Title: **smAvo: Packhouse Optimization Using Smart Avocadoes in South Africa**

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Keywords: smAvo, packhouse optimization, avocadoes, postharvest, Civiltronics

Article type: Research Paper

Highlights

- A smart sensor platform for post-harvest optimisation of avocado packhouses.
- Low-cost measurement and quantification of post-harvest stresses.
- Large-scale instrumentation of avocado packhouses.
- Development of a statistical packhouse classification system.
- Demonstration of neural network implementation for accurate packhouse classification.

Abstract:

Cultivation of avocadoes serves as a key economic driver for many countries, including South Africa. Nearly all fresh produce produced forms part of a complex, interconnected transportation chain. Packhouses, representing a wide range of capacities and degrees of mechanization, serve to classify, treat and package the fresh produce prior to distribution by road, rail and ocean to its destination. Reducing the damage or postharvest stresses is paramount to ensure consistent quality of the ripened fruit. Packhouse operations represent the phase associated with the greatest degree of mechanical handling. Until now, quantification of packhouse activities exerted on the fruit has not been quantified with sufficient accuracy to identify characteristics of an optimized packhouse. This paper demonstrates the successful application of a novel sensor platform that measures the linear acceleration and rotational velocity of a typical avocado for 24 packhouses spread throughout South Africa. Unique statistics were developed pertaining to the distribution of contact forces, peak accelerations and rotational velocities, freefall events, freefall distance and impact energy experienced by avocadoes. A Damage Index Score (DIS) was developed to classify the relative performance of the sampled packhouses, alongside identification of key areas of concern where the greatest intensity and variation of postharvest stresses are observed. Improvement of avocado quality as a result of improving deficient practices and equipment ultimately reduces waste, prevalence of postharvest diseases and improves the income for farming communities.

Keywords: smAvo; Packhouse optimization; Avocadoes; Postharvest; Civiltronics

1. Introduction

To meet the rising demand placed on agriculture, a concerted effort by governments, investors and innovative agricultural technologies will be required to ensure more profitable, efficient, safe, and environmentally friendly practices (De Clercq et al., 2018). Approximately 340 commercial and 78 emerging avocado growers are active in South Africa, ranging from small-scale farmers to major corporations (Donkin, 2018), representing exports more than $100 million in value during 2016 (DAFF, 2017). The European Union remains the dominant export market for export-driven producers located in countries such as South Africa, Israel and Chile (Bill et al., 2014). The common denominator among these producers is the presence of packhouse processing facilities, a key component of the "tree-to-fork" transportation chain spanning local and international borders (Dodd et al., 2010). Artificial Intelligence (AI) stands to directly benefit (Anderson et al., 2021) the 20 sustainable development goals (SDGs) (Vinuesa et al., 2020) as set out by the 2030 Agenda for Sustainable Development (UNGA, 2015) for up to 71% of studies conducted. Complementary, emerging trends and technologies such as digital twins (Lim et al., 2020), will further cement the ongoing digitization of data driven (Trilles et al., 2020) farming practices.

Avocado grading is a function of size, skin color, presence of blemishes, spray residues and other appearance abnormalities. Once ripe, physical damage (internal and external) and physiological disorders resulting from all stages of the supply chain (Fernando et al., 2019), such as lenticel damage (Lindh et al., 2021) and cold storage (Burdon et al., 2021), can appear on the skin of the fruit as dark spots reducing its desirability and value. Bruising of the fruit can be defined as subcutaneous tissue failure without rupture of the skin through impact, compression and vibration. Certain factors such as the ripening process can be artificially controlled (Arpaia et al., 2018) and are well understood. Packhouses by comparison, are composed of many mechanical elements and handling processes that are poorly understood and difficult to instrument. The lack of suitable non-destructive instrumentation prevents the development of accurate numerical models (Liu et al., 2017) that could potentially be utilized to optimize areas where the greatest amount of postharvest stress occurs (Milne & Steyn, 2021). The impact of vibration and large amplitude accelerations (Steyn et al., 2011; Pretorius & Steyn, 2012) alongside interfacial stresses (Pretorius & Steyn, 2019; Li & Thomas, 2014) associated with poor riding quality of road infrastructure (Ruiz-Altisent & Ortiz-Canavate, 1992) on tomatoes, are known to reduce the shelf-life markedly (Pretorius and Steyn, 2016; Workneh, 2017). Temperature and relative humidity are also crucial factors to consider (Toerien, 1986; Bower, 1988; Vorster et al., 1990), but are more easily controlled and maintained during transportation and storage. Instrumentation and power requirements for monitoring fresh produce transported over extended distances remain challenging despite advancements in sensor technologies (Steyn, 2017).

As a result, optimized postharvest management practices are required alongside stringent quality assurance systems (Buthelezi et al., 2019). Postharvest conditions, at best, can only maintain the quality of the fruit as received from the farm. For apples, up to half of the observed infections could be attributed to the handling characteristics during picking as noted by Combrinck (1996). The primary factors attributed to quality losses (Mahawar et al., 2020) experienced along the postharvest transportation chain are mechanical injury and handling during harvesting, diseases such as anthracnose and stem-end rots (Escobar et al., 2021), environmental conditions, overripe and desiccated fruit and pest damage. Control points are required beyond the packhouse environments, which should include pre-packers, all transportation phases, supermarkets and consumers (Milne, 1998). Simple interventions, such as the addition of tarps, reduces mechanical vibration sufficiently to halve the injury rate of fruits (Zauberman et al., 1969).

Remedial measures which rely on cost-to-benefit estimates cannot accurately consider the complex dynamics encountered to calibrate and validate models dependent on the riding quality of roads (Steyn & Bean, 2013). Vehicle tracking devices have proven effective to acquire larger datasets (Wessels & Steyn, 2015; Wessels & Steyn, 2018), notably in rural regions (Steyn et al., 2015). These are not however representative of the mesoscale behavior associated with discrete particle dynamics in a confined, interlocking matrix arrangements (Broekman & Gräbe, 2021).

One of the first attempts at building dedicated instrumentation analogues was the IS100 instrumented sphere (Tennes et al., 1998). The 120 mm cube or 140 mm sphere could provide information about the vector accelerations and variation in velocity, with subsequent improvements reducing the dimensions to 89 mm and 57 mm of the course of four years. Morphologically compatible sensors include the development of the PTR100 and PTR200 for evaluating potato damage (Canneyt et al., 2003); the wireless data transmission capabilities, while limited in its performance, was shown to be viable. Hydraulic principles can also be applied to infer the static load using pressure sensors, as was demonstrated by Herold et al. (1996) for onions (Herold et al., 1998). The last decade saw a renewed interest in the development of instrumentation for potatoes (Praeger et al., 2013), namely the Smart Spud (egg-shaped, 108 mm length, 73 mm diameter, 274 g) and the TuberLog (tuber-shaped, 90 mm in length, 65/50 mm diameter, 200 g). For applications involving smaller fruits (sphere, 25.4 mm diameter, 14 g), the Berry Impact Recording Device (BIRD) (Yu et al., 2011) which saw the development of two hardware generations (Xu & Li, 2015). More recently, a similar instrument was developed for citrus applications by Vallone et al. (2020).

This paper presents the detailed research objectives established as the foundation for the packhouse investigation. An overview of the smart avocado – termed *smAvo* (Broekman et al., 2020) - developed specifically for instrumenting packhouse environments, alongside the methodology followed to obtain consistent results, is summarized as additional background and context. This is followed by the post processing pipeline process developed within Python to calculate representative statistics pertaining to the packhouse performance from this large collection of data. The statistics are used to classify the relative performance of the sampled packhouse population along with a discussion of key aspects contributing to increased postharvest stress and variability throughout the packhouse processing phases. The paper concludes with the performance evaluation of both a linear statistical classifier and Fully Connected Neural Network (FCNN) implementation as a precursor for the deployment of similar smart sensor platforms on an industrial scale.

2. Objectives

The following three research objectives were defined at the start of the research project:

- Packhouse verification of a novel smart avocado sensor platform (*Instrumentation Development and Verification*);
- Collection of avocado packhouse processing conditions (*Packhouse Instrumentation Methodology*), and
- Analysis of avocado packhouse conditions (partly covers the first two objectives of the project).

3. Materials and Methods

An overview is provided of the instrumentation, data collection methodology, data post-processing requirements and its implementation as well as the primary statistical descriptors considered to comprehensively quantify the degree of postharvest experienced by the synthetic avocadoes.

3.1. Instrumentation

Civiltronics (Steyn & Broekman, 2020) is the realization of civil engineering in the midst of the 4th Industrial Revolution (4IR), integrating knowledge and techniques from new and emerging technologies traditionally relegated to the domain of electronic engineering, computer science, information technology and materials science. Smavo (Fig. 1) is a standalone, customized and versatile sensor platform developed specifically for the purpose of instrumenting agricultural packhouses (Broekman et al., 2020). The difficulty associated with external sensory instrumentation of biological materials necessitates the need for a synthetic twin of the discrete media under investigation.

The electronic components and power supply are enclosed within a protective, waterproof exoskeleton fabricated using Fused Deposition Method (FDM) 3D printing technology. The total mass and volume of the instrument was measured to be 198 g and 319 ml, respectively, with the width, depth and height measured as 71 mm, 76 mm and 98 mm, respectively. The Thermoplastic Polyurethane (TPU) material is ideally suited for morphological compatibility with biological materials such as avocadoes and tomatoes subject to mechanized handling operations. Whilst there is no comparable literature on FDM fabrication techniques to imitate avocadoes, best practices were followed with the material technology available at the time, alongside qualitative consideration for the surface finish. The larger volume associated with avocadoes allows for the inclusion of a hermetically sealed enclosure to prevent water ingress which proved problematic during the development stage. The entrapped air in the voids of the 3D printed enclosure aids in providing the required buoyancy (reducing the density to less than that of water). For ease of use (powering the instrument on and off) and to retain the seal of the enclosure, a reed switch and magnet is integrated within the enclosure and exoskeleton, respectively.

Fig. 1: Smavo 5 illustrating the high contrast TPU filament for easy identification

Smavo is designed around the TinyDuino sensor platform manufactured by TinyCircuits (2021) based around the popular Arduino family of microcontrollers. This integration of the integrated development environment (IDE), software and firmware allow for rapid prototyping of the sensor platforms. The following abilities are present based on the selection of expansion boards (shields) included in the final design (Broekman et al., 2020):

- TinyZero processor board (ASM2021-R-A) with included battery charger;
- MicroSD TinyShield (ASD2201-R) for non-volatile data storage;
- TinyShield proto board (ASD2009-R-T) which functions as a spacer;
- Real-time clock (RTC) TinyShield (ASD2831-R) for accurate time-keeping;
- Combo sensor TinyShield (ASD2511) containing all the sensors including the Inertial Measurement Unit (IMU), and
- GPS TinyShield (ASD2501-R) for geolocation capabilities during transportation by road.

Validation and testing of the sensor platform were achieved with various trials conducted in conjunction with ZZ2, a major commercial avocado grower in South Africa, ranging from transportation by truck to processing activities through a large packhouse. The detailed results of these endeavors fall outside of the scope of the article, with the reader referred to Broekman et al. (2020) for additional information.

3.2. Data collection

From the 37 packhouses available for instrumentation, a total of 24 were included in the instrumentation program. The individual packhouses were each assigned a unique, two-digit hexadecimal identifier to ensure anonymity due to the sensitive nature of the final results associated with the research project. Instances where two different packlines were instrumented at the same facility are considered as separate packhouse samples. These packhouses are distributed across a large geographic area across three provinces (Limpopo, Mpumalanga and KwaZulu-Nata), representing a broad range of mechanization, container selection (bins and crates) and capacities.

Two highly skilled technicians were trained to instrument all the packhouses, ensuring consistent and representative measurement data. Where possible, the four Smavo instruments (Fig. 2) were used for two consecutive runs to both increase the number of data samples and provide redundancy in case of failure. The detailed hardware operation and data collection methodology provided to the technicians is available from the data repository (Broekman & Steyn, 2020). A total of 138 Smavo data samples were collected of which 7 was discarded due to the packline related stoppages. Crates and bins represent 90 and 41 of these samples respectively. These data collectively represent some 2 660 files or 12.73 million measurement vectors, spanning 17.1 hours of runtime. Depending on the availability of time, a second round of data was collected for a given packhouse, providing up to 8 viable samples for a given packhouse. As a minimum, only 3 packhouses have a total of 3 Smavo samples. The total number of packhouses that consist of 4, 5, 6, 7 and 8 Smavo samples are 7, 2, 6, 2 and 5, respectively. Failures associated with fragile battery connectors and human error did account for a variable number of samples per packhouse, hence the use of four instruments that provide some measure of redundancy.

Fig. 2. Smavos boxed at the end of a particular packline run

3.3. Post Processing Pipeline

The post processing pipeline was inspired by the success of Kli-Pi (Broekman & Gräbe, 2021) - a standalone ballast particle analogue developed to investigate the dynamic track responses of the railway superstructure components. Python was chosen as the programming of choice, providing a wide range of supporting libraries and platform agnostic integration. The data are represented and analyzed as both individual runs in addition to a weighted mean to represent each packhouse as an aggregated sample, differentiated by the container type (bins and crates). Every Smavo data sample consists of a unique, 2-digit hexadecimal identifier, e.g. A4, followed by the type of container (b-prefix for bins and c-prefix for crates) and the Smavo instrumentation identifier. An automated HTML (hypertext markup language) report is generated which includes the primary statistical information, which is subsequently saved as PDF (portable document format). Statistical descriptors, each describing or inferring a particular component or characteristic associated with the packline environment, must be considered as part of the final classification scheme.

Based on the preliminary investigations, qualitative observations and existing literature (Ruiz-Altisent & Ortiz-Canavate, 1992; Opara & Pathare, 2014), the linear acceleration and rotational velocity of the Smavos encode a significant amount of information associated with the dynamic environment and surrounding physical support structures interacting with the instrumentation. As such, emphasis is placed on transforming, if not synthesizing, the high frequency, tri-axis accelerometer and tri-axis gyroscope data into statistical descriptors to quantify physical properties associated with the packline processes.

3.4. Statistical descriptors

The following statistical descriptors were included in the analysis process:

- **Processing duration**. The approximated time between entering the packline and packaging the Smavo in a box or container. The Smavos exhibited a tendency to spread in the packline, despite all of the instruments being introduced as a single collection at the start of the process, typically from a single bin;
- **Vector rotation count**. The number of rotations, as calculated from the rotational velocity (the combined orthogonal tri-axis measurements) recorded at 1 Hz. Early in the data acquisition process it was noted that both the length and number of mechanized rollers used for waxing and spray treatments of the avocadoes differed significantly between packhouses. This yields a large signal-to-noise ratio for improved accuracy. The lower sampling rate is utilized due to the relatively large rotational inertia of the avocado and limited availability of Random-Access Memory (RAM) of the Smavo;
- **Freefall occurrences and duration (distance)**. The MEMS-based IMU exhibits a unique property related to freefall events. Freefall – typically encountered at conveyer transitions or during the tipping of the bins and crates onto the packline – yields an acceleration value approaching zero (0) G. This is followed shortly thereafter by large deceleration from the opposing contact surface or neighboring avocadoes. Using the equation of a falling body together with the known freefall time, the freefall distance is equal to half the earth's gravitational acceleration multiplied by the freefall squared. Note that the estimated freefall distances are typically underestimated (and by extension, an overestimation of the number of freefall events), since the Smavo will randomly encounter neighboring avocadoes that are also in freefall. A cut-off threshold of 0.4 G is implemented to reduce the number of erroneous classifications. The total number of freefall events, minimum, mean, maximum and total freefall distances are reported as part of the statistics;
- **Peak-to-peak vector acceleration**. For the acceleration data, the effective vector accelerations (the combined orthogonal tri-axis measurements) are used to calculate the largest peak-to-peak accelerations. The algorithm iteratively reduces the acceleration delta (difference) such that at least 2 000 of the largest peak-to-peak vector accelerations are identified. This avoids noise typically encountered with acceleration data, but more importantly, consistently identifies the largest change in the acceleration. The 75th, 99th and 100th (maximum) percentile of this peak-to-peak vector acceleration sample is included as the representative statistic together with the mean (50th percentile) and standard deviation of the peak-to-peak vector accelerations, and
- **Cumulative Kinetic Energy (CKE)**. The Cumulative Kinetic Energy (CKE) metric was developed as a quantitative statistic which infers the total amount of mechanical work exerted on a sensor platform (Smavo), which is sensitive to both the peak accelerations and accounts for the entire duration of the data collection period (Broekman & Gräbe, 2021). Following from Newton's second law of motion, the mechanical work exerted on a rigid body is equal to the change in kinetic energy. The acceleration data is integrated to obtain the approximate velocity of the Smavo. The CKE is a useful statistic as it accounts for the entire acceleration profile of a given dataset. The CKE history is calculated for every Smavo, forming the final statistic used in the analysis.

These statistics are reported on both a per-sample description (individual Smavo recordings) and a weighted mean for every packhouse and container method used based on the number of valid samples available.

4. Results

The results pertaining to the per-sample and per-packhouse statistics are represented to illustrate a holistic overview of the entire sampled population, followed by a detailed discussion in the subsequent chapter.

4.1. Processing duration

The processing time of a Smavo is defined as the duration between introducing the instrument into the packline and when it has been packed into a container, defining the end of a run. The expected processing time for an avocado is 7.7 minutes with a standard deviation of 3.1 minutes. The shortest and longest processing time for an individual Smavo run was recorded as 2.8 and 16 minutes, respectively (Fig. 3, top). The inter-sample variation is relatively small (Fig. 3, bottom).

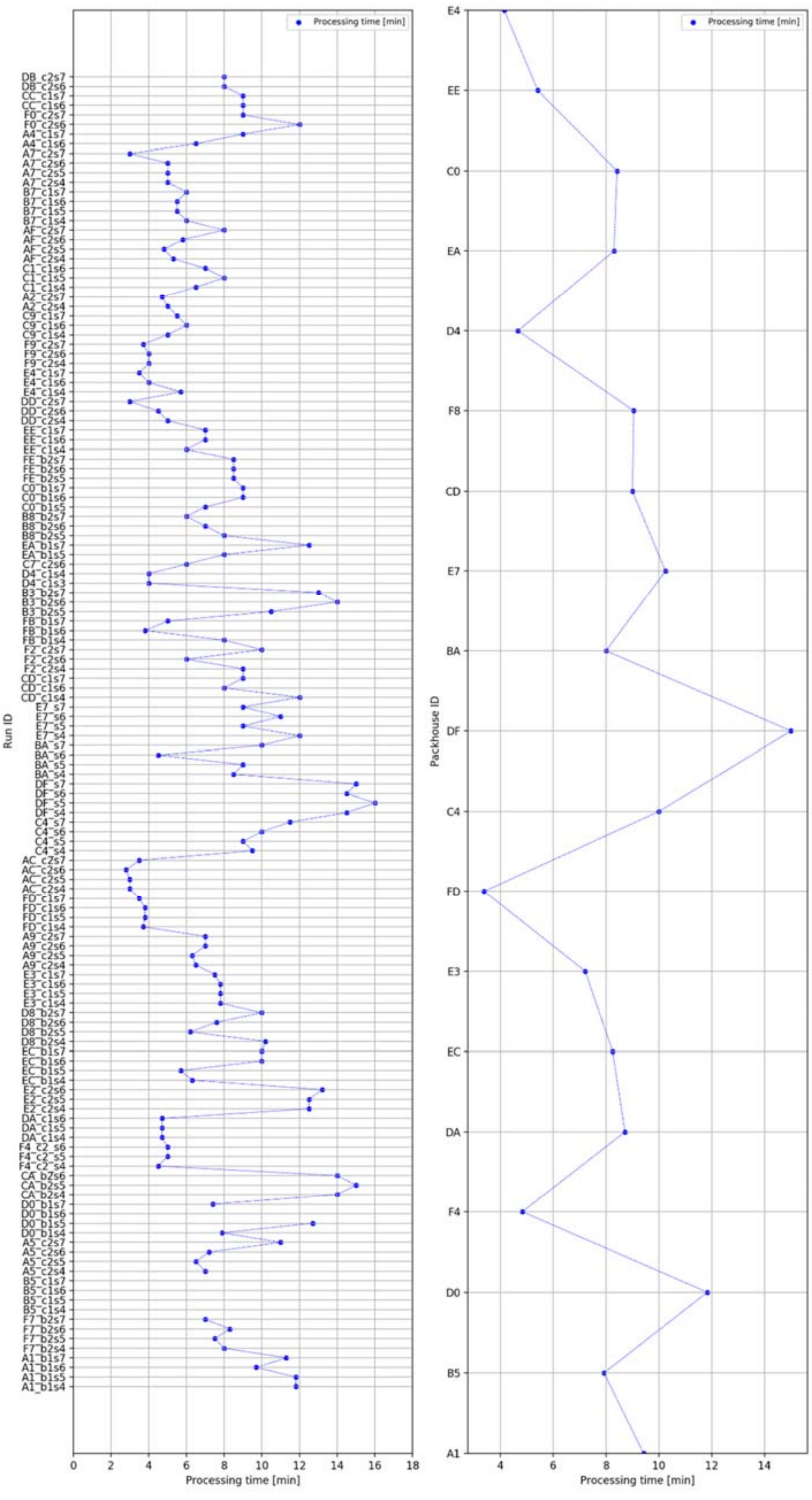

Fig. 3.Processing time for the per-sample (top) and per-packhouse (bottom) data

4.2. Vector rotation count

The average Smavo recorded the mean and standard deviation vector rotations as 81 and 49, respectively (Fig. 4). Considering all the Smavo measurements, the minimum number of vector rotations measured was a 20 for a single run, compared to 320 vector rotations for the most active run.

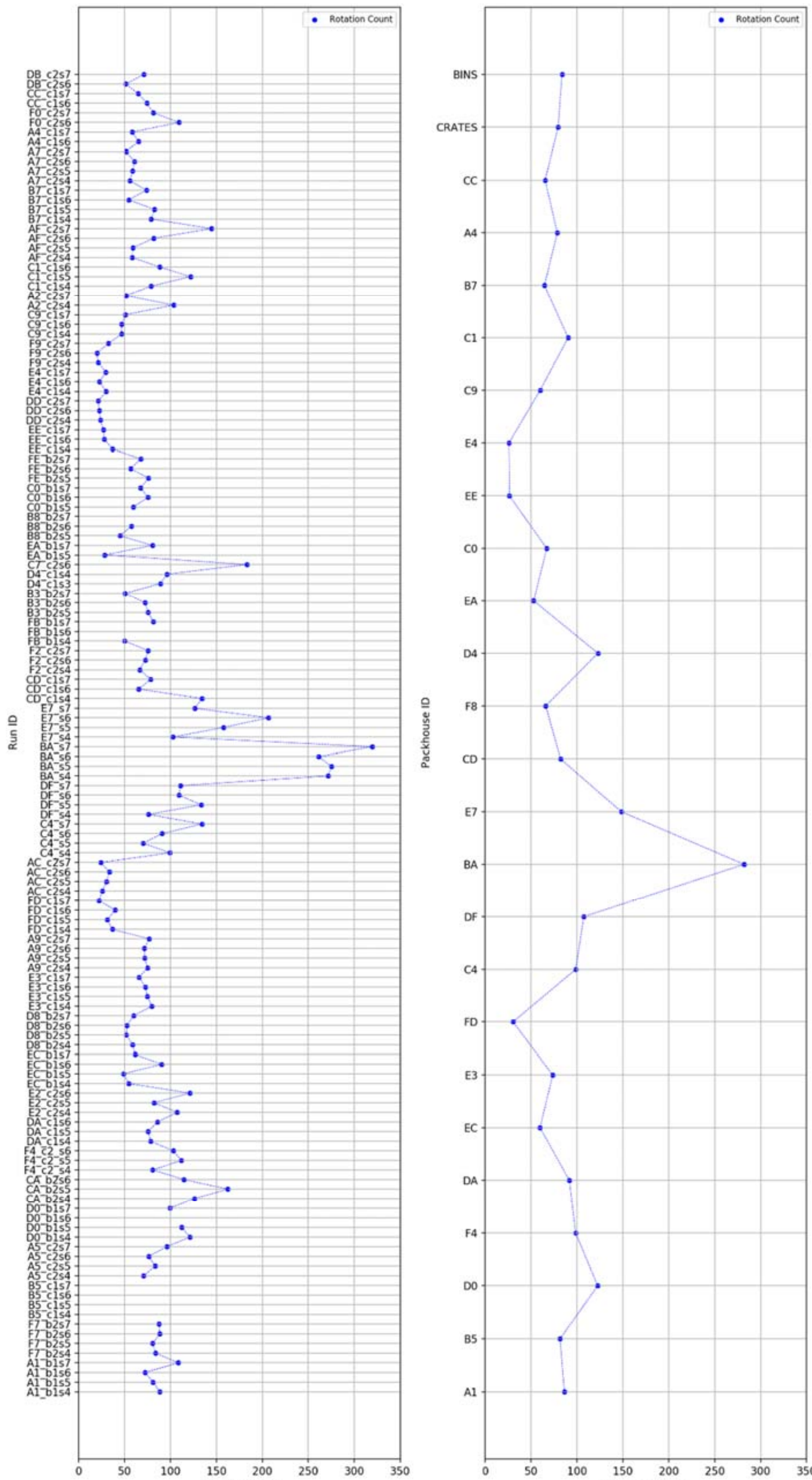

Fig. 4. Vector rotation count for the per-sample (top) and per-packhouse (bottom) data

4.3. Freefall occurrences and distances

Large variations were encountered for the per-sample and per-packhouse freefall statistics. Fig. 5 (top) illustrates the freefall occurrence count and mean freefall distance, alongside the maximum and total or cumulative freefall distance (Fig. 5, bottom) for the per-sample measurements. The weighted per-packhouse freefall statistics are summarized by Fig. 6. The expected freefall count, mean, maximum and total freefall distances were calculated to be 29, 28 mm, 112 mm and 795 mm respectively.

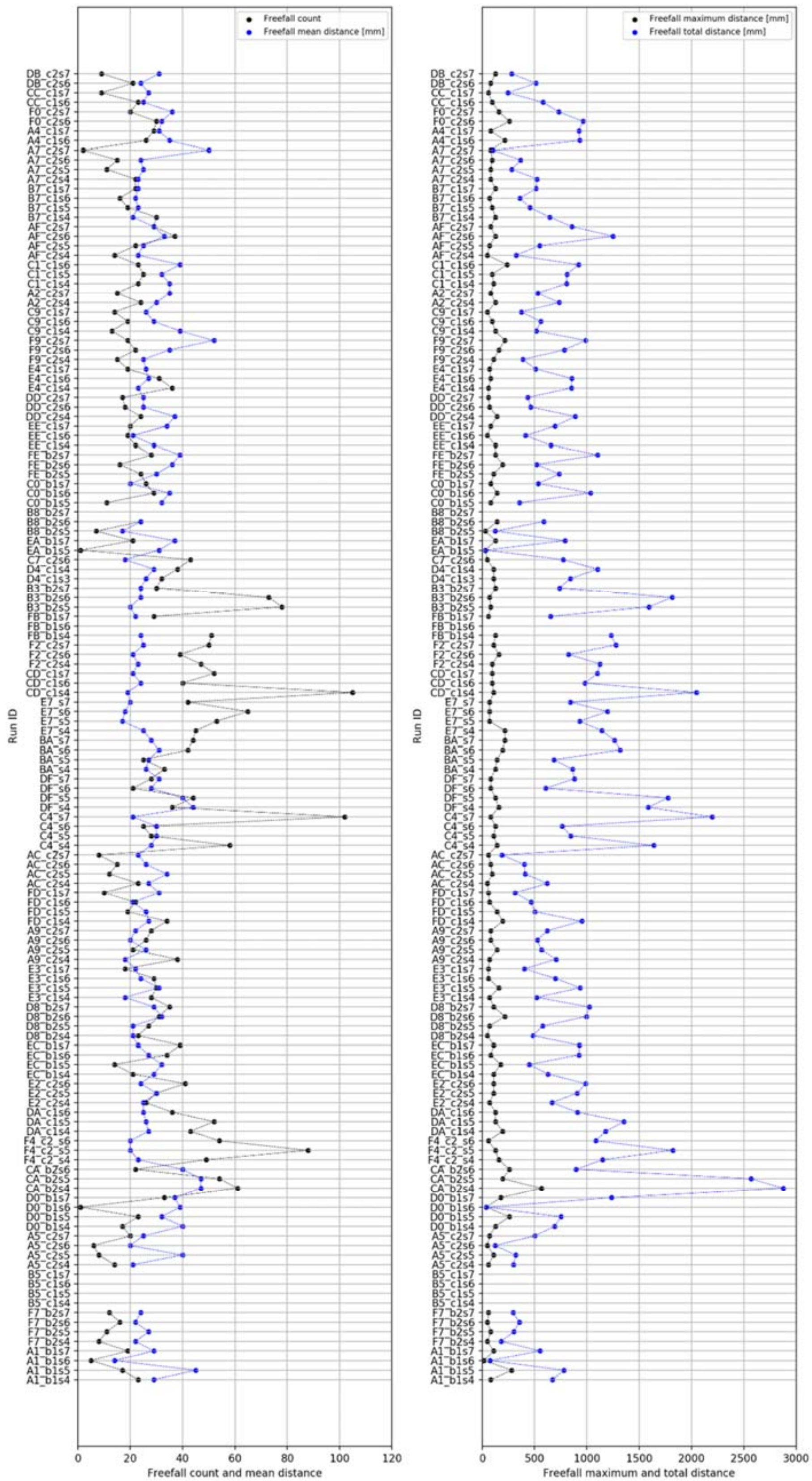

Fig. 5. Freefall measurements for the per-sample data: freefall count and mean distance (top), freefall maximum and total distance (bottom)

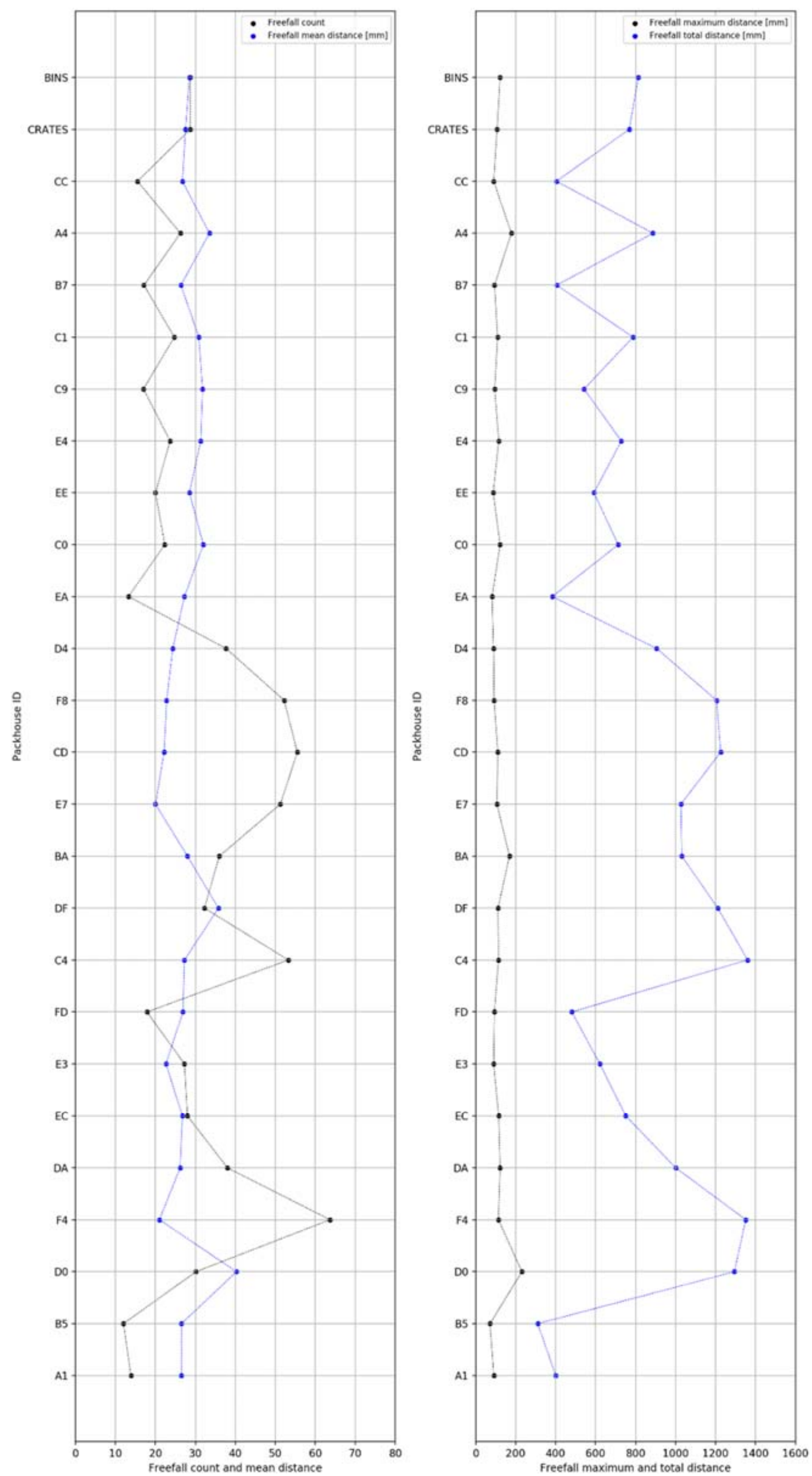

Fig. 6. Freefall measurements for the per-packhouse data: freefall count and mean distance (top), freefall maximum and total distance (bottom)

4.4. Peak-to-peak vector acceleration

Fig. 7 illustrates the peak-to-peak vector acceleration statistics (50^{th}, 75^{th}, 99^{th} percentile and standard deviation) for the per-sample (Fig. 7, top) and per-packhouse (Fig. 7, bottom) statistics. Compared to the other statistics, less variation is observed among the samples and packhouses. Table 1 summarizes the variation of the peak-to-peak vector acceleration statistics, where the 50^{th}, 75^{th}, 99^{th} percentile and standard deviation can be expected to measure 1.622 G, 1.881 G, 6.532 G and 10.50 G, respectively. The maximum recorded peak-to-peak vector acceleration for the dataset was 13.49 G.

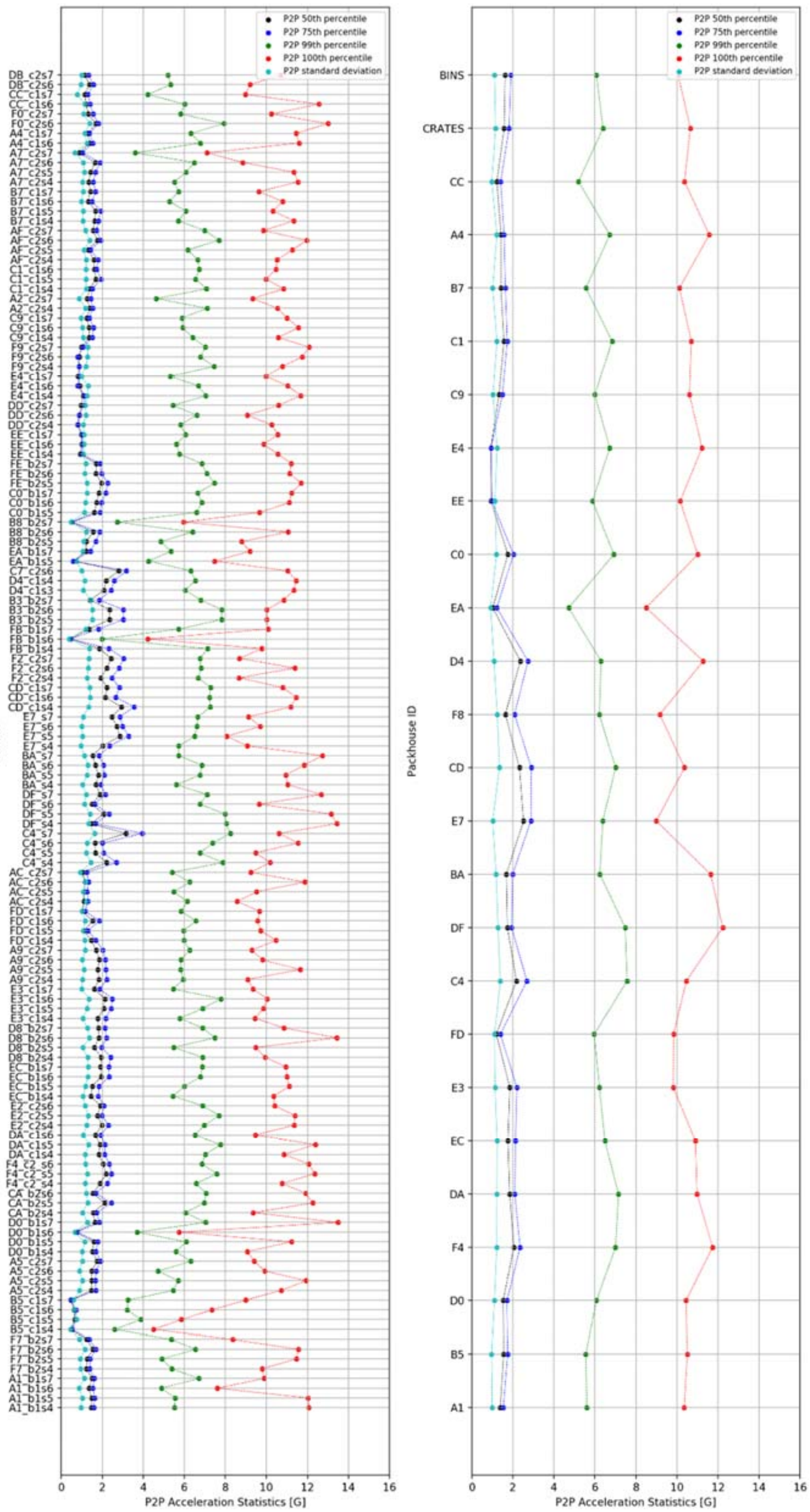

Fig. 7. Peak-to-peak (P2P) vector acceleration statistics for per-sample (top) and per-packhouse (bottom) data

Table 1: Peak-to-peak vector acceleration statistics

	Peak-to-peak vector acceleration statistics (1st order) [G]			
	50th Percentile	75th Percentile	99th Percentile	Maximum
Minimum	0.411	0.431	1.986	4.223
Mean	1.622±0.489	1.881±0.621	6.532±0.949	10.503±1.327
Maximum	3.153	3.967	8.245	13.494

4.5. Cumulative Kinetic Energy (CKE)

Fig. 8 illustrates the per-sample (Fig. 8, top) and per-packhouse (Fig. 8, bottom) CKE statistic. Most striking is the disparity between geographical areas, with each province corresponding approximately to a third of the graph (left, center and right).

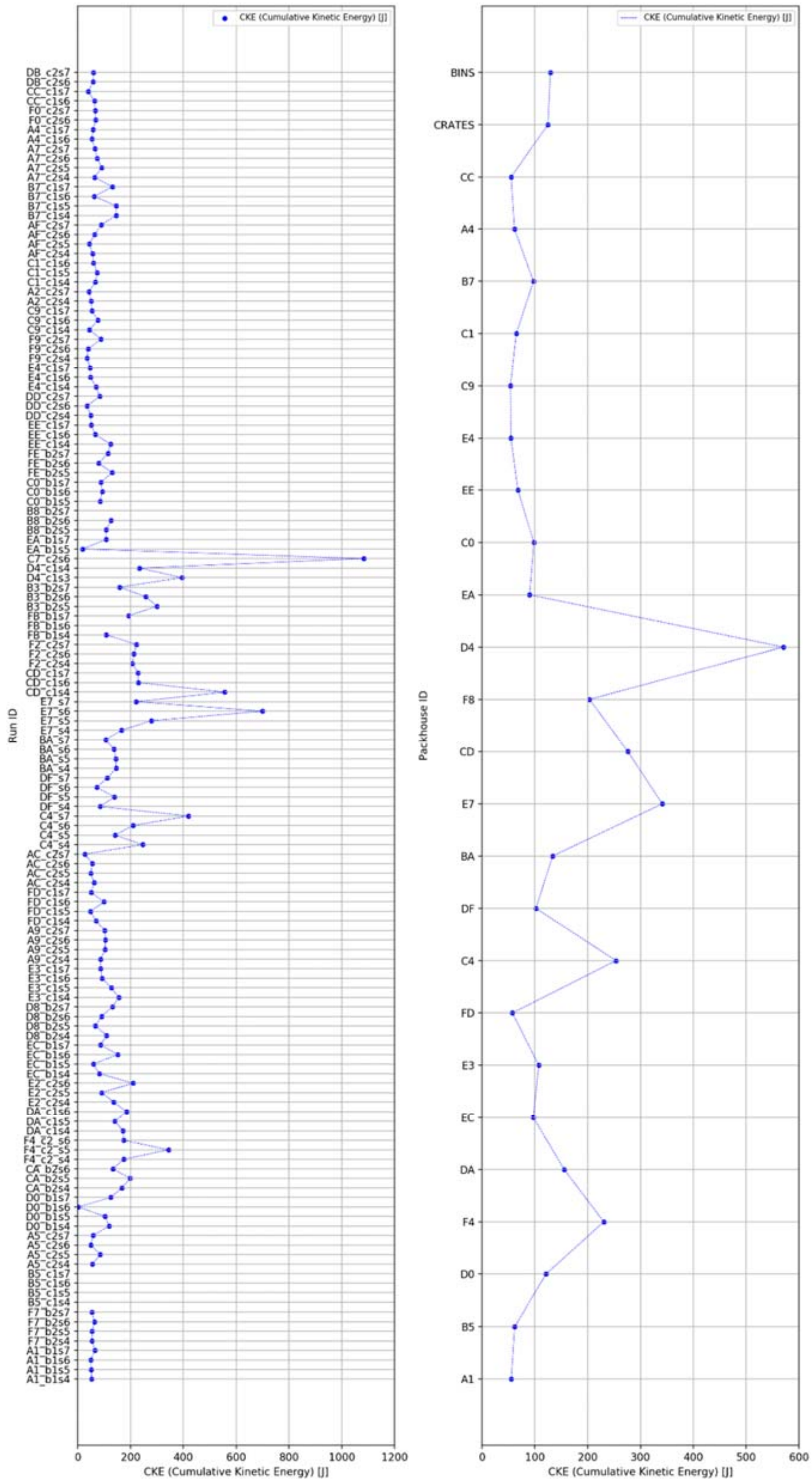

Fig. 8. CKE (Cumulative Kinetic Energy) for the per-sample (top) and per-packhouse (bottom) data

5. Discussion

This chapter considers the introduction of a quantitative classification method to distinguish among unoptimized, average and optimized packhouses based on the statistics gathered from the sampled population. A more in-depth discussion follows regarding the underlying mechanics leading to the observed differences, areas of concern and recommendations for improving packhouse operations, reducing the resulting postharvest stress experienced by the avocadoes. The subsequent chapter considers two models (linear regressions and a neural network) for the packhouse classification based on the primary statistics.

5.1. Packhouse Processing Quadrant (PPQ) and Damage Index Score (DIS)

The total freefall distance statistic is considered a representative metric for the degree of mechanical handling. The CKE by comparison is sensitive to acceleration amplitudes, and to a large extent, the influence of mechanical rollers, which is not included in the freefall metrics. Together, these statistics form the basis of the Packhouse Processing Quadrant (PPQ). Fig. 9 illustrates the PPQ for all 133 data samples. The PPQ is bisected along the horizontal axis by the average freefall total distance (795 mm) and along the vertical axis by the average CKE (129 J), dividing the graph into four distinct quadrants:

- The bottom left quadrant is considered optimized packhouse performance and is assigned a Damage Index Score (DIS) of 1;
- The top-left quadrant is associated with excessive handling and assigned a DIS of 2;
- The bottom-right quadrant is associated with excessive freefall characteristics and assigned a DIS of 3, and
- The top-right quadrant is considered unoptimized packhouse performance and assigned a DIS of 4.

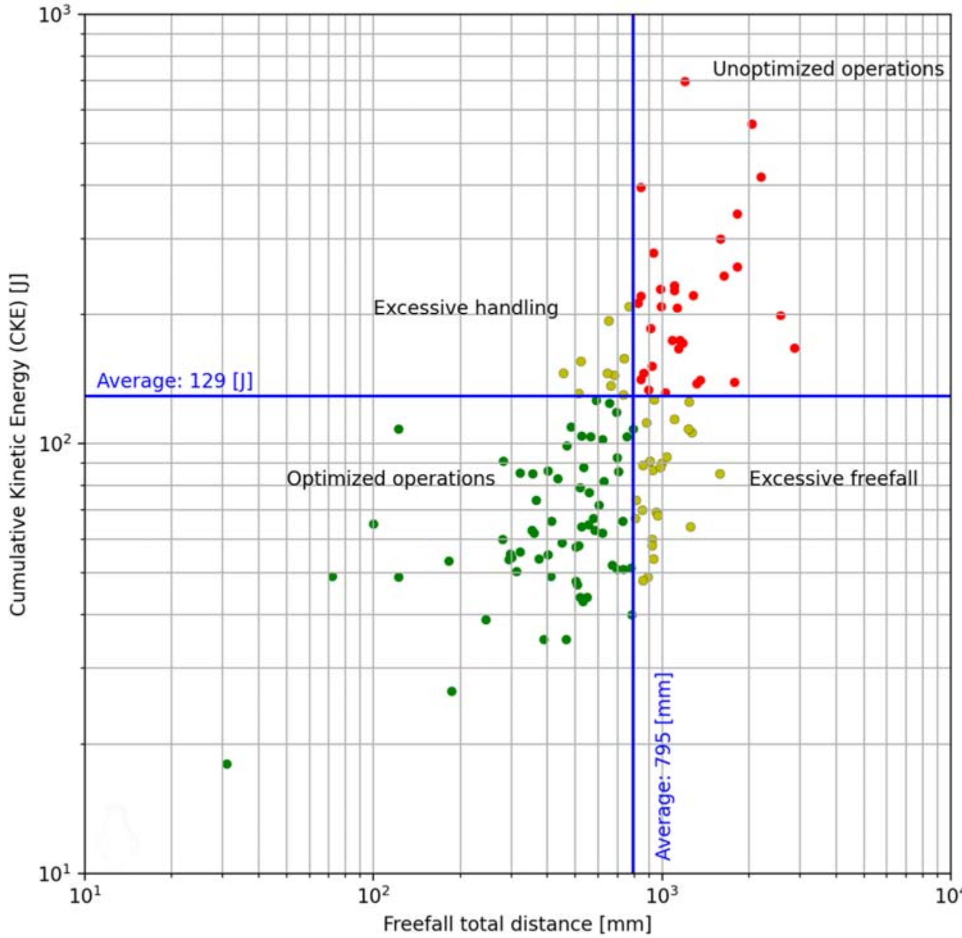

Fig. 9. Packhouse Processing Quadrant (PPQ) illustrating the comparison between the Cumulative Kinetic Energy (CKE) and the freefall total distance

The Smavo represents a discrete sample from a much larger fruit population, which are considered representative of the average performance for each respective packhouse. It should be emphasized that this classification scheme is not considered an absolute scale where a packhouse is considered inherently *good* or *bad*. Instead, the sampled population defines the threshold criteria for the population itself, identifying the packhouses which could benefit from further optimization. The DIS classification for each packhouse is illustrated alongside the mean, maximum and total freefall distance along with the CKE (Fig. 10). For the purposes of the detailed discussion, packhouse D4 (also includes secondary sample C7), EC and C9 (also includes secondary sample A2) are considered examples of *unoptimized*, *average* and *optimized* packline operations, respectively. This qualitative selection, considering all the statistics together, is based on the results from Fig. 10 that summarizes sample data for every packhouse.

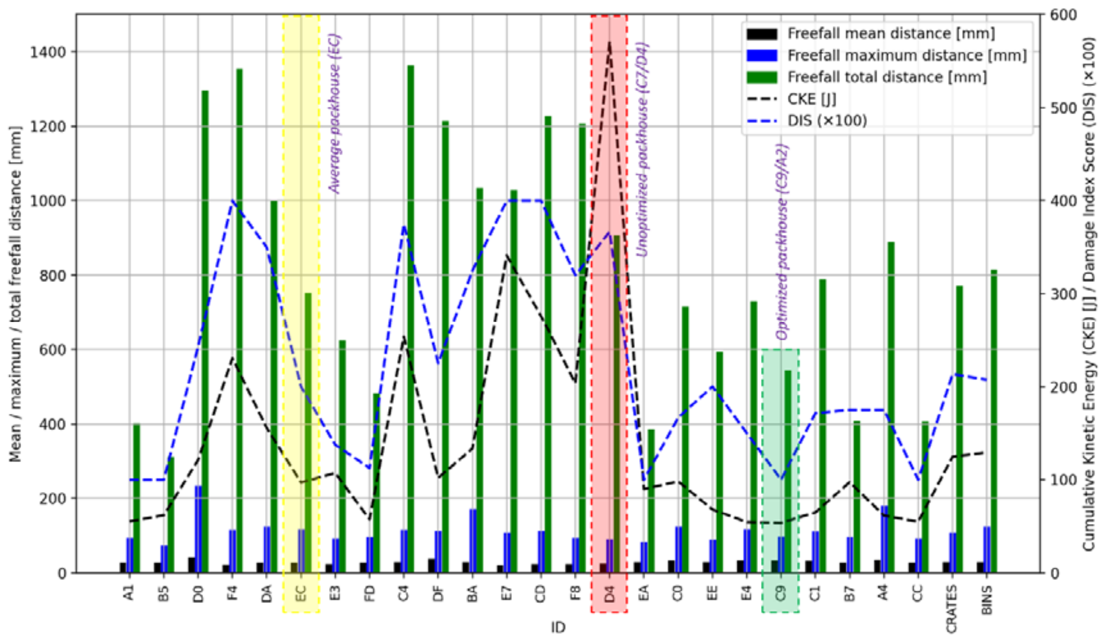

Fig. 10. Summary of the per-packhouse freefall, CKE and DIS statistics

5.2. Acceleration variation and geometric distribution

Fig. 11 illustrates the acceleration histories of the unoptimized (C7, Fig. 11 top), average (EC, Fig. 11 center) and optimized (A2, Fig. 11 bottom) packhouses. The unoptimized packhouse exhibits protracted, high intensity accelerations associated with the mechanized rollers. The optimized packhouse by comparison illustrates smaller amplitude accelerations associated with the rollers over a short period of time. Static acceleration measurements are associated with the water baths where the avocadoes remain largely stationary. The rotation of the crate at the start of the packline is clearly visible at the 1-minute mark for the average packhouse (Fig. 11, center) whereby the shape of the changing acceleration measurements is reminiscent of a sinusoid. Fig. 12 illustrates the corresponding distribution of the acceleration values of the unoptimized (C7, Fig. 12 top), average (EC, Fig. 12 center) and optimized (A2, Fig. 12 bottom) packhouses. The shape of these distributions is distinct for the three different classifications with a notable absence of high intensity acceleration measurements (in the region of 4 G to 8 G) for the optimized packhouse.

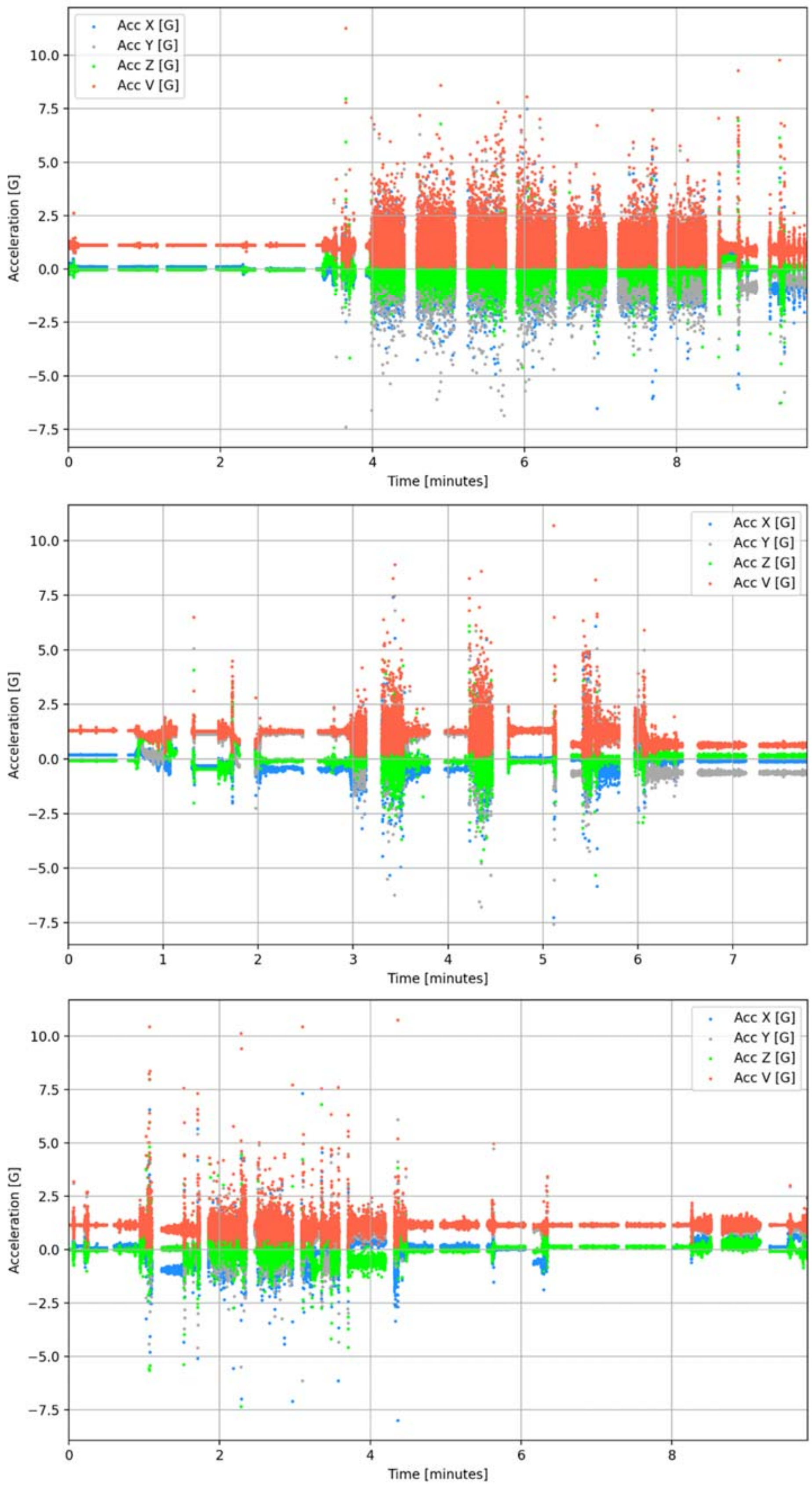

Fig. 11. Acceleration histories of the unoptimized (C7, top), average (EC, center) and optimized (A2, bottom) packhouses

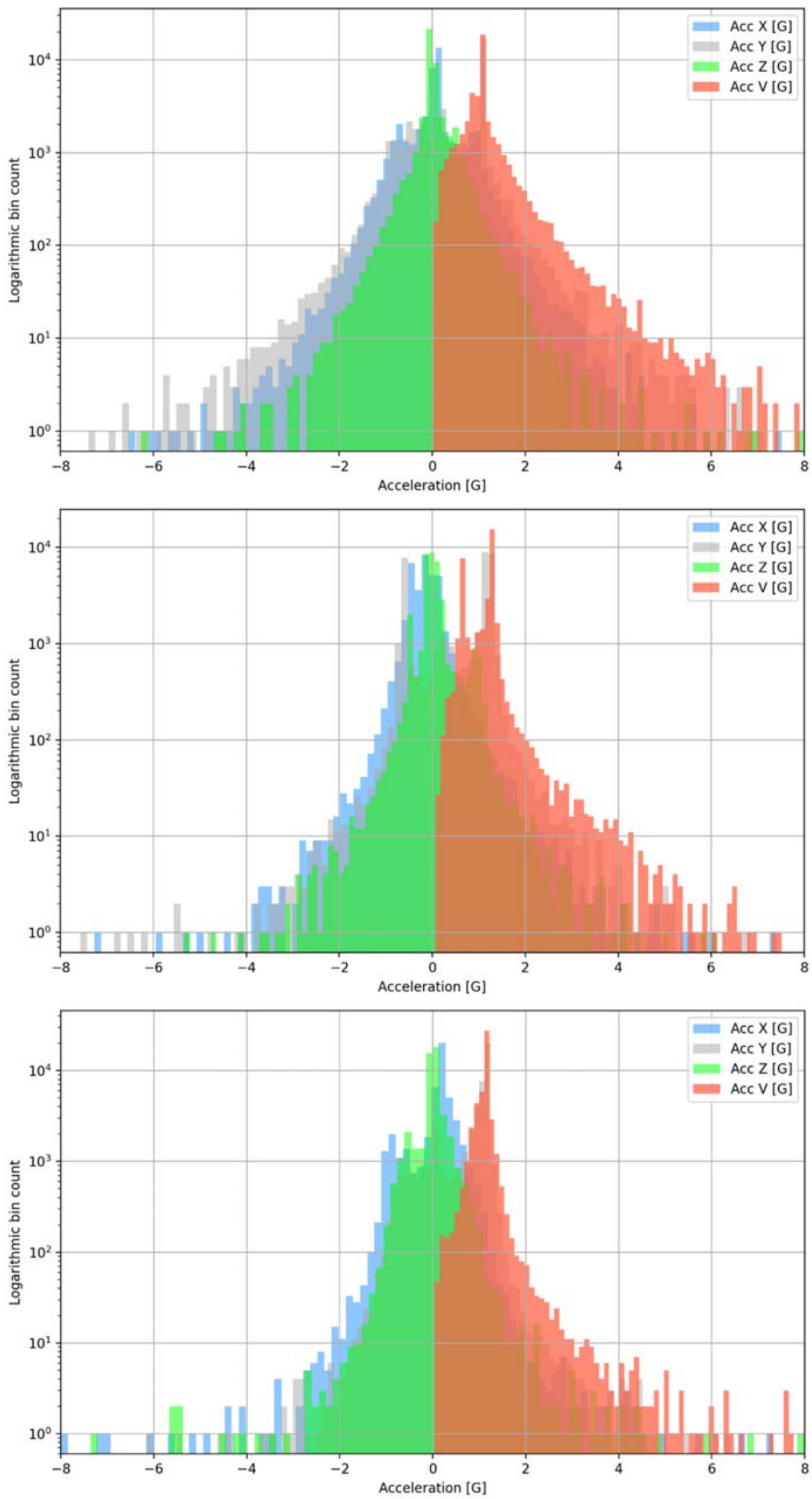

Fig. 12. Distributions of acceleration measurements of the unoptimized (C7, top), average (EC, center) and optimized (A2, bottom) packhouses

The tri-axis acceleration measurements can be projected onto a unit sphere (Fig. 13) to visualize the geometric distribution of the acceleration vector, and equivalently, the net force, acting on the surface of the Smavo. Fig. 13 illustrates 10 000 randomly selected acceleration vectors of the unoptimized (C7, Fig. 13 left column), average (EC, Fig. 13 center column) and optimized (A2, Fig. 13 right column) packhouses from three different perspectives about the Z-axis. The color of each vertex pertains to the percentile ranking of that individual sample: <16% (aqua), 16% to 50% (green), 50% to 84% (yellow-green), 84 to 97% (orange) and >97% (red). The largest concentration of net acceleration forces is located about the XY-plane of the Smavo, corresponding to both the smallest cross section and the axis of largest inertia (Fig. 14). Based on visual assessments, the orientation of the instrument is identical to that exhibited by the neighboring biological counterparts. Minimizing the time which the avocadoes rotate in the rollers reduces the density and intensity of the net contact forces the avocado encounters. This is reflected in the rotation count history (Fig. 15) of the three packhouse examples whereby the optimized packhouse reduces the rotation count by more than two thirds compared to the unoptimized packhouse.

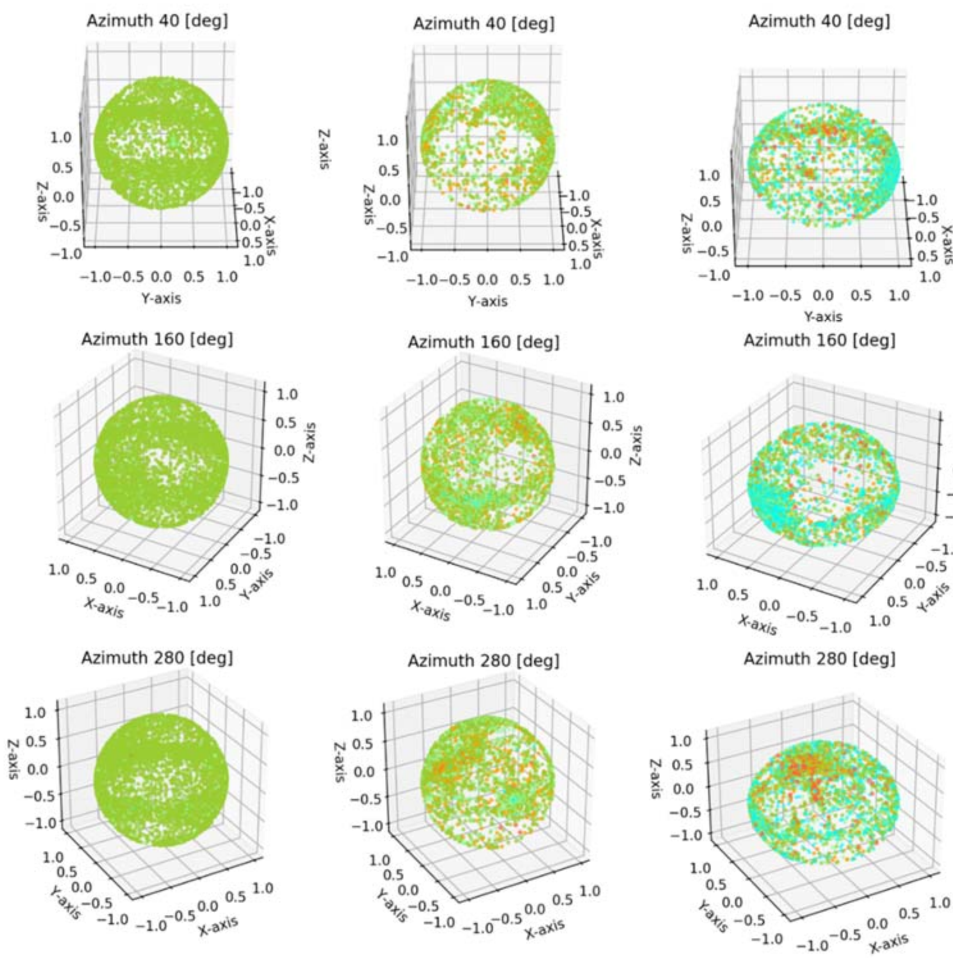

Fig. 13. Geometric distribution of vector accelerations of the unoptimized (C7, left column), average (EC, center column) and optimized (A2, right column) packhouses from three different perspectives

Fig. 14. Longitudinal orientation of the Smavo (CD_c1s4) associated with mechanical rollersf

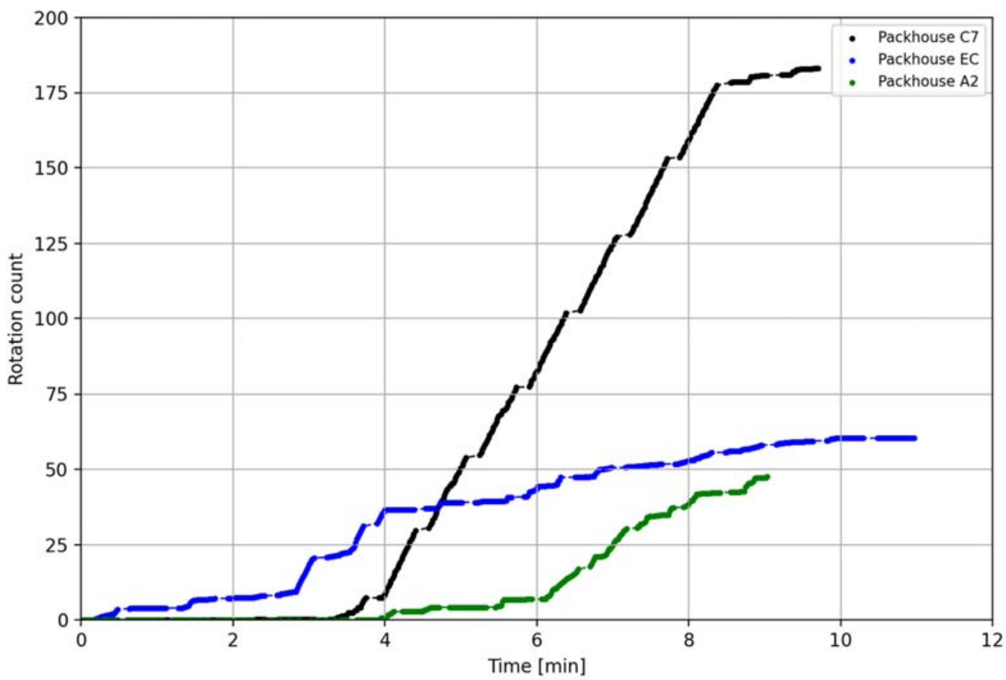

Fig. 15. Rotation count histories of the unoptimized (C7, black), average (EC, blue) and optimized packhouses (A2, green)

5.3. Mechanical rollers

From the acceleration histories and rotation count statistics it is evident that the mechanized rollers exhibit a large influence over the classification of the packhouses. Still images of the video recorded during the instrumentation phase (Fig. 16) revealed the extent to which the avocadoes continually and violently tumble in the rollers. Most if not all packlines implemented a different designs for the roller elements, including the rotational speed, diameter and the distance between the brushes.

Crucially, the time the avocadoes idled in the rollers for a given packhouse varied substantially. This phenomenon is analogous to the operating principle of a forward-biased diode. A sufficient forward voltage (constant supply or *pressure* of avocadoes) must be supplied for the charge carriers (avocadoes) to cross the PN-junction (advancing from one roller to the next). Conversely, for every avocado which moves from one roller to the next, an empty hole carrier moves in the reverse direction, supplying additional space for a new avocado to enter the packline. Failure to maintain this constant supply of avocadoes results in only a small number of avocadoes exiting the roller stage (leakage current of the equivalent diode), increasing the postharvest stress for the idling avocadoes remaining in the rollers. The optimized packline (Fig. 17) largely eliminates this shortcoming with the introduction of a number of narrow, parallel rollers. This restricted width forces individual avocadoes onto the rollers, reducing the idling time substantially. The gradient of the packline further reduces the inter-roller freefall distance and acceleration experienced by the avocadoes.

Fig. 16. Roller implementation of a poorly optimized packhouse (E7)

Fig. 17. Roller elements of the optimized packhouse (A2)

5.4. Freefall events and distances

Table 2 provides a summary for the freefall history of the unoptimized (C7, top), average (EC, center) and optimized (A2, bottom) packhouses. Even though the minimum freefall distance is not associated with the optimized packhouse, the number of freefall events is more numerous for the average and unoptimized packhouse. Comparing the freefall history of the optimized packhouse (Table 2) to the rotation count history (Fig. 14, top) highlights the correlation with the smaller number of freefall events. Larger freefall distances (30 to 120 mm) are associated with transitions between different sections of the packline, notably the conveyor belts, which were encountered with all the packlines. Minimization of the freefall distance reduces the probability of bruising, as is the case for pomegranate fruits where a maximum distance of 40 cm advised (Hussein et al., 2020). Some packlines, though not all, incorporate an angled plate at these transitions to convert the potential energy into kinetic and frictional energy (Fig. 18), reducing the vertical acceleration component.

Table 2: Summary of the freefall statistics for the three packhouse samples

Packhouse	Freefall count	Minimum [mm]	Mean [mm]	Maximum [mm]	Total freefall distance [mm]
Unoptimized (C7)	43	12	18	49	774
Average (EC)	39	12	23	110	928
Optimized (A2)	15	12	35	82	531

Fig. 18. Screenshots representing freefall events across different packhouses

5.5. Cumulative Kinetic Energy

Fig. 19 illustrates the CKE of the unoptimized (C7, top), average (EC, center) and optimized (A2, bottom) packhouses. The CKE, proportional to the square of the change in velocity, serves as a sensitive metric able to effectively differentiate between small differences among the different packhouses. The CKE is sensitive to the continuous rotational behavior of the rollers, more so than freefall events which are short-lived transient events. The gradient of the CKE corresponds to the rate of work (power) imparted on the Smavo, largely remaining constant for the mechanical rollers. The rotation speed and diameter of the rollers have a significant impact on the resulting acceleration and CKE measured by the Smavo. Compared to measurements conducted for transportation by road, the CKE statistic is smaller by a significant margin. The postharvest stress profiles are however complete opposites with packline operations distributing high intensity contact forces nearly uniformly over the surface of the avocadoes, compared to prolonged, low amplitude, concentrated contact forces for all other transportation phases.

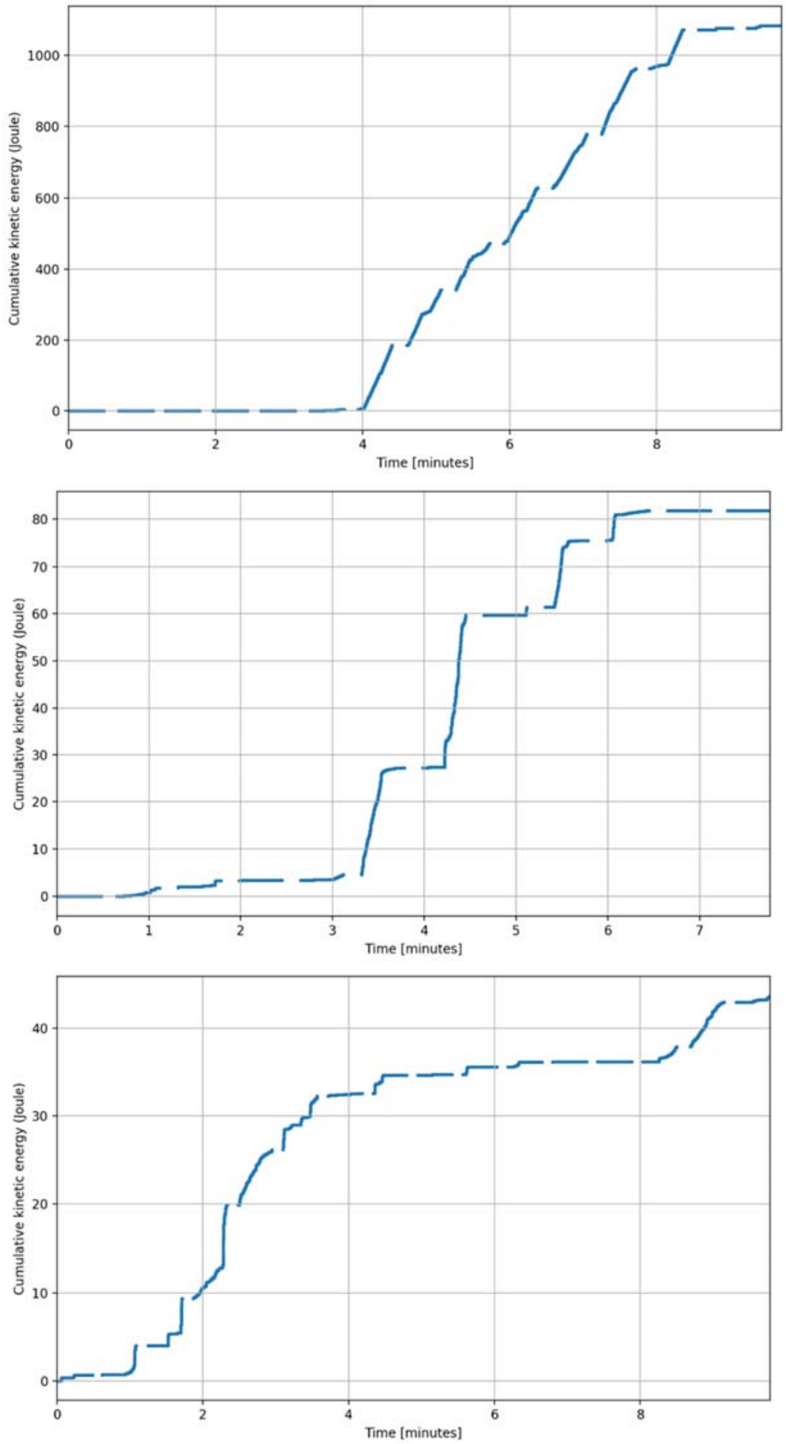

Fig. 19. CKE comparison between the unoptimized (C7, top), average (EC, center) and optimized (A2, bottom) packhouse

5.6. Geographic influence

Considering the weighted average DIS statistics for each of the three provinces, these ranged from a score of 1.575 to 2.662. These results correlate with the qualitative feedback recorded by the field technicians responsible for the instrumentation when asked to rank the packhouses from most favorable / least postharvest stress to most unfavorable / greatest postharvest stress. Furthermore, it was reported by the technicians that the packhouse staff were "*usually aware of problem areas*" and were "*keen to use modern technologies to identify and or confirm problems*", as the typical or average packhouse employed a "*combination of older and newer technology and machinery*".

5.7. Container influence

Different opinions exist in the local avocado industry pertaining to the benefits or disadvantages associated with the use of either bins or crates. This should however be considered from two different frames of reference. There is a short temporal scale confined to the tipping or dropping process of the avocadoes into or onto the packline, and the combined influence, where the selection of container class is a function of the capacity and mechanization of the packline and not a mutually exclusive variable. Based on the stochastic nature of the statistics presented, the comparison between the two different containers is considered as the weighted mean for the sampled population (Fig. 20). On average, the DIS of a packhouse utilizing bins (2.073) compare more favorably than one using crates (2.133). The standard deviation, maximum and 99th percentile peak-to-peak vector acceleration are also in favor of the average packhouse utilizing bins.

It is interesting to note that the expected freefall count remains constant irrespective of the method implemented. The average packhouse incorporating crates tend to have reduced CKE, 75th and 50th percentile peak-to-peak vector accelerations, maximum and total fall distance, number of freefall events, rotation count and duration. These statistics reflect the notion that a smaller, less mechanized packlines will most likely implement crates which represent reduced capacity and shorter runtimes compared to packlines implementing bins. The increased values of the larger percentiles of peak vector accelerations are likely attributed to the loading method at the start of the packline, which is less sophisticated than packlines implementing water baths underneath the falling avocadoes.

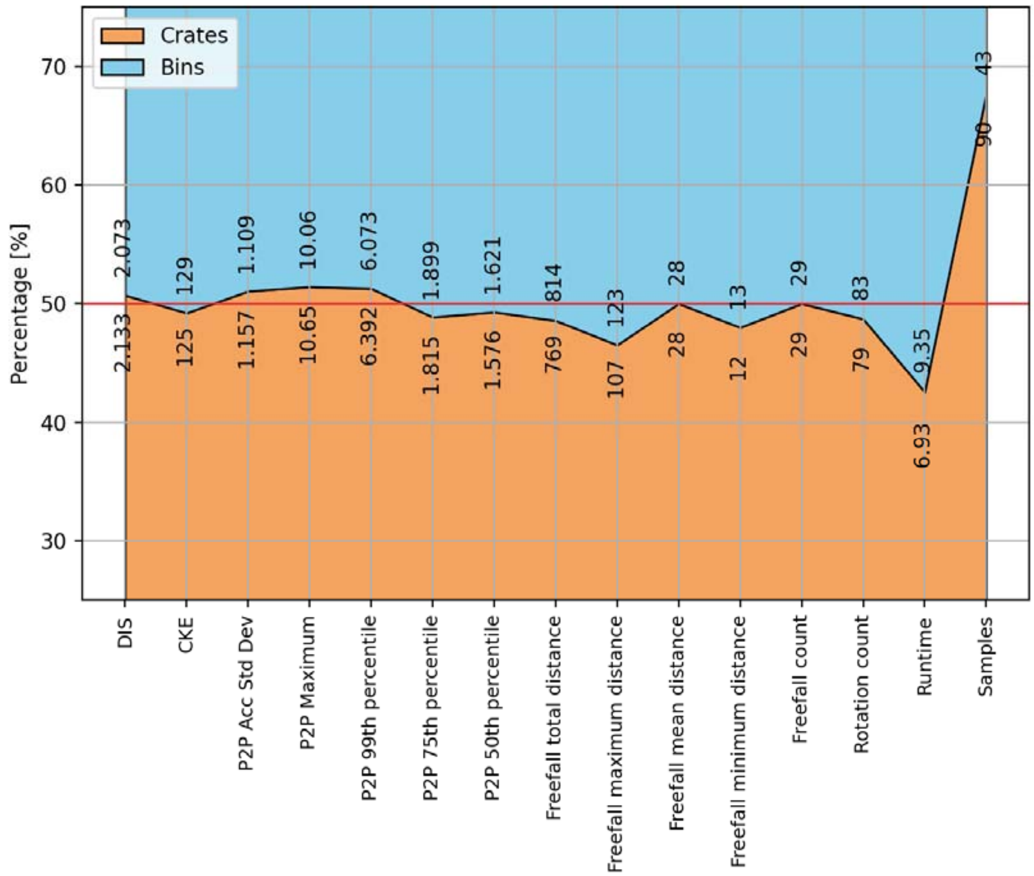

Fig. 20. Comparison between crate and bin container statistics

Methods of introducing the Smavos into the water bath or onto conveyors (using either bins or crates) varied widely according to the degree of mechanization. Three of the most popular containers included:

- Drop: specifically confined to smaller crates, dropping of the avocadoes either by hand or a simple tipping mechanism onto a small platform or grid. This was however associated with larger freefall distances and rougher handling conditions compared to the other two methods;
- Rotate: rotating the larger bins 180° and depositing the avocadoes over either a water bath or solid platform. While the approach is sound, high decelerations were observed alongside high-intensity, high-frequency oscillations with neighboring avocadoes (Fig. 21), and
- Dip: present in one of the highly mechanized packhouses, the bins are "dipped" into the water which allow the avocadoes to float in a forward direction, out of the bins. No freefall events are present with this method, but it does require more sophisticated mechanical systems (and resulting cost) to implement.

Out of these three methods, packlines implementing the dip method are the preferred method as the process of dropping the avocadoes are eliminated entirely, as based on the quantitative results alongside the objective opinion of the technicians responsible for instrumenting the packhouse with the Smavos. Additionally, the dip method is associated with packlines that are characteristic of more modern technology and machinery which reduces the overall degree of postharvest stress for that packhouse.

Incidentally, the unoptimized and average packhouses used in this discussion implemented the drop and rotate loading methods respectively. Fig. 22 illustrates examples of drop, rotate and dip methods. The first row illustrates the drop method that is typically encountered in smaller packhouses and operated by a dedicated worker. Various methods were implemented to reduce the deceleration forces exerted on the avocadoes; Fig. 22 (*Drop C4*) illustrates and ordinary garden hose wrapped around the steel bars for softening the impacts. Various configurations of rotating the bin were encountered, ranging from progressive tipping onto a conveyor (Fig. 22, *Rotate (BA)*), a hybrid impact plate / water bath (Fig. 22, *Rotate (CD)*; *Rotate (FB)*) and direct water baths (Fig. 22, *Drop (EC)*). The dip method which represents the most advanced method (Fig. 22, *Dip (C0)*).

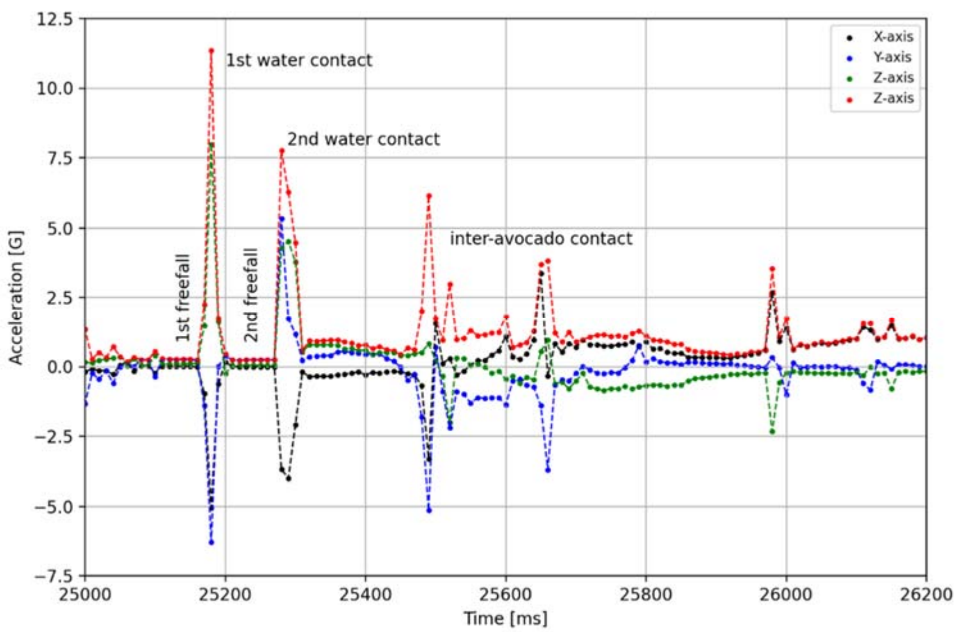

Fig. 21. Smavo freefall event associated with the rotation of a bin releasing the avocadoes into the water bath (EC)

Fig. 22. Selected example of the drop, rotate and dip methods at the start of the packline

5.8. Optimized packhouse

The most optimized packhouse (A2), represents one of the most modern packhouses featuring new, high-technology equipment including narrow, angled conveyor systems with small freefall heights and optical quality assurance systems integrated within the packline. Fig. 23 illustrates a collection of photographs of the packline in operation.

Fig. 23. Image collage illustrating different facets of the optimized packhouse

5.9. Results in context

A rich history of experimental investigations has shown the significance of repeated impacts (machinery and hard surfaces), abrasion and excessive compression on the bruising, and its severity, in fruits. Despite the identified causes of wastage of fruit (South Africa in particular), there is a lack of quantitative data on the possible implementation of loss reduction strategies (Opara et al., 2021). Instrumentation developed to date, such as the instrumented spheres, are designed to register high amplitude vibrations (20 G) (Ruiz-Altisent & Ortiz-Canavate, 1992) with poor resolution (1 G) compared to that of the Smavo and modern MEMS-based accelerometers. The improved sensor performance in turn reduces the variability associated with measurements from other commercial devices (Li & Thomas, 2014; Praeger et al., 2013). The softer material construction associated with the Smavo reduces the peak amplitude associated with harder materials of other instrumentation that result in higher amplitude accelerations that are difficult to measure accurately. Compared to the smAvo, no other information pertaining to the battery lifetime, waterproofing characteristics and reprogramming capabilities for the instrumentation is available.

In the case of apples, there exists a strong relationship between the distance travelled, presence of adequate packaging material, the degree of apple bruising and the number of high amplitude acceleration events (Ruiz-Altisent & Ortiz-Canavate, 1992). The introduction of cushioned surfaces where possible, in particular long-distance travel is the easiest mitigation method. Various authors have considered modelling the damage mechanisms related to the handling of fruit as elastic solids, requiring parameters such as mass, initial velocity, input energy, impulse, radii of curvature, macro- and microstructural properties of the fruits. However, the sensitivity of impacts alone cannot be fully explained by the impact energy alone and must include the physical properties, structure and physiology of the fruit. This in turn has led to the development of various bruise indices (Opara & Pathare, 2014) for fruits ranging from apples, onions, tomatoes, potatoes, blueberries, sugar beet, citrus and mango, with limited information available for avocadoes. Despite the advancements, there is still no agreement among academic and industry institutions on the method to gauge the amount or susceptibility of bruising of horticultural produce. While the Smavo does not present a one-size-fits-all approach to a numerical damage assessment, it does quantify the variability of a large population of packhouse environments inducting postharvest stresses, freefall characteristics, rotation counts and damage indices that directly correlate to impact energies and design of mechanized elements – key metrics not provided by other instruments. Compared to limited scale laboratory evaluations, Smavo presents for real-world interpretation of packhouses (and other elements of the value-chain) in significant detail not considered before.

6. Classifier models

The PPQ, DIS and other relevant statistics enable the development, and ultimately the implementation, of classification models, provided the underlying data representation (of the packhouses) remain unaltered. The CKE and total fall distance statistics are however reliant on more computationally expensive and memory intensive operations, more so for integrated microcontrollers with limited resources. Alternative models, namely linear regression and a simplified neural network, were explored to potentially leverage the larger number of statistics available for accurate classification and generalization. The correlation matrix (Fig. 24) generated from the per-sample Smavo statistics provide a visual representation among the different variables. Values approaching 1 are indicative of stronger, positive correlations. Note that the matrix is symmetric, with a correlation of 1 along the diagonal for identical pairs of statistics. Of interest are the correlation scores for the DIS (Fig. 24). The strongest correlations are that of the freefall count (*Freefall count*, 0.74) and 50th (*Acceleration V 50%*, 0.68) and 75th (*Acceleration V 75%*, 0.67) percentile peak-to-peak vector accelerations. In contrast, the duration (*Processing Duration*, 0.3), maximum freefall distance (*Freefall Maximum*, 0.25) and the maximum peak-to-peak vector acceleration (*Acceleration V Max*, 0.096) illustrate a weak correlation with the DIS metric. These observations are to be expected given that the DIS is a function of kinetic energy (velocity and acceleration) and the freefall distance that under typical operating conditions remain approximately constant.

Linear relationships do not define an accurate model with which the packhouse classification can be reliably predicted. The freefall count only provides a R^2-value of 0.55 for the packhouse classification (DIS), equating to 46% accuracy. To this end, a simplified FCNN (Goodfellow et al., 2016) architecture is proposed, incorporating the following input variables that are suitable for online (real-time) computation of the packhouse DIS: processing duration, vector rotation count, freefall count, freefall mean and maximum distance, 50th, 75th, 99th percentile and standard deviation peak-to-peak vector acceleration (9 variables). The model was developed using TensorFlow (Abadi et al., 2015) and Python. The model consists of an input vector layer (9 input variables), three densely connected hidden layers (ReLU activation) with 16, 24 and 8 neurons respectively, and an output layer (softmax) consisting of four nodes, each corresponding to a different DIS. This configuration equates to a total of 804 trainable parameters, suitable for edge intelligence applications (Deng et al., 2020). During training, two dropout layers (15% dropout) were included in-between the three hidden layers, improving the test accuracy marginally. A test-train ratio of 70% to 30% was selected for training using randomized sampling of the dataset, with the training dataset subdivided for a train-validation ratio of 75% to 25%. The loss function was defined for categorical cross entropy, using the RMSProp optimizer. Training proceeded with a batch size of 8 for a total of 200 epochs. Increasing the number of epochs resulted in overfitting of the model due to the limited size of the dataset.

During training, a training and validation accuracy of 91% and 81% respectively were reported. The classification accuracy of the trained model using the test dataset yielded an accuracy of 82% (Fig. 25). The classification accuracy surpasses of the neural network surpasses that of the linear regression model by a significant margin, establishing the groundwork for future integration of an accurate classification model for the next generation of intelligent sensor platforms.

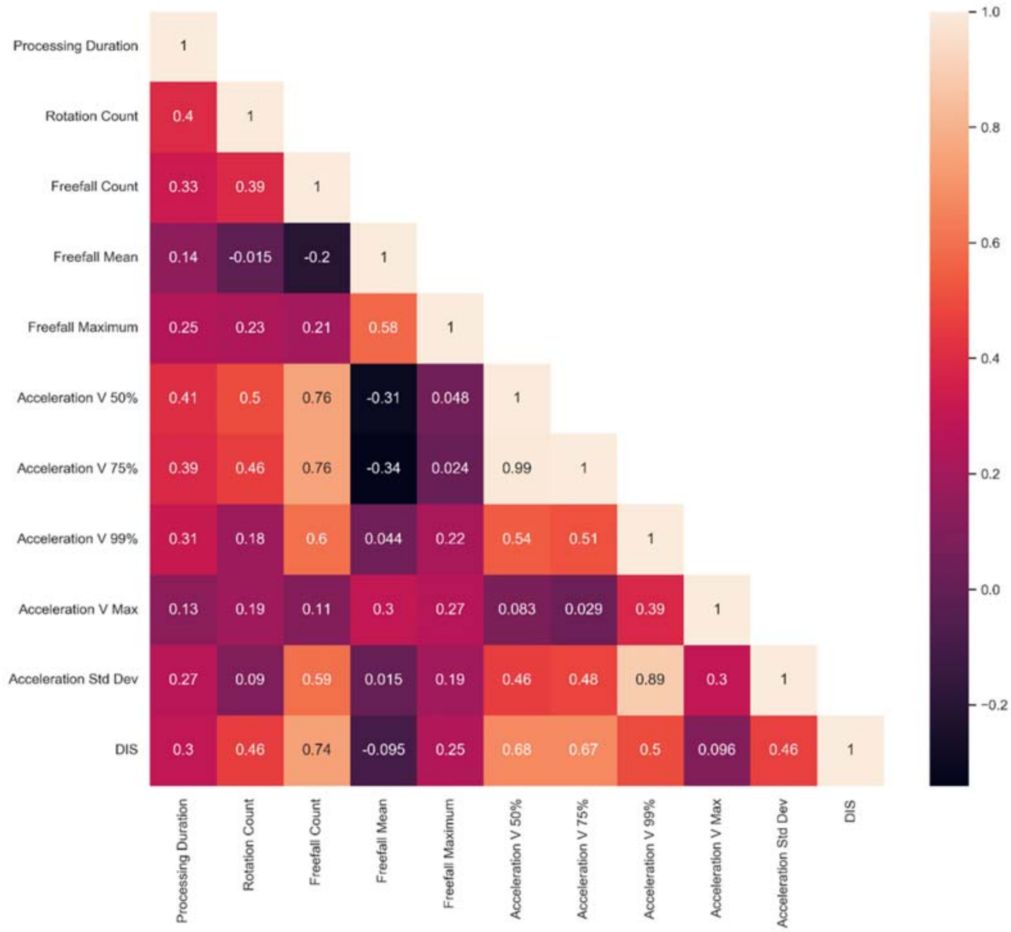

Fig. 24. Correlation matrix of the per-sample Smavo statistics

Ground Truth DIS				Inference DIS Classification				
1	2	3	4	1	2	3	4	Correct?
1.00	0.00	0.00	0.00	0.97	0.00	0.03	0.00	√
0.00	1.00	0.00	0.00	0.00	0.95	0.01	0.03	√
0.00	0.00	0.00	1.00	0.00	0.04	0.04	0.93	√
1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	√
0.00	0.00	0.00	1.00	0.48	0.52	0.00	0.00	
1.00	0.00	0.00	0.00	0.88	0.00	0.12	0.00	√
0.00	1.00	0.00	0.00	0.50	0.50	0.00	0.00	
0.00	1.00	0.00	0.00	0.00	0.01	0.02	0.98	
1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	√
0.00	0.00	0.00	1.00	0.00	0.32	0.07	0.61	√
1.00	0.00	0.00	0.00	0.16	0.15	0.58	0.11	
1.00	0.00	0.00	0.00	0.96	0.00	0.04	0.00	√
1.00	0.00	0.00	0.00	0.98	0.02	0.00	0.00	√
0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	√
0.00	0.00	0.00	1.00	0.00	0.01	0.03	0.96	√
0.00	1.00	0.00	0.00	0.90	0.10	0.00	0.00	
0.00	0.00	1.00	0.00	0.03	0.93	0.03	0.02	
1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	√
1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	√
1.00	0.00	0.00	0.00	0.99	0.01	0.00	0.00	√
0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	
0.00	1.00	0.00	0.00	0.01	0.89	0.05	0.06	√
1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	√
0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	√
1.00	0.00	0.00	0.00	0.80	0.02	0.18	0.00	√
0.00	1.00	0.00	0.00	0.03	0.67	0.30	0.00	√
0.00	0.00	0.00	1.00	0.00	0.02	0.05	0.93	√
1.00	0.00	0.00	0.00	0.91	0.00	0.09	0.00	√
0.00	1.00	0.00	0.00	0.00	0.97	0.01	0.02	√
1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	√
1.00	0.00	0.00	0.00	0.90	0.00	0.10	0.00	√
0.00	1.00	0.00	0.00	0.00	0.96	0.00	0.03	√
0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	√
1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	√
0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	√
1.00	0.00	0.00	0.00	0.73	0.00	0.27	0.00	√
0.00	1.00	0.00	0.00	0.00	0.24	0.06	0.69	
1.00	0.00	0.00	0.00	0.86	0.13	0.00	0.00	√
1.00	0.00	0.00	0.00	0.97	0.00	0.03	0.00	√
0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	√

Fig. 25. Sample test data comparing the DIS ground truth (left) and the neural network inference (right) results

7. Conclusions

Research to date have shown the value in pursuing postharvest optimization of fresh produce in the postharvest sector. Smavo (short for smart avocado), an intelligent sensor platform, was developed specifically to instrument the agricultural transportation chain. The Smavo sensor platform has met its original design specifications to record accurate, high-frequency acceleration and rotational velocity data, quantifying postharvest stress incurred. The instrumentation has been extensively tested, validated and iteratively improved to accommodate the challenging environment characteristics associated with a packhouse, whilst allowing for repeatable measurements, requiring minimal technical training to deploy in the field. Using multiple Smavos in a controlled environment validated the repeatability of the data along with required reliability and accuracy of the sensor measurements. A total of 24 packhouses, spread over the KwaZulu-Natal, Limpopo and Mpumalanga provinces, accounting for varied processing capacities, degree of mechanization and containers selection (bins and crates), were successfully instrumented throughout the 2020 harvesting season. Consistent and representative data were collected by trained instrumentation operated tasked with the field work.

Post-processing of the collected data generated representative statistics pertaining to the vector axis acceleration (incorporating all three orthogonal acceleration axes), and peak-to-peak vector accelerations, freefall events and freefall distance, Cumulative Kinetic Energy (CKE), vector rotation and Damage Index Score (DIS) which combined, describe both the characteristic operating environment of the respective packlines. The statistics are combined to compare every packhouse relative to the larger sampled population. Every packhouse can be classified and grouped relative to the larger population of packhouses, referred to as the Packhouse Processing Quadrant (PPQ).

This classification or ranking identifies packhouses that can be optimized or improved to increase the quality of the avocadoes, based on information gained from the larger population of packhouses, some of which are classified as optimized based on the measurements. A DIS of 1 is considered an optimized packhouse, whereas a DIS of 4 is considered an unoptimized packhouse. Mechanical rollers were identified as one of the most detrimental elements of the packline, inducing prolonged, high amplitude accelerations. In addition, the duration that the Smavo was subject to this motion and rotation, varied substantially for a given packhouse. Optimized packhouses (packlines) with smaller diameter rollers rotating at a slower rotational velocity (compared to unoptimized packhouses) are associated with improved postharvest stress statistics (DIS). The negative effects of the mechanical rollers are amplified by the inconsistent volume of avocadoes moving through the packline, leading to idling of the avocadoes. On average, bin containers exhibit a marginally reduced DIS compared to crates. These results are a by-product of smaller processing volumes and less sophisticated mechanized operation for the bin operations. Loading methods employing dipping of the avocadoes at the start of the packline eliminates freefall and high-intensity, inter-avocado accelerations.

8. Recommendations, Limitations and Future Development

One of the easiest changes to implement remain adequate training of packline staff who are responsible for handling and sorting the avocadoes to reduce as many instances of freefall and impact forces as possible, as also identified by Opara & Pathare (2014). This extends to the management of the avocado flux moving through the packline to avoid stoppages leading to prolonged flotation of the avocadoes in the water, a higher probability of infection and the idling of the avocadoes in the mechanical rollers. Geographical differences were also identified among the three provinces, the underlying causes of which remain unclear.

A neural network model (82% accuracy) was developed to predict the DIS of a given packhouse based on a selection of statistics, outperforming the best linear models (46% accuracy). This neural network provides the starting point for more accurate and integrated instrumentation of packhouses, reducing the reliance on large quantities of raw data. Instead, it incorporates real-time calculation of relevant statistics that can be relayed autonomously throughout the packline for the realization of closed-loop control systems and true digital twins. Further improvements in the accuracy of the robustness of such a model can be realized if the dataset is expanded to increase the number of data samples.

New generations of microcontrollers provide the ability (and processing capacity) to deploy small neural networks as part of the integrated sensor platform for applications suited to the agricultural industry. Emerging long-range wireless communications are ideally suited for the development of the next generation of intelligent, power efficient Smavos, alongside automation and improved condition monitoring of packhouses in a cost effective and scalable manner. This study did not consider other aspects related to the environmental parameters of the packhouses (water temperature, ambient temperature and relative humidity) or the different avocado cultivars present varied sensitivity to postharvest stress.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

This work was supported by the South African Avocado Growers Association (Project 33/19) (South Africa), the Tomato Producers Organization (Project 29/19) (South Africa), the DST Post Harvest Innovation Programme (Projects 29/19 and 33/19) (South Africa) the National Research Foundation (Project 119797) (South Africa) and ZZ2 (South Africa).

Acknowledgements

We gratefully acknowledge the guidance and expertise provided by the following persons and institutions: Sarel Coetzer and David Ventura for successfully undertaking the extensive instrumentation program of the avocado packhouses; Prof. Lise Korsten and Dr. Malick Bill (Department of Plant and Soil Sciences, University of Pretoria) during the development phase of the instrumentation and interpretation of the results; Johannes Grobler, Hendus Janse van Rensburg and Frannes Joubert (ZZ2) for their assistance during the initial field trials and calibration using their facilities; Wikus Steyn (Department of Electrical, Electronic and Computer Engineering, University of Pretoria) for his assistance and provision of 3D printing hardware to fabricate the 3D printed Smavo enclosures; Ken Burns (TinyCircuits) for his assistance in shipping the TinyDuino hardware to South Africa.

CRediT authorship contribution statement

André Broekman: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Roles/Writing - original draft. **Wynand JvdM Steyn**: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing - review & editing.

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