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SIMULATION BASED REGRESSION ANALYSIS FOR RACK CONFIGURATION OF AUTONOMOUS VEHICLE STORAGE AND RETRIEVAL SYSTEM

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ABSTRACT

In this study, a simulation based regression analysis for rack configuration of an autonomous vehicle storage and retrieval system (AVS/RS) is presented. We develop a mathematical function for rack configuration of an AVS/RS that reflects the relationship between the output (response) and the input variables (factors) of the system. In the regression model, the output is the average cycle time for storage and retrieval and the input variables are the number of tiers, aisles and bays that determine the size of the warehouse. The simulation model of the system is developed using ARENA 12.0, a commercial software. We use MINITAB statistical software to complete the statistical analysis and to fit a regression function. Two different approaches are used for developing the regression analysis – stepwise regression and the best subsets. We optimize the regression function using the LINGO software. We apply this approach to a company that uses AVS/RS in France.

1 INTRODUCTION

Autonomous vehicle storage and retrieval systems (AVS/RSs) represent a relatively new technology for automated unit-load storage systems (Malmborg 2002). In this system, autonomous vehicles (AVs) function as storage/retrieval (S/R) devices. The most important difference between an AVS/RS and a traditional crane-based automated storage and retrieval system (AS/RS) is the movement pattern of the S/R device. The AVs in an AVS/RS follow rectilinear flow patterns for horizontal travel. However, in AS/RSs, storage cranes are aisle-captive and capable of simultaneous movement in the horizontal and vertical dimensions store or retrieve unit-loads. The travel pattern in an AS/RS is generally more efficient within storage racks. Neverthless, an AVS/RS has a significant potential advantage in the adaptability of system throughput capacity to transactions demand by changing the number of vehicles operating in a fixed storage configuration. For example, increasing the number of vehicles decreases the transaction cycle times and utilization which are also key measures of system performance.

It is crucial to design an AVS/RS in such a way that it can efficiently handle the current and future demand requirements while avoiding bottlenecks and excess capacity. Due to the relative inflexibility of the physical layout and the equipment, it is important to design it right the first time. To be able to evaluate all possible design scenarios for a suitable physical layout of a warehouse with an AVS/RS, we develop a regression analysis that represents the relationship between a particular AVS/RS's output performance average cycle time, and input variables numbers of tiers, aisles and bays. Development of a regression function makes possible, a better understanding of the true relationship between input variables and the output. In this study, the real data are obtained from a company that uses this system in France.

2 LITERATURE REVIEW

An AVS/RS transports a unit-load using rail guided automated vehicles that follow three-dimensional rectilinear movement patterns Figure 1 illustrates the key components of an AVS/RS. Figure 1a is a three-dimensional view of an AVS/RS, whereas Figure 1b is a plan view. The major system components of the AVS/RS technology are lift mechanisms that are mounted along the periphery of the storage rack to provide vertical movement. The dominant cost component of the AVS/RS technology is the vehicle. Lifts are used for vertical movement of the vehicles. Lifts are typically not the bottleneck in an AVS/RS but they have a significant influence on throughput capacity because vertical movement is generally slower than horizontal movement. They can also contribute substantially to transaction cycle times.

In most unit-load S/R systems, space-conserving random storage policies are used because of capital cost considerations (Heragu 2008). Under a random storage policy, the location of a specific load in a storage system is a random variable over time. This policy ensures space occupancy rate maximization by allowing different loads to occupy the same address at different times (Malmborg 1996).

AVS/RS technology can provide cost effective automation for unit-load S/R systems with varying transaction volumes because it enables the designer to vary the number of S/R devices (i.e., AVs), depending on the number of S/R transactions in a system. With traditional crane-based technology, aisle-captive S/R devices utilize highly efficient Chebychev movement patterns within aisles. However, the high cost of crane-based systems (one crane is required per aisle) raises the threshold for cost effective automation and crane-based AS/RSs can be justified only for high throughput operations in a stable demand environment.

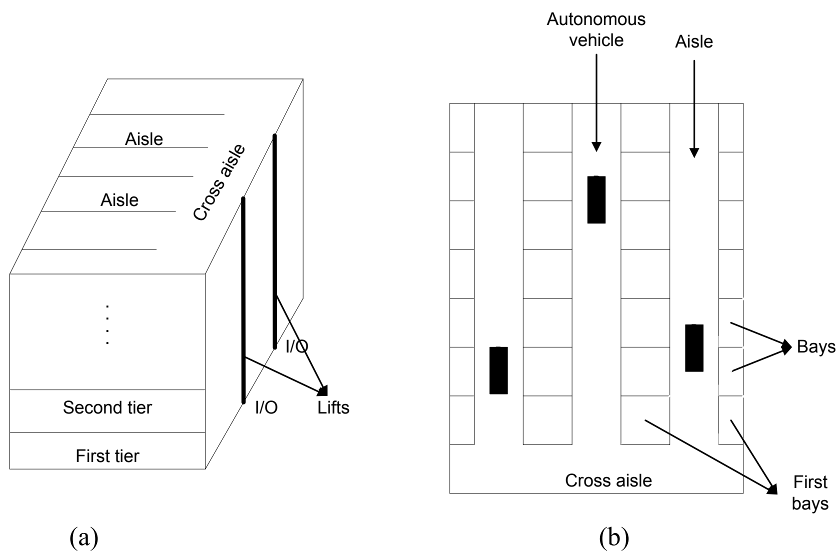

Figure 1: The key components of an AVS/RS

There are various studies that evaluate the performance of AVS/RSs (Malmborg 2002, Malmborg 2003, Kuo, Krishnamurthy and Malmborg, 2007, Kuo, Krishnamurthy and Malmborg, 2008, Fukunari and Malmborg 2008, Fukunari and Malmborg 2009, Zhang et al. 2009). Different from those studies, we model the AVS/RS from a rack configuration view. The performance of an AVS/RS also depends on the physical layout because it affects the travel distance of AVs, so the cycle time. The physical layout of an AVS/RS can be defined in terms of three dimensions, number of tiers, aisles, and bays (see Fig. 2). In this study, first, we develop the simulation model of the AVS/RS. Second, we complete experiments for the pre-defined levels of the system's input variables. And last, we develop a regression analysis using two different approaches that best reflects the relation between the output and inputs. We use ARENA 12.0, a commercial simulation software, to develop the simulation results and MINITAB to develop the regression function.

3 PROBLEM DESCRIPTION AND SIMULATION

In an AVS/RS, there are two types of transactions arriving into the system -storage and retrieval transactions. Storage transactions refer to the storage of a unit-load from the input/output (I/O) point to an available location in the racks. Retrieval transactions refer to the retrieval of a unit-load from its current location. All storage transactions are assumed to arrive at the I/O point and all retrieval transactions end at the I/O point.

The AVS/RS uses lifts to store or retrieve unit loads from the bays located on tiers other than the first, and vehicles for horizontal movement within a tier. Vehicles travel in three dimensions at an AVS/RS warehouse; e.g., travel between tiers takes place on the z axis; travel between aisles takes place on the y axis and travel between bays takes place on the x axis (see Fig. 2). Therefore, the sizes of the warehouse, in other words, the number of tiers, aisles and bays are crucial on travel time of AVs.

In the AVS/RS warehouse, racks on either side of an aisle consist of bays, and each bay can hold three unit-loads. So, the warehouse storage capacity is calculated by multiplying the number of tiers, number of aisles, number of bays, two (both sides) and three. The result is then the total number of pallet positions.

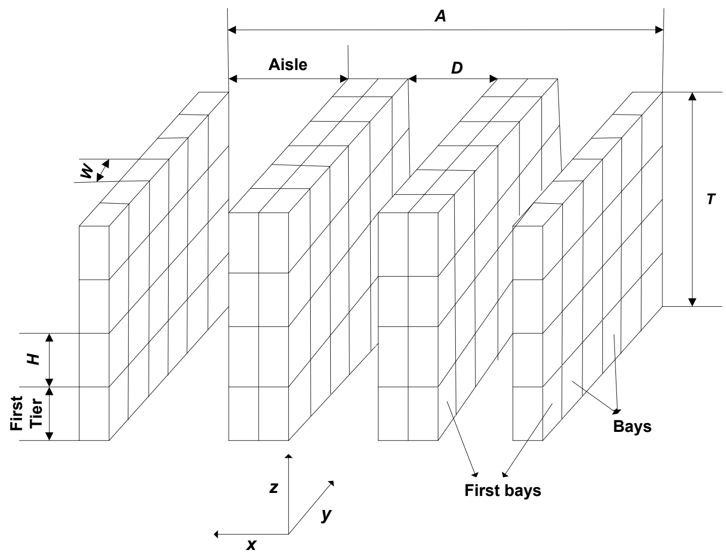

Figure 2: Warehouse design of the AVS/RS

3.1 Simulation Assumptions

The actual system has 21 vehicles and 7 lifts. The storage area is divided into 7 zones, depending on the number of lifts. Each zone has 1 lift, and 3 specific vehicles are assigned to each lift. The lifts are located at the middle of each individual zone, e.g. the first lift is located at the end of the 3rd aisle.

The other assumptions of the AVS/RS are given below:

1. The dwell point of a vehicle is the place where the last storage or retrieval transaction is completed.
2. The dwell point of the lift is where the last vertical movement is completed.
3. The system uses pure random storage policy.
4. The actual distance between two aisles, the width of a bay and the height of one tier in an actual AVS/RS installation are used to calculate the travel times.
5. Each zone has I/O locations near the lift.
6. The arrival rates for storage and retrieval transactions are independent Poisson processes and equal.
7. The transactions are served by the vehicles on a first-come, first-served (FCFS) rule. The vehicles requiring lifts for vertical movement are also served by FCFS order.
8. The vehicle transfer time into the lift is assumed to be zero.
9. The warehouse storage capacity must be greater than 42,000 unit-loads.

3.2 Notations

The notation used in the AVS/RS model is given below:

A	: number of aisles	L	: the number of lifts
B	: number of bays (columns) per aisle	Yx	: the distance from the first bay to the cross aisle
D	: the distance between two aisles	T_T	: the load or unload transfer time between the lift and the I/O point.
T	: number of tiers	v_v	: the velocity of the vehicle
W	: the width of one storage bay	v_L	: the velocity of the lift
H	: the height of one tier	$T_{L/U}$	: the time to load/unload to or from the storage rack
V	: the number of vehicles	λ_S	: the arrival rate of storage transactions per hour
λ_R	: the arrival rate of retrieval transactions per hour		

Because of the agreement with the company, we are not able to give the specific values of the parameters defined above, except the values summarized below:

V	= 21	L	= 7
λ_R	= 225 unit-loads	λ_S	= 225 unit-loads

3.3 Constraints

The AVS/RS warehouse has a limited area. Therefore, there are constraints on the maximum numbers of tiers, aisles and bays. Besides, as mentioned in the 9th simulation assumption in Section 3.1, there is a constraint on the total number of unit-load storage positions. Because our aim is to minimize the cycle time, we assume that the warehouse capacity should be equal to 42,000 unit-loads. This capacity is determined by considering the expected maximum storage demand that may occur during a period of time. In other words, the manager expects that in the AVS/RS, the possible maximum storage position that may be needed in a period is 42,000 unit-loads. So, the plant manager seeks the best rack configuration that provides the required number of storage positions. As mentioned previously, the rack configuration of an AVS/RS can be defined in terms of three dimensions, numbers of tiers, aisles and bays. If the number of tiers is small, then the warehouse footprint will be large to accommodate the required number of storage positions. If the number of tiers is high, then the footprint will be small. Under the first type of design (few tiers) the vehicles may become a bottleneck, because they will need to realize long horizontal travels. However, in the second condition (large number of tiers), the lifts may become bottleneck because this time long vertical movements will be required. Therefore, the performance of the system will also be affected by the number of vehicles and lifts in the system. Thus, the regression analysis should be completed under various vehicle and lift combinations. However, in this study we complete the regression analysis only one combination of V and L values which are 21 and 7, respectively. This study will be extended as a future study for developing regression analysis under various vehicle and lift combinations of the system.

Because the total number of storage positions in the system is calculated by $T*B*A*2*3$; when we divide 42,000 unit-loads by six, we obtain a value of 7,000 for $T*B*A$. This means that the combination of three input variables, T, B and A, should be designed such a way that their product should provide for 7,000 unit-loads. In addition to this constraint, because there are limited areas on z, x and y axes, it is assumed that the T, A and B can get the maximum values, 8, 65 and 25, respectively. The warehouse has a rectangular shape.

4 REGRESSION MODELING

Because the AVS/RS under study is quite complex it makes it difficult for a manager to identify how the parameters affect the average cycle time in the system. Regression analysis enables to understand and evaluate the performance of the system in terms of input variables.

Regression analysis is a statistical tool for the investigation of relationships between output and input variables. Usually, one seeks to ascertain the causal effect of one variable on another e.g., the effect of a price increase on demand, or the effect of changes in the money supply on the inflation rate, etc. To explore such issues, the investigator assembles data on the underlying variables of interest and employs regression to estimate the quantitative effect of the causal variables on the variable that they influence.

Regression analysis with a single explanatory variable is termed *simple regression*, with multiple explanatory variables it is termed *multiple regression*. We develop a multiple regression model, in this study.

The output of the system is the average cycle time of transactions, which is measured in minutes. Cycle time is the time between when a request originates until it is completed. Along with resource utilizations, it is a comprehensive performance measure and employed extensively in many industries. AVS/RS cycle times are determined by the storage rack configuration, vehicle movement kinematics, storage policy and vehicle dwell point policy. In this study, the vehicle movement kinematics, storage policy and vehicle dwell point policy are assumed to be fixed (see section 3.1). However, the rack configuration is of interest. The input variables are the numbers of tiers, aisles and bays. While the number of tiers determines the height of the warehouse, the number of aisles and bays determine the footprint of the warehouse.

4.1 Simulation Experiments

To develop the regression model, first three independent input variables' levels are determined. Then, the simulation model is run for these levels of the input variables. The simulation model is assumed to be a non-terminating system, allowing us to conduct a steady state analysis. The warm-up is three months. The length of each simulation run then 1,180,800 minutes ((365*2*24*60) + warm-up period). The model is run for ten independent replications.

In the simulation model, the *common random numbers* (CRN) variance reduction technique is used. CRN is a popular and useful variance reduction technique when we compare two or more alternative configurations. It requires synchronization of the random number streams, and uses the same random numbers to simulate all configurations. In CRN, a specific random number used for a specific purpose in one configuration is used for exactly the same purpose in all other configurations. Thus, variance reduction is ensured.

For the *T* input variable 4 levels -5, 6, 7 and 8; and for the *A* input variable seven levels -35, 40, 45, 50, 55, 60 and 65 are considered. Here, the level of the *B* input variable varies according to the *A* and *T* values. Each time it is calculated by dividing 7,000 by *T*A*. For example, if $T = 7$ and $A = 40$, then *B* is 25 (7,000/(7*40)) and if $T = 8$ and $A = 50$, B is 18. It should be noted that due to the warehouse area constraint the maximum values of *A* and *B* could be 65 and 25, respectively. *A* can get a minimum value of 35 which is calculated by dividing 7,000 by the product of maximum values of *T* and *B* (7,000/(8*25) = 35). With the same logic, the minimum value of *B* is 13. In designing experiments, where necessary the division is rounded up to the closest integer. In addition, we also complete experiments at the boundary levels of *B*. For example, at $B = 25$, *A* is calculated as 7,000/(25**T*). In some cases, for example at small values of *T* and *A*, the *B* value may be greater than the maximum constraint, 25. Under these conditions, those experiments are not completed (e.g., $T = 6$ and $A = 40$, $B = 29$). The levels of the input variables and the completed experiments are summarized in Table 1.

Table 1: The input variable levels and completed experiments

T	*A*	*B*	*T*	*A*	*B*	*T*	*A*	*B*	*T*	*A*	*B*
5	65	22	6	65	18	7	65	15	8	65	13
5	60	23	6	60	19	7	60	17	8	60	15
5	55	25	6	55	21	7	55	18	8	55	16
			6	50	23	7	50	20	8	50	18
			6	47	25	7	45	22	8	45	19
						7	40	25	8	40	22
									8	35	25

As seen from Table 1, a total of 21 experiments are completed with ten replications each.

4.2 Regression Function Analysis

First, we trace the factors to determine whether or not a curvature exists. At none of the input levels a curvature is detected. So, we model the system by a multiple linear regression.

In a regression model, ANOVA analysis is used to decide which terms to include in the regression function. For example, if there are three input variables under study, then at most seven terms can be included in the regression function. These possible terms are, main effects -*T*, *A*, *B*; two-way interactions -*T*A*, *T*B*, *A*B*; and three-way interactions -*T*A*B*. The ANOVA can suggest which terms to include by providing the statistically significant effect(s). However, in this experimental study, we are not able to complete a full factorial design because of the area constraint for each factor combination (see Table 1). As we cannot conduct full factorial design, we cannot apply ANOVA, either (Montgomery, 1996).

However, we may use four alternative methods for the regression analysis. These are: forward selection, backward elimination, stepwise regression and best subsets. Of these, we use, *stepwise regression* and *best subsets*, to evaluate the possible regression functions and determine the best one (Montgomery, 1996).

Stepwise regression is the combination of *forward selection* and *backward elimination* methods. The purpose of the stepwise regression method is to find a meaningful subset of independent input variables which explains dependent variable efficiently. In this method, at each iteration all terms both in and out of the model are reassessed using their partial *F* statistics. The term not in the model with the largest partial *F* statistic, larger than F_{IN} is added to the model. The term in the model with the smallest partial *F* statistic, smaller than F_{OUT} is removed from the model. Terms can enter the model and be removed from the model more than once.

The *best subset* method finds the possible *n* best subsets of *i* terms ($i = 1, 2, \ldots, k$) of the regression model. For each subset, it calculates the coefficient of determination -R^2 and adjusted R^2 -R^2_{adj} values, so that we can choose a subset that has a good balance of high R^2_{adj} and small number of terms. R^2 provides a measure of how well outputs are likely to be predicted by the regression model. The bigger the value the better fit the model is. However, only considering R^2 is not adequate to evaluate a regression function because the R^2 value always increases with the addition of a new input variable to the function, even if it is not significant. If the R^2_{adj} value is significantly lower than R^2, it normally means that one or more explanatory variables are missing. Therefore, usually R^2_{adj} value is used for evaluating a regression function and it is preferred for R^2_{adj} to be big and close enough to the R^2.

4.3 Stepwise Regression Results

The statistical analyses are completed in MINITAB at 95% confidence level. The *stepwise regression* results obtained by MINITAB are as in Table 2:

Table 2: The *stepwise regression* results by MINITAB

Step	**8**
Constant	1.0045
T	0.283
T-value	6.81
P-value	0.000
*T*A*	0.00112
T-value	-2.4
P-value	0.018
B	0.070
T-value	6.29
P-value	0.000
*T*B*	-0.0069
T-value	-3.67
P-value	0.000
S	0.0506
R-Sq	90.66
R-Sq (adj)	90.28

Terms having *P*-values smaller than 0.05 are statistically significant response terms. MINITAB shows the significant terms, after completing the stepwise regression analysis. According to Table 2, the results show that four terms are significant on response at 95% confidence level and should be in the regression function. These terms are, *T*, *T*A*, *B* and *T*B* (*P*-value < 0.05). The R^2 and R^2_{adj} values are also seen at the end of the table (90.66% and 90.28%). Because they are big and close enough to each other, we assume that the model is acceptable. However, after obtaining the significant terms that should be in the regression function, we also complete the usual regression analysis for the model. Namely, we form the regression function with those four terms and evaluate the R^2, R^2_{adj} and *P*-values. We also check whether or not the regression model adequacy is met. The model adequacy means that residuals are normally distributed, have mean of zero and have a constant variance. If one or more of these conditions are not met, a suitable transformation such as, inverse, logarithm, natural logarithm, square root, inverse, inverse square root, etc. should be applied on the output to achieve the model adequacy. After implementing the regression analysis, we see that the regression model adequacy is met. In addition, all these four terms are statistically significant (*P*-value < 0.05). The regression function's R^2 and R^2_{adj} values are obtained as 90.7% and 90.3%, respectively. Therefore, we assume that the regression model is a good fit. The regression function obtained by MINITAB is given by:

$$1.00 + 0.283*T - 0.00112*T*A + 0.0696*B - 0.00688*T*B \tag{1}$$

4.4 Best Subset Regression Results

The second approach, *best subset regression*, is also implemented on the outputs. The results obtained by MINITAB are shown in Table 3:

Table 3: The *subset regression* results by MINITAB

Terms	R^2	R^2_{adj}	T	A	B	T * A	T * B	A * B	T * A * B
1	86.0	85.9		X					
1	85.6	85.5					X		
2	89.4	89.2	X		X				
2	87.2	86.9	X	X					
3	90.1	89.8	X		X		X		
3	89.7	89.4	X	X				X	
4	90.7	90.3	X		X	X	X		
4	90.4	90.0	X	X	X		X		
5	90.8	90.3	X		X	X	X		X
5	90.7	90.2	X		X	X	X	X	
6	90.8	90.3	X		X	X	X	X	X
6	90.8	90.2	X	X	X	X	X		X
7	92.3	91.7	X	X	X	X	X	X	X

In this table, R^2 and R^2_{adj} values are calculated for each alternative design. "X" in the table shows the terms in the regression function. The first column shows the total number of terms that will be in the regression function. From Table 3, we can choose the best regression subset by considering highest R^2 and R^2_{adj} values. In the table, when the number of terms in the regression function decreases, the R^2 and R^2_{adj} values also decrease. However, this decrease is not significant in every condition. For example, when we want to choose the function with five terms, the R^2 and R^2_{adj} values are 90.8% and 90.3%, respectively. And, these values become 90.7% and 90.3% for the function with four terms. Because the R^2 and R^2_{adj} values do not vary significantly with the four term regression model, it is usually better to choose the function with few terms rather than with more terms. This is because it is always easier and not much confusing to deal with few terms in a function.

For instance, in Table 3 the last subset has seven terms (all the terms) in the regression function and has the biggest R^2 and R^2_{adj} values, 92.3% and 91.7%, respectively. However, usually because all the terms may not be significant on the response, we may want to seek for an alternative design with fewer terms. When we go through the alternative regression designs with fewer terms, we obtain almost the same R^2 and R^2_{adj} values as in the previous case. The R^2 and R^2_{adj} values are usually around 90% until the four-term functions. If, we also utilize our former method's result (stepwise regression), then we choose the regression function with four terms. This is because the R^2 and R^2_{adj} values are high enough and also it includes few terms in the model. Hence, the considered terms are: T, B, $T*A$ and $T*B$ and this function's R^2 and R^2_{adj} values are 90.7% and 90.3%, respectively.

It should be noted that the fitted function in (1) has high R^2 and R^2_{adj} values, 90.7% and 90.3%, respectively. It also meets the regression model adequacy. If the R^2 and R^2_{adj} values were not as large as we would like and/or the model adequacy was not met, then we would apply a suitable transformation on the output and/or try including higher order term(s) in the regression model. However, the current model in (1) provides all the requirements. Hence, we accept this regression function as a good fit.

It should also be noted that in function (1) we can place only the limited values of A, B and T (see Table 1). For example, for $T = 5$, A can only get the values between 55 and 65, and B can get the values between 22 and 25. For $T = 6$, A can only get the values between 47 and 65, and B can get the values between 18 and 25. For $T = 7$, A can get the values between 40 and 65, and B can get the values between 15 and 25. For $T = 8$, A can get the values between 35 and 65, and B can get the values between 13 and 25. The other values will not be represented by the regression function. In addition, the chosen values for A, B and T should also provide $A*B*T$ = 7,000 unit-loads. For example, for the values of $T = 8$, $A = 58$, and $B = 15$ from (1) we obtain the cycle time as 2.95734 minutes.

From the function in (1) we see that whereas $T*A$ and $T*B$ have negative effects on the output, T and B have positive effects. We want to minimize the average cycle time. We optimize the function in (1) using the above constraints in LINGO. As a result, the optimum points are obtained as, $A = 65$, $T = 6$ and $B = 18$ leading to 2.7509 minutes average cycle time. As seen the optimum points are obtained at the boundary conditions on the number of aisles. This reason is probably because of the acceleration and deceleration time delays of the vehicles. Instead of traveling on two short coordinates, *x* and *y*, it is better to travel on a long and a short coordinate.

5 CONCLUSION

In this study, we presented a regression analysis for rack configuration of an AVS/RS. The case study is applied on a warehouse that uses AVS/RS in France.

In the regression model, the system's number of vehicles and lifts are assumed to be fixed. For the regression analysis output is chosen as the average cycle time of storage and retrieval processes and the input variables are the number of tiers, aisles and bays that determine the size of the warehouse. The simulation model of the system is developed using ARENA 12.0, a commercial software. The statistical analyses are completed in MINITAB statistical software. Two different approaches are used to find the best fit regression function; stepwise regression and the best subsets. *Stepwise regression* is the combination of *forward selection* and *backward elimination* methods. The *best subset* method finds the possible *n* best subsets of *i* terms ($i = 1, 2, \ldots, k$) of the regression model. In the best subset method, we choose the best number of terms that reflects the regression function by considering the R^2 and R^2_{adj} values. We also utilize the stepwise regression results to decide the number of terms in that method. At last a function with four terms is chosen as the system's regression function. After deciding on the terms, a regular regression analysis and adequacy test for the regression function are completed. As a result the function given in (1) is assumed to be a good fit for representing the relationship between the input variables, number of tiers, aisles, bays, and the output, average cycle time. Last, we also show the possible optimum points of this function. We use the software LINGO to minimize the function. The optimum points are obtained as $A = 65$, $T = 6$ and $B = 18$ leading to 2.7509 minutes average cycle time.

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