing time was 5 minutes for AFS and 10 to 12 min for the operator-run mixing wagon. Running the mixing wagon under the ML assistance resulted in a comparable mixing time with a median value of 12 min (8.0-18 min range).

Table 3 reports the result of the analysis of the fibre length distributions. Fibre lengths are all positively skewed, and most data points are close to the mean; however, the IQR of the measurement resulted in 2.80, 270, and 3.40 cm for AFS, conventional mixing and ML-assisted mixing wagon procedures, implying that the spread of the middle 50% of values is most prominent for the TMR samples resulting from ML-assisted mixing wagon.

Table 4 reports the statistics of the comparisons of the mean values with the reference fibre length of 5.00 cm. In the literature, the 5 cm reference length is the stubble height recommended for forage production, which results in a high digestibility of silage (Holohan *et al*., 2021; O'Kiely, 2014). Here, it can be noticed that both AFS and the ML-assisted mixing wagon resulted in fibre lengths significantly different from the target. In contrast, this does not happen for the ordinary TMR preparation with the conventional mixing wagon: here, the 95% confidence interval includes the target value, meaning the farmer experience could better manage the variability of the ingredients throughout the monitoring period.

CV enables systems to extract meaningful information from digital images, allowing for detection, identification, and automation through integrating inputs from the physical world: it combines image processing and pattern recognition techniques, resulting in image understanding (Wiley and Lucas, 2018). However, computer vision cannot be expected to replicate like the human eye (Van Dyck *et al*., 2021).

For cows to maintain proper rumen function, they must consume forage particles of adequate length. The variability amongst TMR ingredients also includes the potential addition of longer fibre components in the case other ingredients are too finely chopped (Beauchemin *et al*., 2003): it is a balance between maintaining proper rumen function (avoiding too fine particle size) and reducing as much as possible the animals' feed sorting action, aiming to a diet not different from the intended nutrition (Suarez-Mena *et al*., 2013). Currently, image vision software can hardly account for such a considerable variability of factors.

The results of the particle size analysis show that all the tested TMR preparation systems resulted in granulometries that are in line with the values that Oetzel (2020) has outlined, meaning that the choice farmers made is in line with the overall consideration of the availability of forages and ingredients. However, the same results highlight the importance of the proper mixing time, following the results of Marchesini *et al*. (2020). As mentioned above, running the mixing wagon following the indications of the CV algorithm resulted in comparable median mixing time but in a fibre length significantly different from the targeted (Table 4). Such an outcome may result from the impossibility of the ML algorithm to replicate the operator experience and consider other meaningful tool life functional factors (*i.e.* the sharpness of the auger's knives), which hardly ever the ML training based on image recognition includes, and that could result from raw-experimental data on purpose produced (Bustillo *et al*., 2022).

Conclusions

The study compares the particle size of the TMR resulting from AFS, an ordinarily run mixing wagon, and the same mixing wagon run following a computer vision ML-based appliance. All the tested systems resulted in TMRs with comparable particle size distributions. However, when comparing the fibre length, only the TMR resulting from the operator-based mixing procedure resulted in line with the targeted measure, while the AFS and the ML-assisted mixing resulted in higher fibre lengths. Such results show that using CV systems is helpful for the consistency of the TMR and represents a valuable solution for animal farming, particularly when employing low- or inexperienced operators. Further studies are, however, needed to improve the training ML algorithm with elements that can better replicate the operator experience.

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