The impact of design criteria on Automated Storage and Retrieval Systems performance: a Design-of-Experiments approach

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Abstract: Automated Storage and Retrieval Systems (AS/RS) have garnered significant attention in both industrial and academic domains due to their ability of enhancing logistics processes in terms of operational and economic efficiency and effectiveness. AS/RS usually requires medium to long-term commitment, and for this reason logistics managers are compelled to assess the impact of AS/RS design criteria on their performance. However, testing a real-life AS/RS before installing it would be too impractical, and thus this task is typically carried out with computer-based scenario simulations or via analytical formulations. These methods provide ex-ante evaluations that should be complemented by ex-post validation of their outcomes, an area where more approaches are needed in the logistics literature. In response to this gap, this paper proposes a Design-of-experiments (DoE) approach applied to a real-life AS/RS installed in a laboratory environment. To this end, the impact of two major design criteria (i.e., AS/RS size and load units' type and weight) on one performance measure (i.e., Cycle Time) are explored. This work engenders both managerial and theoretical implications. For the former, this work may provide logistics managers with robust results to inform their investment decisions; for the latter, the proposed approach can be used to improve the accuracy of both simulation models and mathematical formulations for ex-ante measurement of AS/RS key performance indicators.

Keywords: Design-of-Experiments, Automated Storage and Retrieval Systems (AS/RS), Cycle time.

1.Introduction

The increasing prominence of supply chain challenges, such as rising ecommerce and supply disruptions, has propelled warehousing automation into the spotlight within the practitioner and academic communities (Narsana e Kinra 2022; Kumar, Narkhede, e Jain 2021). Automated Storage and Retrieval Systems (AS/RS) are in fact widely used in various industrial contexts due to their capability of enhancing the efficiency of logistics processes (Vorasawad, Park, e Kim 2023). Generally, AS/RS are characterized as computer-controlled systems that autonomously store and retrieve goods from designated storage locations through mechanical devices (Hameed, Rashid, e Al Amry 2020).

Designing an efficient AS/RS is essential for optimizing operations and maximizing productivity (Kumar, Narkhede, e Jain 2021). Furthermore, AS/RS require significant long-term investments, leading logistics managers to meticulously evaluate the impact of design criteria on the performance levels of AS/RS before their implementation. Therefore, ex-ante performance appraisal methodologies comprise a massive share of the literature on AS/RS (Lagorio et al. 2020). Within these methodologies we can cite, for example, computer-based simulations (see a recent literature review by Ferrari & Mangano (2023)) or analytical formulations (Xu et al. 2016; 2020; Lehmann e Huß 2021).

Some authors have argued in this context that more ex-post validations of ex-ante methodology are needed, especially with regards to AS/RS (Lagorio et al. 2020). This consideration is even more striking considering the increasing diffusion of these systems in the logistics market (Yahoo Finance 2023).

An ex-post performance assessment methodology widely used is the Design-of-Experiments (DoE), a statistical methodology that is instrumental in optimizing processes by systematically investigating the effects of multiple input variables and their interactions (Mason, Gunst, e Hess 2003). DoE has been extensively applied in the manufacturing industry (see literature reviews on the application of DoE on product innovation (Arboretti et al. 2022) or on lithium-ion batteries performance (Román-Ramírez e Marco 2022)). This methodology is also applied to other industries such as the food industry (Antony et al. 2024) and the service industry (Antony et al. 2020). Even though, according to Antony et al. (2020), Logistics represents almost 20% of DoE studies in the service industry, its applications on AS/RS are only on simulated environments rather than real implementations.

In this context, the validation of simulation models through experimental campaigns employing DoE principles is paramount in bridging theoretical research with practical applications (Ferrari et al. 2024). Addressing this research gap, our paper introduces a DoE applied to a real AS/RS that operates within a laboratory setting. Herein, we delve into the influence of two fundamental AS/RS design criteria—AS/RS size and load units' type and weight—on a key operational performance metrics, namely Cycle Time.

The paper is structured as follows. First, a literature review on AS/RS design criteria and variables, together with selected applications of DoE in AS/RS contexts is presented. Then, Section 3 outlines the research approach, which is based on a General Full Factorial design. The main findings from the data analyses are shown in Section 4, and finally Section 5 draws the main implications and conclusions of this study.

2.Literature Review

2.1 AS/RS design

Analyzing the existing literature on AS/RS design criteria provides valuable insights into the various factors that need to be considered during the design process. A well-designed warehouse should consider factors such as efficient space utilization through storage capacity, proper warehouse flow and layout, material handling equipment, and safety measures (Kumar, Narkhede, e Jain 2021). Common design choices regarding AS/RS typically revolve around decisions concerning the handling machine type (HM), number of aisle, and rack dimensions. Fandi, Kouloughli, e Ghomri (2022) primarily concentrate on identifying the optimal type of HM and determining the ideal balance between rack length, width, and height that minimizes cycle time. In the same vein, Accorsi et al. (2017) and (Borovinšek et al. 2016) focus on the AS/RS size. Beyond the AS/RS size in terms of length, width, and height of the racks, other design criteria might include the number of unit-loads that each bin can accommodate (Chen, Li, e Gupta 2015). Hence, unit-loads size may also be considered among other variables. Other prevalent operational considerations include storage strategies and regulations for vehicle dwell points (Roodbergen e Vis 2009). Finally, it is important to take into account the specific requirements and constraints of the enterprise, as well as the internal and external environment (Huang 2019).

2.2 DoE in AS/RS contexts

In the realm of logistics, the utilization of Design of Experiments (DoE) remains relatively restricted despite its wide acknowledgment and application within quality management domains (Coello e Glistau 2020). The approach of DoE allows for the acquisition of essential information while minimizing costs and maximizing efficiency, aligning with the primary aim of experimental statistical design in practice (Coello e Glistau 2020).

Unlike traditional warehouses, AS/RS introduce shuttle-based storage and retrieval systems, necessitating a deeper understanding of their operational dynamic (T. Lerher 2018). Through the application of DoE principles, researchers aim to identify significant factors impacting the performance of automated storage and retrieval systems, such as the Shuttle-Based Storage and Retrieval System (SBS/RS) (Tone Lerher 2017).

Many studies in this field rely on simulations rather than physical applications, with variables including vertical and horizontal movement speeds and accelerations. An application of DoE, coupled with simulation tools like ARENA 14.0, presents a significant opportunity for system designers to optimize the performance efficiency of SBS/RS (Ekren 2020).

3.Methodology

This section elucidates the methodological framework employed for the experimental setup, the data collection, and the subsequent analysis of data.

3.1 Experiment design

DoE encompasses a variety of experimental designs, each tailored to address specific research questions with efficiency and precision. Among these, the General Full Factorial design stands out for its comprehensive nature. Incorporating variables at both two and three levels, the study aligns with a General Full Factorial design paradigm (Montgomery 2017). This approach is distinguished by its capacity to evaluate all conceivable combinations of variables at the predetermined levels, an attribute that substantially augments the thoroughness and robustness of the analysis. The General Full Factorial design not only facilitates a nuanced understanding of main effects but also enables a detailed exploration of interaction effects among variables, thereby offering invaluable insights into the complex dynamics that govern the process under investigation.

In line with the objective of this work, the response measured in the proposed DoE is the warehouse Cycle Time. The warehouse design criteria mentioned in the Literature section comprise the factors or primary variables, as shown in Table 1. The factors pertain to two major areas of warehouse design, namely the Unit Load (UL) chosen and the size of the AS/RS. Regarding the former criterion, two levels were chosen for length and height to comply with the ODETTE industry standards[1]. Furthermore, three levels were chosen for the weight loaded inside each UL, representing three manual handling scenarios: i) an empty UL; ii) a UL with total weight within the maximum recommended limits for manual lifting, lowering and carrying items in work environment (International Organization for Standardization 2021); iii) an average UL. Regarding the latter, we have chosen arbitrary values for the factor levels, to ensure a moderate degree of movement of the handling machine (HM).

[1] https://www.odette.org

Table 1: DoE factors and levels

Factor	Description	Number of levels
UL Length (ULL)	Length of the UL.	Two levels: 300 mm and 600 mm.
UL Height (ULH)	Height of the UL.	Two levels: 120 mm and 220 mm.
Weight (W)	Weight loaded inside each UL	Three levels: 0 kg, 7.5 kg, 15 kg
Fill Grade (FG)	Percentage of storage positions occupied at the start of the experiment.	Three levels: 40%, 60%, 80%
Tier (T)	Number of tiers in the AS/RS.	Two levels: 5 and 7.
Column (C)	Number of columns in the AS/RS	Two levels: 6 and 8.

In addition to the primary variables of interest, this study incorporates covariates, i.e. variables that cannot be directly controlled but can be monitored (Montgomery 2017). The inclusion of these covariates is crucial for accounting for external factors that may influence the outcome of the experiment, thereby ensuring a more accurate and comprehensive analysis. In this context, in any AS/RS the outcome measures are also affected by the specific algorithm that dictates the storage positions within the rack. Hence, the following covariates were added (Table 2).

Table 2: DoE covariates

Covariate	Rationale	Values
Number of Deep Positions (DP)	The AS/RS can store a UL in different positions within the rack	Total number of deep positions
Horizontal Movements (HT)	The AS/RS decides on which column to store the UL	Number of horizontal movements made by the HM during an experiment
Vertical Movements (VT)	The AS/RS decides on which tier to store the UL	Number of vertical movements made by the HM during an experiment.
Front Movement (FT)	The AS/RS decides on which front to store the UL	Total number of front positions

In this preliminary study, we limit the scope to storage process, with the retrieval process to be explored in future research. In order to approximate a more realistic operational scenario, we decided to store 5 ULs for each experiment, rather than only one.

The sequence of experiments was built to randomize the factors pertaining to the warehouse size (i.e., number of tiers and columns). The factors that should not be randomized due to excessively long experimental setup (hard-to-change factors) are FG, W, ULL, ULH.

3.2 Data collection

We calculated the cycle time for each experiment as the difference between the storage request of the first UL and the end of the storage process of the last UL. These data, along with the recording of the factors and covariates, were retrieved from the Warehouse Controller System (WCS) of an AS/RS installed in a university laboratory (Ferrari et al. 2024; 2022). This AS/RS is a Maxi-Shuttle (MS) aisle-captive system resembling a mini-load stacker crane, which is able to move totes using single, double and multiple commands.

3.3 Data Analyses

Analysis Of Variance (ANOVA) is employed to analyze the data, aiming to ascertain the statistical significance of the variables' effects across the observed responses. This analytical step is paramount in delineating the complex interplay of factors, thereby informing the modeling phase.

In the exploratory stages of model building, Stepwise Regression is employed as an automatic technique to identify the optimal subset of predictors. This method, supported by several statistical software packages including MINITAB®, systematically adds and removes predictors at each step based on Alpha-to-Enter and Alpha-to-Remove thresholds, which are set at 15% in this study. This alpha level, widely recognized in the scientific literature (Montgomery et al., 2010), is chosen to ensure the inclusion of only those variables that exert a significant impact on the responses. Such a structured selection process enhances the precision, explanatory power, and relevance of the regression models developed for the response variables, thereby refining their interpretability and the overall effectiveness of the analysis. The adequacy of the obtained model is demonstrated by using diagnostic checking tests such as the coefficients of determination and the residual plots, that are analyzed to verify the basic assumptions to perform the ANOVA (Mason et al., 2003).

The final step of the data analysis comprises a linear regression analysis based on stepwise response. This analysis is aimed to determine the regression equation and identify estimated parameters.

4.Findings

First, some descriptive statistics regarding the output variables are reported in Table 3. The results show a relative standard deviation of 3.91% for cycle time.

Table 3 Descriptive Statistics

Variable	Mean	StDev	Minimum	Median	Maximum
CT [s]	100,51	3,91	89,50	101,25	107,25

In the following sections the main findings from the ANOVA and the Stepwise analysis are outlined.

4.1. Findings from the ANOVA

The following table presents the results of the ANOVA.

Table 4 ANOVA for *Cycle Time*

Source	DF	Adj SS	Adj MS	F-Value	*p*-value
Model	38	2055.61	54.095	43.71	<0.001
Covariates	4	662.08	165.520	133.75	<0.001
FT	1	312.95	312.947	252.88	<0.001
HT	1	29.11	29.111	23.52	<0.001
VT	1	21.73	21.733	17.56	<0.001
DP	1	234.37	234.375	189.39	<0.001
Linear	8	362.63	45.329	36.63	<0.001
ULL [mm]	1	239.22	239.217	193.30	<0.001
ULH [mm]	1	11.57	11.570	9.35	0.003
W [kg]	2	1.39	0.696	0.56	0.572
FG	2	9.65	4.825	3.90	0.023
C	1	1.79	1.786	1.44	0.232
T	1	2.04	2.042	1.65	0.202
Error	105	129.94	1.238		
Total	143	2185.55			

The regression model was found to be statistically significant (F = 43.71, p-value < 0.001), indicating that the variables considered in the model collectively explain the observed variation in the dependent variable. The covariates (FT, HT, VT, DP) demonstrated a significant effect on the response (p-value < 0.001), suggesting that these factors significantly influence cycle time. Conversely, certain first-order factors such as weight (W), number of columns (C) and number of tiers (T) did not exhibit a statistically significant association with cycle time (p-value > 0.05).

However, some second-order interactions were found to be statistically significant (p-value < 0.05), such as ULL * C, ULH * FG, and ULH * C. These results suggest that the dimensions of the UL along with the number of columns (C) influence cycle time, highlighting a significant interaction between these factors.

The lack of significance of weight and number of columns in the model may be attributed to the physical structure of the warehouse, where limited movements within the structure do not significantly affect traversal times.

The values of S, the standard error of the regression, and the goodness-of-fit measures R2 (R-sq), adjusted R2 (R-sq(adj)), and predicted R2 (R-sq(pred)) are reported in Table 5.

Table 5 Model summary

S	R-sq	R-sq(adj)	R-sq(pred)
1,11244	94,05%	91,90%	88,85%

The standard error of the regression (S), calculated as 1.11 s, was calculated to assess the variability of the residuals around the fitted regression line. The R2 value indicates that the model is able to explain approximately 94.05% of the observed variation in the response variable, while the R2 predicted value indicates that approximately 88.85% of the variation in the dependent variable can be explained by the model when applied to new data.

4.2 Stepwise Analysis

Building on the findings from the ANOVA, stepwise regression was applied to refine the model by reducing the number of predictors. Of the six first-order factors, the stepwise method reduced the number to three, excluding parameters W [kg], C and T due to their lack of significance at the 15% significance level. Moreover, in terms of second-order interactions, only ULH [mm]*FG remained significant. Notably, the value of predicted R2 has shown improvement, increasing from 88.85% to 90.09%.

The Pareto Chart indicates that the most significant factor is UL dimension, followed by FG*ULH and FG. These findings suggest that the model can elucidate a greater proportion of variability, thereby furnishing more robust outcomes compared to the initial analysis.

The second-order regression equation is derived from the stepwise analysis. The parameters of the regression model along with their corresponding standard errors are reported in Table 6, and the final regression equation is presented in Eq. (1).

Table 6 Parameter Estimates of Stepwise regression model for Cycle Time

Parameter	Estimate	SE Estimate	p-value
β0	4.7287	0.21628	<0.001
β1	0.0044	0.04259	<0.001
β2	-0.0044	0.03531	<0.001
β3	3.1665	0.16583	<0.001
β4	0.0360	0.00214	<0.001
β5	0.0915	0.01685	0.001
β6	44.3215	4.27540	0.068
β7	-0.1927	0.02436	0.034

The results suggest that the covariates FT, HT and DP have a positive correlation on the Cycle time, contrary to VT, which shows a negative correlation, albeit low.

The results of the Stepwise analysis can be subsumed in Equation 1.

$$CT[s] = \beta 0 \cdot FT + \beta 1 \cdot HT + \beta 2 \cdot VT + \beta 3 \cdot DP + \beta 4 \cdot ULL + \beta 5 \cdot ULH + \beta 6 \cdot FG + \beta 7 \cdot ULH \cdot FG \quad (1)$$

5.Discussions and Conclusions

The findings of this study shed light on several key factors influencing the performance of AS/RS and engenders both managerial and theoretical insights.

5.1 Managerial insights

On a practical level, our findings offer tangible implications for real-world AS/RS implementations. By demonstrating how our approach can be applied in a real-case scenario, we provide practitioners with actionable insights for optimizing system design and operational efficiency. Through the adoption of our methodology, organizations can make informed decisions during the design, implementation, and management phases of AS/RS implementation projects.

As a case in point, our analysis reveals that storage decisions made by the machine (HM), as depicted by the covariates FT and DP, significantly impact cycle time. This underscores the critical importance of incorporating HM decision-making processes into the design phase of AS/RS implementations. By recognizing the pivotal role of these storage decisions, designers can better optimize system configurations to minimize cycle times and enhance overall efficiency.

Moreover, our research highlights the often-overlooked significance of UL size. While this variable has traditionally received less attention in AS/RS design, our findings suggest that it can exert a considerable influence on system performance. As such, designers should carefully consider unit load length alongside other design parameters to ensure optimal system operation.

Interestingly, our analysis also indicates that certain design variables such as number of tiers and columns carry less weight in determining cycle time.

5.2 Theoretical insights

From a theoretical standpoint, our study introduces a novel approach to the ex-post assessment of AS/RS performance. By identifying and quantifying the impact of various design variables on cycle time, we contribute to a deeper understanding of system dynamics and provide a framework for evaluating system effectiveness post-implementation. This opens avenues for future research aimed at refining AS/RS design methodologies and enhancing system performance. For instance, the DoE methodology could be adopted to include other key performance measures such as energy consumption or throughput.

5.3 Generalizability of results and study limitations

The main limitation of this study is related to the space constraints and characteristics of the system under study. In fact, the AS/RS used in this study is installed in a laboratory and belongs to a specific configuration among the many available in the industry. This limitation hinders the generalization of the results concerning the impact of number of tiers and columns on the AS/RS performance, which could be tested by applying the DoE approach in a larger AS/RS.

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