

How Stable is a Pallet? A Framework for Analyzing the Dynamic Stability of Stacked Pallets

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Abstract—Pallets are a primary means of storing and transporting industrial goods. In this paper, we propose an evaluation framework to examine the dynamic stability of a stacked pallet, with key considerations on the spatial arrangement and the dynamic loading state of how different items or Stock Keeping Units (SKUs) of varying dimensions and weights are stacked on a pallet. We compare different pallet stacking patterns generated using well-cited 3D-bin packing (3DBPP) and mixed palletization algorithms to check the viability of the proposed evaluation methods. Our comparative study suggests that a dynamically stable pallet can guarantee static stability, whereas the contrary is false. We expect that the proposed stability analysis framework will enable practitioners to objectively compare and evaluate the practical performance of various pallet loading pattern generator algorithms (for mixed-dimensional SKUs) and mixed-palletization systems.

I. INTRODUCTION

The Fifth Industrial Revolution (Industry 5.0) [1] is a new and evolving transformative phase of industrialization where humans and intelligent systems (e.g., machines, robots, digital services) collaborate synergistically to realize production processes that can achieve high productivity, optimal quality, and sustainable human-centricity. A key process relevant for Industry 5.0, especially in manufacturing and logistics, is the intelligent packing of objects or Stock Keeping Units (SKUs) of mixed dimensions and weights inside bins (also of different dimensions), with additional specifications to ensure stability and safety; this is also known as the three-dimensional bin packing problem (3DBPP) [2]–[6]. 3DBPP solutions typically generate a plan or a feasible 3D stacking pattern of SKUs to be placed inside a bin. This plan or stacking pattern can be used by human workers and/or robots to collaboratively perform the physical loading of SKUs, potentially reducing overall loading time and operational costs while increasing throughput.

The classical 3DBPP [2], [3] is an optimization problem in which objects or items of varying sizes and weights must be packed within the boundary of the bin in such a way that the maximum number of items is stacked while the unutilized volume within the bin is minimized [4]. Moreover, 3DBPP can be approached as an offline or online optimization problem depending on context. In the offline context [6], [7], the SKU information (such as dimension, weight, and quantity) is known in advance. However, in the online planning situation [8], no prior information is known

about the SKUs to be loaded; so, the algorithm must decide the 3D placement location of each SKU during runtime, as and when they arrive for loading. Given the complexities of both online and offline contexts, 3DBPP is considered an NP-hard problem [9].

Furthermore, among the several 3D bin structures typically used in industrial applications [4], [5] (e.g., carton boxes, shipping containers, air cargo containers, etc.), stacking of SKUs on pallet can be considered the most challenging task [6], as a pallet only contains a base structure with no side walls. Hence, while planning an optimal stacking pattern for a mixed pallet with SKUs of varying sizes and weights, the algorithm must prioritize the optimal weight distribution of SKUs across the pallet to ensure static stability [10] while best utilizing the available volume. However, even in the case of a statically stable stacked pallet with mixed SKUs, a slight physical disturbance (which is common during logistics and transportation) [10] can agitate the stacking pattern and the pallet to become unstable, which can lead to falling of SKUs and irreversible SKU damages. Therefore, in addition to static stability, the dynamic stability concerns [11] must also be addressed while generating the stacking pattern.

Several studies have contributed significantly to improving the static stability of mixed SKUs stacking on a pallet. In [2], the authors offer a greedy randomized adaptive search approach using the wall-building algorithm to produce a stable pallet with heterogeneous SKUs. The mixed integer programming concept is introduced in [3] to solve the 3DBPP, emphasizing palletization stability, and its feasibility is assessed via physical experiments. A novel formulation with a column-generation framework based on pallet layers to generate a tight, static stabilized pallet with mixed SKUs is introduced in [4]. In [5], the authors formulate the 3DBPP using practical limitations such as vertical support, load bearing, planogram sequencing, and weight limits. Moreover, an instance generator algorithm is conveyed to generate a static stabilized pallet pattern for heterogeneous industrial SKUs. In [8], the physical stability of the pallet and rotation limitations of the SKUs are included in a constrained Markov decision process that serves as a deep reinforcement learning approach for solving an online 3DBPP.

A novel method with experimental validations of the static stability of a palletized cargo wrapped in stretch film under laboratory conditions is introduced in [11]. The trials show that a proper selection of stretch film and a cargo wrapping model significantly reduces the risk of cargo damage. In [6], the authors propose a metaheuristic-based planning algorithm for a set of mixed SKUs to generate feasible pallet configu-

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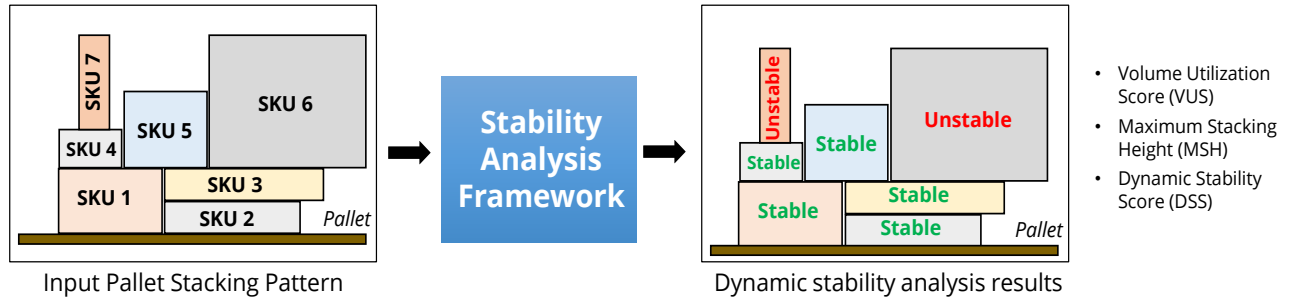


Fig. 1: Proposed framework to perform a stability analysis of stacked mixed-SKU pallets with dynamic responses

rations that satisfy the practical constraints such as load bearing, stability, height homogeneity, overhang, weight limits, and robotized layer picking. The 3D-Single Bin-Size BPP (3D-SBSBPP) and layer-building heuristics are formulated using mixed integer linear programming (MILP) to generate high-quality bin configurations with high temporal efficiency.

An evaluation framework to check the static stability of a pallet using rigid body simulation is introduced in [10], where the packing plan is considered as a directory. The resulting packing lists contain the location, orientation, and front-left-bottom (FLB) coordinates of an SKU. Volume utilization score, maximum stacking height, average of support areas (all SKUs), interlocking ratio, and the physical stability score (stacked SKUs) are considered while analyzing the static stability. In [7], a hybrid quantum-classical framework is proposed to address real-world 3DBPP while considering the bin dimension, weight constraints, SKU features, and SKU ordering priority. It is tested for twelve distinct cases to show its viability under real-world constraints.

The aforementioned studies mostly consider the static stability of a stacked pallet. However, during transportation, even a small disturbance may cause one or more SKUs to fall from the pallet [12]. Therefore, while packing a pallet with mixed SKUs, it is also necessary to consider the dynamic stability aspect [13] of each SKU in addition to the static stability. Furthermore, the logistics and manufacturing sectors are looking for an evaluation software [10], [14] to assess the dynamic stability of individual SKUs of a planned (stacked) pallet before physical loading, thus assisting a human operator to properly locate an SKU or SKUs that may fall (from pallet) during transportation. In light of these difficulties, in this paper, we offer a generalized framework for qualitatively analyzing the static stability of a stacked pallet (with mixed SKUs) and the dynamic stability of individual SKUs as presented in Fig. 1. In particular, we make the following key contributions.

- 1) We formulate a novel dynamic behavior of an SKU (positioned on top of another SKU or SKUs) of a stacked pallet pattern (Fig. 1) using the concept of stacked rigid block dynamics [15]. Then, we examine the dynamic response of that SKU by a small impulse disturbance. Depending on the response, we distinguish whether that particular SKU is stable or unstable, followed by a score. The proposed strategy

has been executed for every SKU (stacked within the pallet) to find a normalized score.

- 2) We evaluate several pallet-stacking-pattern-generation algorithms with mix-dimensional SKUs and compare their static performance metrics and dynamic stability scores to identify the best stacking pattern. To the best of our knowledge, such an evaluation framework is not available in the literature till date.

The rest of the paper is organized as follows: In Sec. II, we formulate the dynamic stability aspects of a stacked pallet. We further analyze the dynamic responses in Sec. III, followed by a scoring assignment. We discuss our evaluation results in Sec. IV and conclude our work in Sec. V.

II. ANALYZING DYNAMIC STABILITY OF A STACKED PALLET

Considering a stacked pallet with n number of SKUs as shown in Fig. 1, the dimensions (i.e., length, breadth, and height) and weight of the i^{th} SKU are (l_i, b_i, h_i) , and m_i respectively. Moreover, the location of the left-most point of the i^{th} SKU (within the pallet) with respect to the pallet coordinate frame (PCF) is assumed to be (x_i, y_i, z_i) . So, the location coordinate of its Center of Gravity ($CG_i \in \mathbb{R}^3$) from PCF would be

$$CG_i = \left[\left(x_i + \frac{l_i}{2}\right) \quad \left(y_i + \frac{b_i}{2}\right) \quad \left(z_i + \frac{h_i}{2}\right) \right] \quad (1)$$

So, combining n number of SKUs, the location coordinates of all the CG points will be

$$CG = [CG_1 \quad CG_2 \quad \dots \quad CG_n]^T \in \mathbb{R}^{n \times 3} \quad (2)$$

In the context of palletization [10], [13], the loading sequence of SKUs (on the pallet) at resting condition is referred to as static stability, which means that no SKU will fall from the pallet after stacking. On the other hand, dynamic stability describes how the SKUs are stacked so that under a minor disturbance, such as during pallet transport, the stacked SKUs can endure the inertia of their bodies. Therefore, it is a well-known fact that a statically stable pallet needs not always be dynamically stable; however, the contrary is always true. So, in this paper, we develop an evaluation framework to determine the dynamic stability score of a stacked pallet (as shown in Fig. 2(a)) under the presumption that if the SKU stacking pattern (of a pallet) is dynamically stable, then, it should be statically stable.

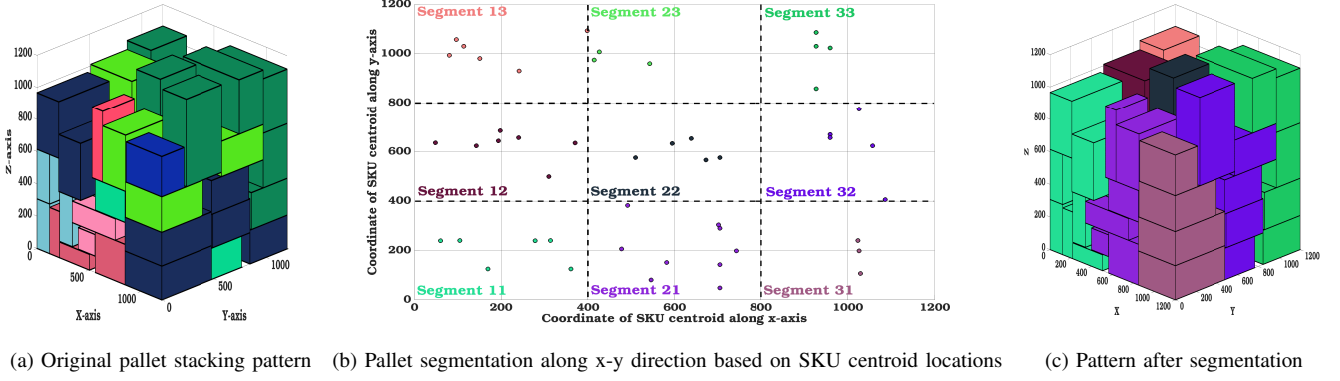


Fig. 2: Determining the outermost layer of a stacked pallet

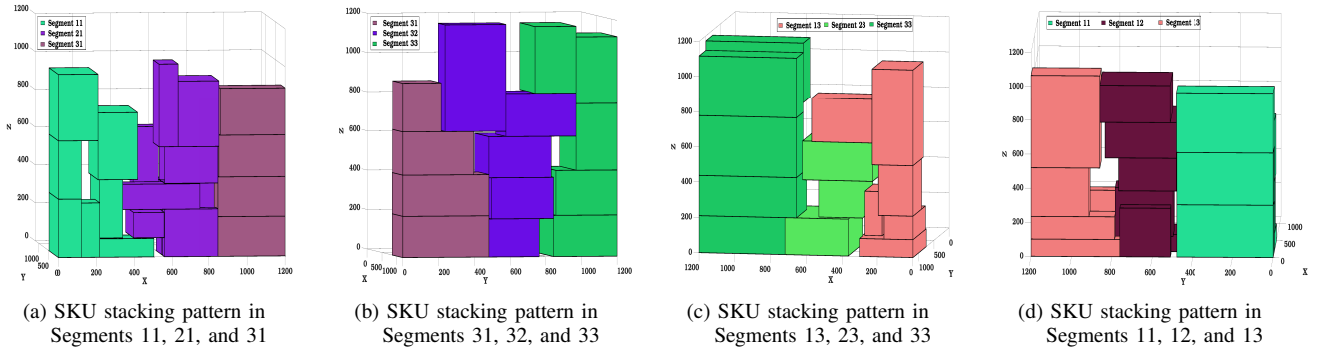


Fig. 3: Segment-wise SKU stacking pattern in each of the pallet segments of the outermost layer of the pallet

A. Determining SKUs at the outermost layer

To analyze the dynamic stability, first, we need to consider the SKUs placed at the outermost layer of the pallet. Because, given a disturbance condition, if any SKU cannot withstand the inertia of its body, it will fall (as it does not have adequate support from its neighbors). Consequently, the stacking pattern of the pallet becomes dynamically unstable.

To identify the SKUs, positioned at the outermost layer of the pallet, we divide the pallet's x and y axes into m equal parts; thus, the total number of segments will be m^2 . Hence, the location coordinates of the *four* corner points of the $(j \times l)^{th}$ segment will be:

$$p^{j,l} = \begin{bmatrix} \frac{(j-1)L_P}{3} & \frac{jL_P}{3} & \frac{jL_P}{3} & \frac{(j-1)L_P}{3} \\ \frac{(l-1)B_P}{3} & \frac{(l-1)B_P}{3} & \frac{lB_P}{3} & \frac{lB_P}{3} \end{bmatrix}^T \quad (3)$$

where, L_P and B_P represent the length and breadth of the pallet. Fig. 2(b) shows an example with 9 pallet segments.

Now, considering the location coordinates of the SKU centroids (Eq. 2) and the pallet segments (Eq. 3), we determine which centroid corresponds to which segment (Fig. 2(b)). Subsequently, depending on this centroid-segment map, we identify the SKUs that belong to the outermost layer of the pallet. For the stacking pattern in Fig. 2(a), its corresponding outermost SKUs are presented in Fig. 2(c). Given the outcome of this step, we can assume that the $(j \times l)^{th}$ segment

contains a set of SKU-centroids (namely, S_{jl}) as in Eq. 4:

$$S_{jl} = \{CG_k, CG_{k+1}, \dots, CG_{k+r}\} \subset CG \quad \& \quad r \in \mathbb{Z} \quad (4)$$

Thus, Eq. 4 represents the SKUs that are in the outermost layer of the $(j \times l)^{th}$ segment of the pallet (Fig. 2(c)). For the stacking pattern of Fig. 2(a), its corresponding patterns in each of the pallet segments are shown in Fig. 3. The four sub-figures Fig. 3(a), 3(b), 3(c), and 3(d) represent the SKU stacking pattern for the pallet segment sets (11, 21, 31), (31, 32, 33), (13, 23, 33), and (11, 12, 13) respectively.

After obtaining the SKU stacking pattern in each of the segments, we need to simulate the dynamic response of each SKU (in each segment) to determine the dynamic stability score, as discussed in the next section.

III. FORMULATION OF DYNAMIC RESPONSE

The dynamic response of an SKU can be examined by evaluating the response (of that SKU) subject to a disturbance across the pallet base. In this work, we specifically presume that no disturbance exists along the z -axis, and any SKU (placed on either the pallet base or another SKU) will not slide due to the disturbance. Let us assume that two SKUs a and b are stacked on a pallet as shown in Fig. 4(a), where b is placed on top of a . The dimension, weight, and moment of inertia of the SKUs a and b are $[(l_a, b_a, h_a), m_a, I_a]$ and $[(l_b, b_b, h_b), m_b, I_b]$ respectively. The horizontal and vertical

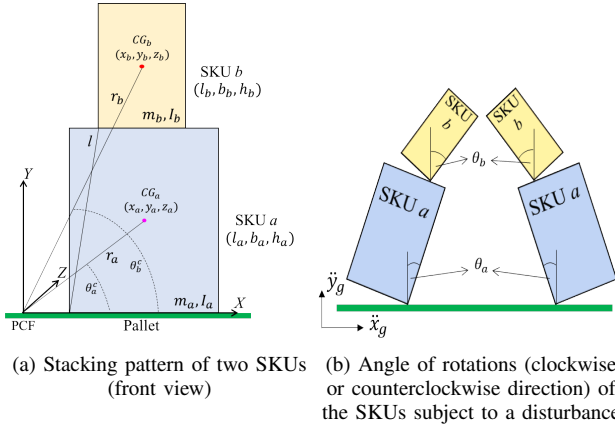


Fig. 4: Dynamic response of SKUs subject to a disturbance

components of disturbance (across the pallet base) are $\ddot{x}_g$ and $\ddot{y}_g$ respectively. So, in order to initiate the motion, the magnitude of disturbance should obey the following condition:

$$-H\ddot{x}_g - l_a\ddot{y}_g > l_a g \quad (5)$$

where, $H = \frac{m_a b_a + m_b (2b_a + b_b)}{m_a + m_b}$. As a result of the disturbance, each SKU creates an angle of rotation (either clockwise or counterclockwise direction) from the y-axis of PCF (Fig. 4(b)). θ_a and θ_b are the angles of rotations of SKU a and b respectively. So, depending on the above considerations, the dynamic equations (in linearized form) of the angles of rotations (of the SKUs) can be derived¹ as follows:

$$\begin{aligned} I_a \ddot{\theta}_a + m_b r_b l \cos(S(\theta_b) \theta_b^c) \ddot{\theta}_b + S(\theta_a) m_a r_a g \sin \theta_a^c = \\ -m_a r_a \cos \theta_a^c \ddot{x}_g - S(\theta_a) m_a r_a \sin \theta_a^c \ddot{y}_g \\ m_b r_b l \cos(S(\theta_b) \theta_b^c) \ddot{\theta}_a + I_b \ddot{\theta}_b + S(\theta_b) m_b r_b g \sin \theta_b^c = \\ -m_b r_b \cos \theta_b^c \ddot{x}_g - m_b r_b S(\theta_b) \sin \theta_b^c \ddot{y}_g \end{aligned} \quad (6)$$

where, r_a , r_b are the distances and θ_a^c , θ_b^c are the angles of the CG-points of the SKU a and b respectively from the origin of PCF (Fig. 4(a)), l is the distance between the left-most corner points of the two SKUs, g is the gravitational acceleration, and the function $S(\theta)$ defines a signum function

$$S(\theta) = \begin{cases} -1, & \text{for } \theta < 0 \\ 0, & \text{for } \theta = 0 \\ 1, & \text{for } \theta > 0 \end{cases} \quad (7)$$

After formulating the dynamic model, our goal now is to simulate the response of each SKU (in each segment) subject to a disturbance. Before performing this step, we need to sort the SKUs (within a segment) based on layers, i.e., for a specific segment, the SKU that is directly on the pallet base should be the first element, whereas the SKU on the top layer of the pallet would be the last element. So, the outcome of this step can be formulated as (assuming the $(j \times l)^{th}$ segment):

$$SS_{jl}^{(sort)} = \{SKU_{k+p_1}, SKU_{k+p_1+p_2}, \dots\} \quad (8)$$

¹A detailed derivation can be found in [15]

such that, $(p_1 + p_2 + \dots) = r$ (Eq. 4), and $CG_{k+p_1}^z < CG_{k+p_1+p_2}^z < \dots$, where, CG_i^z defines the coordinate along z-axis (Eq. 1). So, Eq. 8 represents that SKU_{k+p_1} is the first SKU on the pallet, followed by $SKU_{k+p_1+p_2}$ and so on for the $(j \times l)^{th}$ segment. To simulate the response for each SKU, we can execute the steps in Algorithm 1.

Algorithm 1 Generating dynamic response of SKUs

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1: define  $d$  // Impulse disturbance
2: define  $SKU_a = \emptyset$ ,  $R = \emptyset$ 
3: for  $i = 1, 2, \dots$  do
4:    $SKU_a = SKU_a + SKU(i)$ 
5:    $SKU_b = SKU(i + 1)$ 
6:    $[P_a, P_b] = \text{CalculateSKUparams}(SKU_a, SKU_b)$ 
7:    $R(i + 1) = \text{EvaluateDynaResponse}(P_a, P_b, d)$ 
8: end for

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The CalculateSKUparams function is utilized to generate SKU parameters, such as dimensions, weight, inertia, etc. The EvaluateDynaResponse function (as formulated in this section) is called to simulate the dynamic response of the i^{th} SKU (for the impulse disturbance d). R contains the simulation outcome. To get the final result, we obtain the dynamic responses of all SKUs within the pallet.

By considering the response of an SKU, we can infer that the placement of an SKU will be considered stable if its angle of rotation (Eq. 6) returns to the steady-state value when the disturbance is eliminated. Moreover, the stability (of an SKU) is also dependent on the time of convergence of the angle of rotation to the steady-state value. So, as per these criteria, we need to assign stability scores in each of the SKU's dynamic responses to inspect the overall stability of the pallet, as discussed in Section III-A.

A. Assigning score to the dynamic response

The angle of rotation of an SKU can show three possible responses: (a) *Stable*: the angle returns to a steady-state value once the disturbance is released, (b) *Oscillatory*: the angle is oscillating even after disturbance is dismissed, and (c) *Unstable*: the angle is not approaching a steady-state value, i.e., unbounded response. Given these possible responses, we assign the stability score (S_i) of the i^{th} SKU as follows:

$$S_i = \begin{cases} 1, & \text{if stable response} \\ 0, & \text{if unstable or oscillatory response} \end{cases} \quad (9)$$

So, the overall dynamic stability score (DSS) of the pallet (considering n number of SKUs) can be formulated as

$$DSS = \frac{1}{n} \sum_{i=1}^n S_i \times 100\% \quad (10)$$

The efficacy of the proposed evaluation framework and the comparison of various pallet stacking patterns (generated using different algorithms) are demonstrated in Section IV.

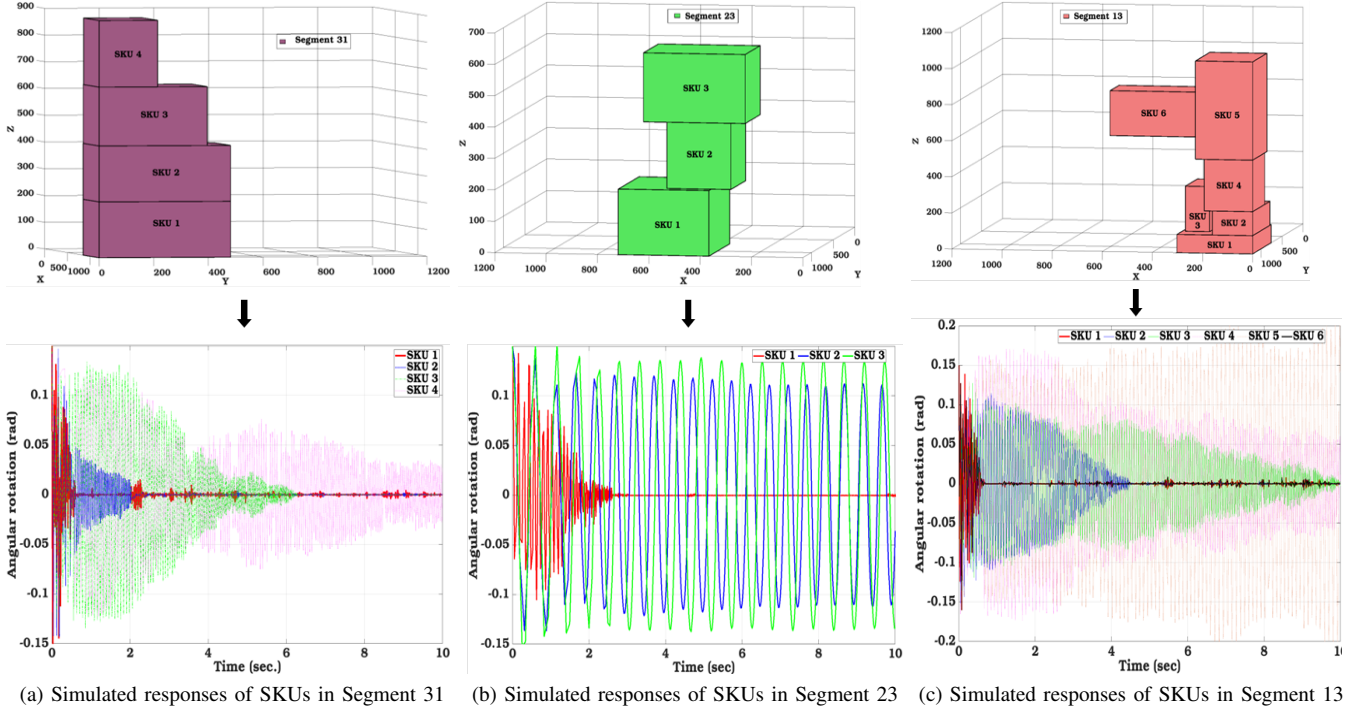


Fig. 5: Simulated dynamic responses of SKUs (in different segments) of the stacked pallet pattern in Fig. 2

IV. RESULTS & DISCUSSIONS

The proposed framework has been evaluated and studied through a 3DBPP simulation using MATLAB 2018b software on a computer with *Intel Core i7* CPU and 16 GB of RAM. A public benchmark dataset is used for this study [16], with a standard pallet of dimensions 1200mm×1200mm×1200mm. Furthermore, in order to simulate the dynamic response, a disturbance model is created with a short duration (50 msec.) impulse signal.

A. Dynamic response analysis

To examine the dynamic responses (of SKUs) of the stacked pallet as displayed in Fig. 2, we need to execute the algorithm 1 to generate the angle of rotation response for a duration of 10 seconds for each SKU. The stacking pattern of SKUs and their corresponding responses are presented in Fig. 5. From Fig. 5(a), it is observed that four SKUs (of Segment 31) are stacked adequately. Hence, all the SKUs generate stable responses (i.e., the angle of rotations returns to the steady-state value once the disturbance is removed from the system). For the stacking pattern in Segment 23 (Fig. 5(b)), the dynamic responses represent that SKU 1 is stable, whereas, SKUs 2 and 3 generate oscillatory responses, with the amplitude of oscillation of SKU 3 being greater than SKU 2. Finally, the dynamic responses of six SKUs (Segment 13) demonstrate that SKUs 1, 2, 3, and 6 are exhibiting stable responses, however, the remaining SKUs generate oscillatory or unstable responses (Fig. 5(c)). Evaluating DSS (Eq. 10) in each of the cases, we obtain a stability score of 100% for segment 31, 33.33% for segment

23, and 66.67% for segment 13 respectively. Considering the outcomes of the above evaluation (as illustrated in Fig. 5), we perceive that the proposed model in Eq. 6 can mimic the angle of rotation (due to a disturbance) of an SKU based on the dimension, weight, inertia, and location information. Hence, by employing such a framework, the stability of a stacked pallet with mixed SKUs of different dimensions, can be assessed efficiently.

TABLE I: Comparative analysis on datasets from [16]

dataset	metric	pattern [7]	pattern [10]	pattern [6]
3dBPP_1	VUS (%)	83%	91%	74%
	MSH (unit)	1200	1144	1123
	DSS (%)	67%	59.8%	75.1%
3dBPP_3	VUS (%)	79%	88%	69%
	MSH (unit)	1001	1123	808
	DSS (%)	69%	55%	74.9%
3dBPP_5	VUS (%)	75%	84%	68%
	MSH (unit)	1054	1014	1007
	DSS (%)	70%	43%	77%
3dBPP_7	VUS (%)	76%	83%	68%
	MSH (unit)	1091	1181	1080
	DSS (%)	69%	54%	79%

B. Comparative analysis

To demonstrate the usefulness of the proposed framework to examine dynamic stability, we use dataset [16] and compare the stacking patterns generated by three different algorithms from recent literature, viz., [6], [7], and [10]. The results are in Fig. 6, and Table I. The stacking pattern (generated from [7]) shows few instances of spacing between

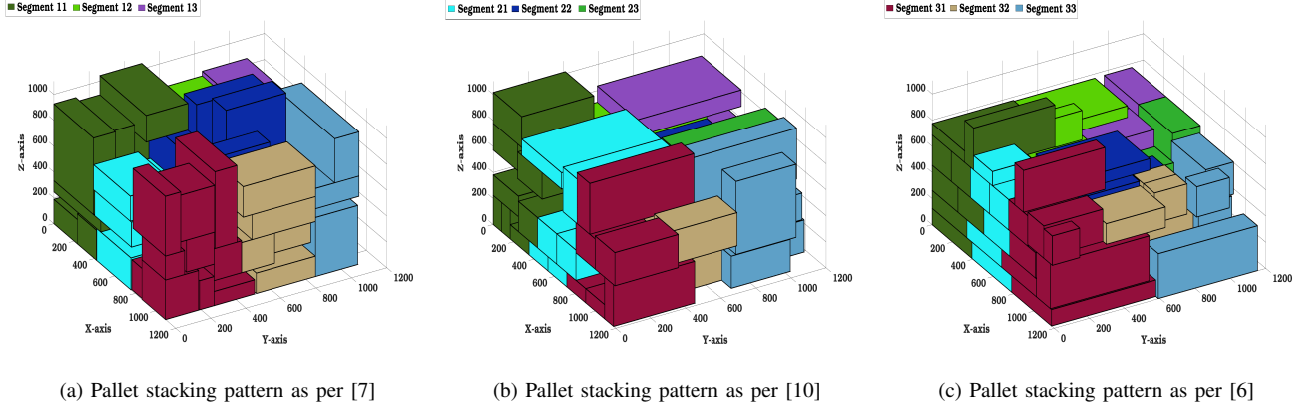


Fig. 6: Comparison of pallet stacking patterns generated by 3 algorithms on benchmark dataset instance 3dBPP_5 [16]

two SKUs placed vertically, causing the top SKU to appear to be floating on the pallet. The stacking pattern formed by [10] (Fig. 6(b)) has even more gaps. The stacking pattern in Fig. 6(c) (generated based on the algorithm of [6]) has higher stability than from [7] or [10].

We perform our quantitative analysis on four distinct datasets [16] by employing the aforementioned algorithms. The outcomes are illustrated in Table I. To compare the stacking patterns generated from these algorithms, we use three performance metrics, viz., Volume Utilization Score (VUS), Maximum Stacking Height (MSH), and Dynamic Stability Score (DSS) (Eq. 10). VUS is the ratio of the sum of volumes of all SKUs loaded on the pallet and the maximum allowed volume (capacity) of the pallet, as a percentage. MSH is the maximum height of the stacked pallet.

If the number of SKUs is fixed, then, low VUS, low MSH, and high DSS indicate an optimal stacking pattern. From the results, it is seen that the stacking pattern produced from [6] is better than the other methods (in terms of VUS and MSH) for all the datasets. Moreover, the DSSs as derived from our proposed framework also display a similar trend. Considering these results, we can conclude that the proposed framework can be used to compute a good estimate of the dynamic stability of a stacked pallet to facilitate comparisons.

V. CONCLUSION

This work presents an evaluation framework to analyze the dynamic stability of a stacked pallet with mixed-dimensional SKUs. We first analyze the segmentation of pallet regions and the dynamic stability (subject to a disturbance) for each SKU and assign a dynamic stability score when loading each SKU. We then combine the SKU scores to obtain a normalized dynamic stability score for a given stacking pattern. Furthermore, we compare the stacking patterns generated by different algorithms on a public benchmark dataset and check the usefulness of the proposed strategy. From our study, we can observe that a stacked pallet, if dynamically stable, should also be statically stable. We believe this technique offers a novel means of objectively evaluating the performance of different high-mix palletization systems (even with pallets

of unequal dimensions and different weight distributions) and their stacking pattern generation algorithms.

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