ARTIFICIAL INTELLIGENCE APPLIED TO ASSIGNED MERCHANDISE LOCATION IN RETAIL SALES SYSTEM

Dr.R.Mary Metilda**Dr.R.Anu RadhaP.Agarshana**

Abstract:

An objective of the study is to examine the practical implications using artificial intelligence based solutions in the case of retail mobile applications to enhance the online shopping experience and improve the engagement by also having in mind the privacy of the user for improving the process of assigning storage locations for merchandise in a warehouse is disadvantage of policies. In the literature that merchandise is assigned to allocation only according to the volume of sales and the rotation and the physical characteristics of the products and their sales pattern to design an integral policy. This presents an alternative to the aforementioned process using Minitab software the based on the information gathered we provided practical methods to integrate artificial intelligence-based solutions to offer a new set of services partially unavailable in physical stores some permissions identified if exploited by malicious users can affect individuals privacy the fact that artificial intelligence is a fast-developing technology constitutes the main challenge in the effort of creating proper regulations. This provides practical directions regarding the benefits of integrating artificial intelligence solutions in retail mobile applications in an ethical manner protecting the user's privacy.

Introduction:

The concept of study is the high competitiveness and speed of the business environment makes it vital that enterprises continuously and effectively optimize the design of their business systems in the shortest time possible. These conditions in the case of the existing systems in retail distribution companies force them to be designed or redesigned to respond quickly to the client. Generally, the factors to consider analysis are guaranteed easy and efficient access to the merchandise proper use of storage locations throughout the warehouse generation of shorter routes and order through put reasonable timesheet**(Hsieh, L. & Tsai, L.** 2005). The assigning product location in a retail sales warehouse system is addressed the literature in this field includes four kinds of storage allocation policies. In random storage the merchandise allocation is randomly selected from all possible empty locations next policy is the selection of vacant positions is biased towards those that are closer in time and or distance to the input output point (**Glock, C. & Grosse, E.** 2012). The two remaining policies are grouped under the concept of dedicated storage fixed location assigns each product to a warehouse using product characteristics such as sales volume weight or fourth policy divides products into classes that are stored in dedicated areas of the warehouse with random storage within a specific area.

*Professor, Department of Management Sciences, Sri Ramakrishna Engineering College
**Associate Professor, Department of Computer Sciences, Sri Ramakrishna Engineering College
***Student, Department of Management Sciences, Sri Ramakrishna Engineering College

The aim of this study improves the retail stores internal operational logistics by identifying the best product allocations seeking to respond to the demand behavior (**Petersen, C. & Aase, G.** 2004). By adopting allocation methods based on sales volume requires a more intensive information approach that might not be available when the order frequency is changing in a dynamic environment in cases like the one analyzed here small businesses usually do not invest enough to improve their processes and this limits their ability to generate information that creates a barrier to their achieving competitive success(**Muppani, V. & Adil, G.** 2008). The approach described is based on the customer process analysis of a distributed throughout a warehouse in the literature there have been individual studies of the use of the techniques mentioned.

Review and Literature:

Order picking has long been identified as the most labor-intensive and costly activity for almost every warehouse; thecost of order picking is estimated the total warehouse operating expense. The order picking can lead service and high operational cost for the warehouse operates efficiently (**De Roster, R., Le-Duc, T. &Roodbergen, K.J.** 2007). Simulation models are increasingly being used to solve problems and to aid in decision-making. This concern is addressed through model verification and validation. A model is considered valid for a set ofexperimental conditions if the model's accuracy is withinits acceptable range, which is the amount of accuracy re-quired for the model's intended purpose (**Sargent, R.** 2007).

Methodological framework:

For validating this model, we are using simulation model client waiting time in order queue and the client waiting time to obtain the merchandise variables were considered to be relevant to the model validation using simulation model (**Glock, C. & Grosse, E.** 2012). We can identify dependent variables and independent variables by assuming a value the sequence of the tools used in this research is presented. Initially it is necessary to create a database performing several simulations runs using Minitab with a model accurately representing the analyzed service system the database is used for different artificial neural networks that enable the identification of consumption patterns association rules or cyclic behavior in clients items**(Hsu, C., Chen, K. & Chen, M.** 2005).

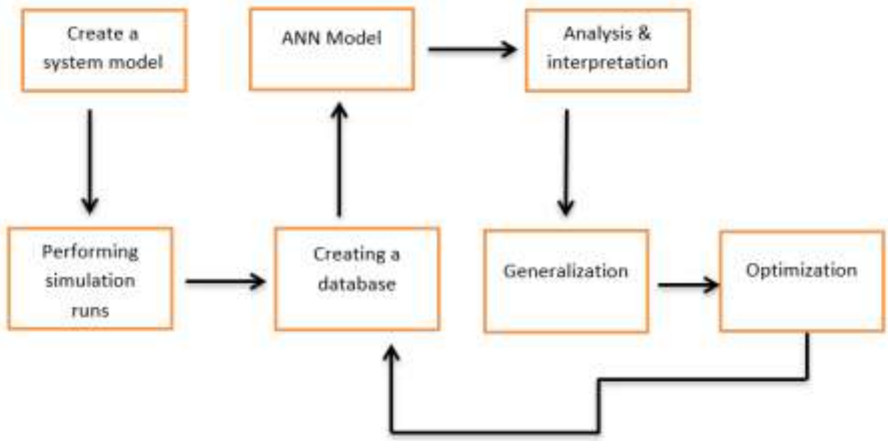


Figure 1: Proposed Methodology

Construction of Simulation Model

Simulation modeling and analysis is the process of creating and experimenting with a computerized mathematical model of a physical system the system is defined as a collection of interacting components that receives input and provides output for some purpose.

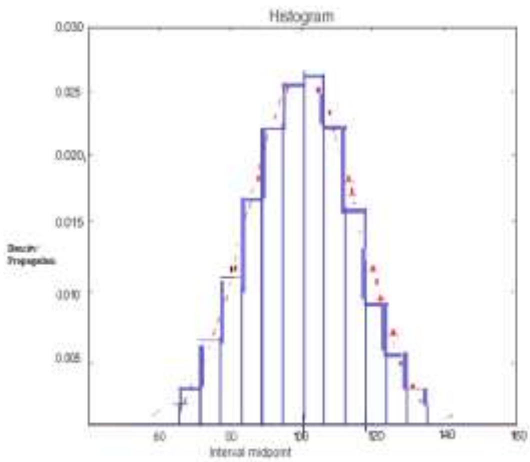


Figure 2: Server Customer Attention Time Modeling

Validation of the Simulation Model

Table 1: Data considered for this study: Waiting time in line, in seconds

Maximum Client waiting time in queue(minutes)	**1**	**2**	**3**	**4**	**5**	**maxima**
Payment Counter	0.4355	0.5171	0.3577	0.357	0.6305	0.63051*
Client waits in time in queue	4.4384	0.5585	0.8750	1.0078	7.8613	7.86130*
Merchandise time obtain to client wait in time	**1**	**2**	**3**	**4**	**5**	**Sample mean**
Payment Counter	24.42	24.36	25.85	23.50	25.20	24.67
Client waits in time in queue	26.05	18.13	16.34	21.91	21.69	20.82

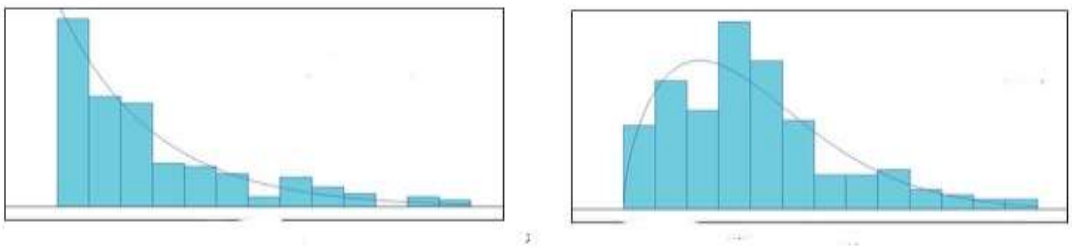
The results produced by the system under study and by the model were compared to validate the simulation model in agreement with the model runs were performed under the same conditions and used the same inputs as those occurring in the real system(**Coss, R.** 1998). To see if the results in the variables of interest were consistent since the picking times are directly related to the product search and picking route the client waiting time in order queue and the client waiting time to obtain the merchandise variables were considered to be relevant to the model(**Sargent, R.** 2007). Validation to compare the above-mentioned waiting times a hypothesis test using Minitab was carried out first checking the normality of the data used in the hypothesis test and the results obtained**(Pulido, H. & De la Vara, R.** 2008).

Results and Discussion:

The results obtained in this study indicate that an artificial neural system with a defined structure can be trained to assign a product to a category belonging to a warehouse zone as an expert would do it is also shown that pattern recognition can be applied as a technique to implement an intelligent product allocation in warehouses of retail companies. That do not produce sufficient data this approach adapts itself to the dynamic behavior of real retail systems where a location may no longer be relevant with time and may require another change due to its increased volume sales furthermore recognition of the predictor variables that identify a certain item as a member of a predefined class cluster of choosing other variables omitting some or considering more could result in the assigning of allocations that do not correspond to the actual dynamics of the system and that affect its overall performance. This approach raises an important range of applications such as the chance of automating areas of reception areas or placing products in locations where they will be stored manufactured etc,.The physical evaluation of allocations in a warehouse converts the static mapping that artificial neural networks perform into an iterative sequential system.

No of customers in order queue   No of Customer in line to obtain the merchandise

Fig 2: Number of customers in the order queue and in line to obtain the merchandise



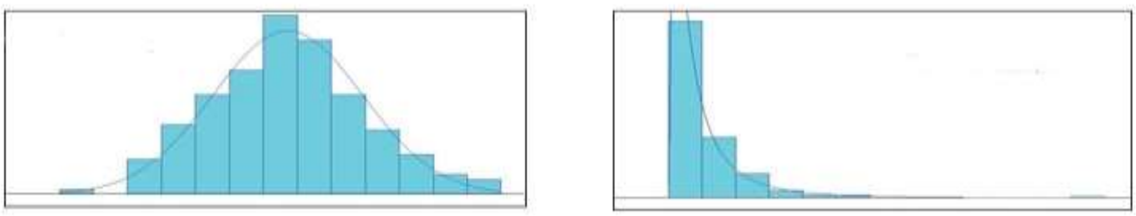


Fig3: Waiting time in the order queue and in line to obtain the merchandise

Findings

Chi-Square Test

Consider the following example to demonstrate the use of the chi-square goodness of fit test the data in the table below were obtained from inter-arrival times in minutes of customers at a service center we would like to verify that the inter-arrival distribution is exponentially distributed**.**

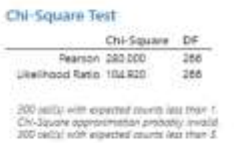
To calculate summary statistics for the data even though we can calculate both the mean and standard deviation of the data the exponential distribution has only a single parameter.

Mean 2.31


Chi-Square Test for Association: Client waiting in queue, Client waiting for merchandise

3.3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000	0.05000		
3.7	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	3
	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000	0.15000		
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	*
All	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	*	20

Cell Contents
Count
Expected count


Chi-Square Test

	Chi-Square	DF
Pearson	280.000	266
Likelihood Ratio	104.820	266

200 cell(s) with expected counts less than 1.
Chi-Square approximation probably invalid.
200 cell(s) with expected counts less than 5.

Standard deviation 2.88

Count 20

We have 20 data points, and we are going to use the recommended approach this means that we will need to use a total of 6 cells in our test with the summary statistics it is possible to set up the null and alternative hypothesis.

Step 1: Ho expo 2.31 and Ha not expo 2.31

Step 2: The level of significance is chosen as 0.05

One-way ANOVA

The goodness of fit test is also easy to implement for the one-way ANOVA here we may want to test the following service time data to see if it could have come from a one-way ANOVA.

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Worksheet 1

One-way ANOVA: Client waiting in queue versus Product purchased by peopl

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.887568	76.88%	26.79%	*

Means

Product purchased by people	N	Mean	StDev	95% CI
3	1	1.700	*	(-0.472, 3.872)
5	1	0.5000	*	(-1.6718, 2.6718)
9	2	3.100	0.849	(1.564, 4.636)
10	3	1.867	1.050	(0.613, 3.121)
11	1	1.600	*	(-0.572, 3.772)
12	1	3.300	*	(1.128, 5.472)
15	1	0.7000	*	(-1.4718, 2.8718)
16	1	3.700	*	(1.528, 5.872)
17	1	2.900	*	(0.728, 5.072)
20	2	1.400	0.707	(-0.136, 2.936)
21	2	1.800	0.990	(0.264, 3.336)
22	1	2.400	*	(0.228, 4.572)
25	1	3.700	*	(1.528, 5.872)
30	2	1.800	0.566	(0.264, 3.336)

One-way ANOVA: Client waiting in queue versus Product purchased by people

Method

Null hypothesis	All means are equal
Alternative hypothesis	Not all means are equal
Significance level	α = 0.05
Rows unused	10

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Product purchased by people	14	3, 5, 9, 10, 11, 12, 15, 16, 17, 20, 21, 22, 25, 30

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Product purchased by people	13	15.719	1.2091	1.53	0.311
Error	6	4.727	0.7878		
Total	19	20.446			

The value of the statistics for this data set are
f-value 1.53
p-value 0.31

Kruskal-Wallis test

Worksheet 1

Kruskal-Wallis Test: Product id versus Product id

109	1	109	9.0	-0.26
110	1	110	10.0	-0.09
111	1	111	11.0	0.09
112	1	112	12.0	0.26
113	1	113	13.0	0.43
114	1	114	14.0	0.61
115	1	115	15.0	0.78
116	1	116	16.0	0.95
117	1	117	17.0	1.13
118	1	118	18.0	1.30
119	1	119	19.0	1.47
120	1	120	20.0	1.65
Overall	20		10.5	

Test

Null hypothesis	H_0: All medians are equal
Alternative hypothesis	H_1: At least one median is different

DF	H-Value	P-Value
19	19.00	0.457

The chi-square approximation may not be accurate when some sample sizes are less than 5.

Consider the following example to demonstrate the use of the Kruskal Wallis goodness of fit test the data in the table below were obtained from arrival times in minutes of customers at a service center in Kruskal-wallis test it results that

Step 1: H0 all medians are equal

Step 2 : H1 at least one median is different

The result of p-value is 0.457

Conclusion

This methodology provides relevant solution to a typical combinatorial optimization problem which is to assign locations to items in a warehouse the objective function referred to in the simulation model considers that this allocation should ensure quick and efficient access to the merchandise the application of the proposed method. The solution is typical fit problem where a set of predictor variables are compared against a searched response variable the use of a system algorithms. That not only considers the allocation based on certain inputs but also generalizes and optimizes the estimation of the outputs to inputs that were not used in proposed system is designed to minimize picking distances based on an intelligent product allocation when arriving from the suppliers.

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