Jidoka enhances unilateral e-marketing and predicts e-stock although uncertainty modus operandi case

Ahmed M. Abed[1 1*]**,**

[1] *Dept. of Industrial Engineering, Zagazig University, Egypt. 44519,*

Ahmed-abed@zu.edu.eg

Tamer S. Gaafar[2]

[2] *Dept. of computer and System Engineering, Zagazig University, Egypt. 44519,*
Tamer_samy_gaafar@yahoo.com

Abstract

Many e-Marketing activities need to competitiveness survival by rapidly responding to customers' requests in jerky circumstances via understand and implement Jidoka. The Jidoka provides E-Systems high speed manipulating for requests information through an allocated algorithm. Jidoka targets to satisfy both customer and enterprise by providing commodities in minimum cost and delivery time. The main limitation faces the algorithm is dealing with an uncertain requests e-marketing path, the limitation that lengthens the requests' Manipulating-Lead-Time MLT and affects their profits. The main challenge in manipulating the customer's request is the nature of e-marketing, which is subject to uncertain requests and uncertain cancelations for the serviceable requests are allowed. The probability distributions for requests are not known (i.e., fully randomly), but can estimate the significant e-stock mean and their standard deviations. In this paper, A proposed allocation algorithm that consists of two sequential phases aims at determining the MLT according to serviceable, returns, and disposal requests over the offer horizon, which reduced by 21% of previous Lead-time and the second estimates the volume of e-stock, which related to a shortage cost analysis that reduced by 47%.

Keywords
Requests manipulating, Uncertainty, robust optimization, linear e-stock.

1. Introduction

The Adventurer e-marketing is a new vision, especially in deploying social-media marketing business. It is unsurprising that this vision is highly popular among people and salespeople, which emerged from their comfortability in closing the deals. This vision has one famous limitation, which is estimating for e-stock that satisfies all customers. Nonetheless, it remains relatively unknown in the academic and scientific communities. Weng Marc Lim (2020), aims to address this knowledge gap by offering greater clarity on this concept, via adopt an interrogative approach targeting to provide a richer understanding of e-marketing approach. Weng Marc Lim hopes to become a seminal reference for academia to understand challenger marketing. Osmonbekov, Adamson, and Dixon (2019, p. 289) say that challenger marketing is a story of probabilities. It is a story of increasing the likelihood of winning, keeping, and growing your business over-time. All collected data tell us is that if you want to place your bets, this [challenger marketing] is the best bet. The Adventurer e-marketing is a concept that encapsulates the powerful ideas captured in two coin's faces: The Adventurer Sale and The Adventurer Customer. This study proposes that the inclusion of inter-people networks may explain different levels of control over the channel partner when there are uncertain requests (e.g., requests) as cited by Ebers & Oerlemans, (2016). Customer's intention to initiate a business relationship with the supplier via the e-marketing process. There are many results that indicate important preferential differences in supplier pre-selection between customers according to two variables, namely quantity and cost in minimum versus maximum value cases. Forecasting demand is a crucial issue for driving efficient e-marketing operations management plans. This is especially the case in the Swvl, Uber, Careem booking and systems like that, where demand word and cancellation are uncertainty as noted by Dean, T., et al., (2016), lack of seasonal data trends usually coexist. Requested requests allocation in e-marketing management studies on how to allocate the limited available products (e.g., seats and trips in this work), which optimally to satisfy the uncertain customers' demands. In the e-marketing activities, advice creating wait booking list even if e-stock run out, due to cancellation activity. This paper focuses on the modeling and optimization of three related issues namely waiting time, service reliability, and losses as discussed by Gould, A. N. et al., (2016). The first section of the paper investigates an important and unique issue in an e-

[1] **Corresponding Author: Ahmed-abed@zu.edu.eg; (Tel: 01022956165) or (00966566174346)*

marketing distribution network, Maria E. N. et al., (2013) that aims to minimum network waiting for flow using a heuristic rule with variable lower bounds as cited by Kang, H., et ai., (2015). The second section of the paper introduces a novel method adopted from multi-offers (i.e., buses path) to optimally allocate the available seats for multi-users prefetching to enhance reliability. The objective is to minimize the request miss level (back request or cancelation level) as cited by Zhang, W. Y. et al., (2011) and Xie, X., et al., (2016), while satisfying the cache list (i.e., seat booking) and the total prefetching frequency (total request frequency) constraints. The third section of the paper studies the capacity (i.e., seats and paths) and request allocation problem in a service delivery network as noted by Sox, C. R. et al., (2011). The objective is to minimize the total cost while satisfying the required service reliability, which measures the probability of satisfying customers' requests within an arrival time interval. This distinctive feature allows the proposed algorithm to have more broadly practical applications in e-marketing widely, e.g., minimizing the total cost for Swvl /Uber/pipeline/airline networks. This paper describes and models these issues as mixed-integer linear programming, and gives a comprehensive computational experiment with Solver to test the solvability of the problem with small-to-medium size instances as noted by Wang, N., et. al., (2006). The aforementioned indicates that e-marketing is uncertain behavior has two opposite activities are available, namely request and cancelation for a specific commodity (e.g., seats in bus trips). If any enterprise targets to gain maximum profit under these circumstances logically, it must analyze the booking and cancelation activities to stand for e-stock availability (e.g., # of seats and trips) and avoid the shortage as discussed by Askin-RG. Et al., (1996) and Talaibek D. et al., (2018). Therefore, this work focuses on tackling this case via two sequential phases, the first have two steps, begins with formulating the e-marketing activities sequences and the second is dealing with them in parallel to satisfy all customers and service them in minimum time with the GA help. The second phase interests in cost analysis.

2. The Manipulating Lead Time Reduction Algorithm [MLTR]

The proposed algorithm consists of two sequential phases as aforementioned. The first phase divide to two sequential steps, based on checking of uncertainty e-stock (i.e., commodity, seats, …) capacity transaction, then tackled all requests by an evolved heuristic method based on GA, while through the second branch of the same phase, interests in minimizing the MLT serviceable time, which determine the e-stock losses at its minimum level as cited by Ibrahim, M.S. et al., (2003). The heuristic fitness rule published for the author 2008, and reviewed via Duan, F. et al., (2008) also.

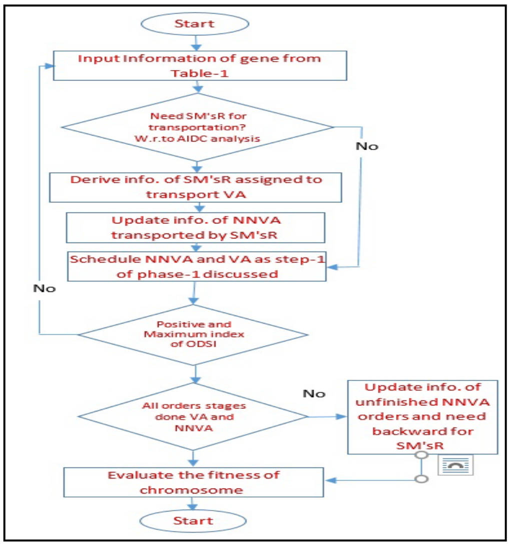

Figure.1: Chromosome modus operandi

2.1. Phase-I, Step-I, e-marketing formulation activities

This phase suggests adding a Super-Market icon (SM'sI: waiting for bookinglist) that appears on the URL of the e-marketing interface for any enterprise, which used the GA genome, which consists of 8 digits distributed as shown in Table-1. This genome records the customers' requested information for booking commodities.

Table-1, The genome that stuck on every output

Genome Bar code designs; X_1 X_2 X_3 X_4 X_5 X_6 X_7 X_8		
X_1		*Source address*
X_2		*Destination address*
X_3 X_4	$ES_{firstRequest}$, $ET_{firstRequest}$	*The Source perform this operation*
X_5 X_6	$ES_{predecessorRequest}$, $ET_{predecessorRequest}$	*The predecessor operation*
X_7 X_8	$ES_{final\ Request}$, $ET_{finalRequest}$	*The Destination Assembly Number*

All requests transported via SM'sI to the schedule as identified in Table-1 to pick its information from its source to its destination according to create an ODSI ((one-dimensional schedule index) discussed later as a fitness rule of GA) to control the movements of outputs and SM'sI path. The steps of the preparatory phase as noted by Singer, S.M. et. al., (2010) and Bannat, A. et. al., (2001) as illustrated in Figure. 1:

1. Scan START Code to distinguish the preemptive or every request or not.
   a. Request information via e-marketing for a gene such as non-preemptive activity, predecessor, e-marketing path /request and SM'sI of the operation.
2. READING Request_ID and stamp the on-line time $T_{FIRST\_SCAN\textbf{(request No.)}}$
3. READING Source schedule _ID as in scheduling Gantt tact chart.
4. READING E-marketing path No. to define the location of the SM's icon at Gantt schedule time.
   a. READING sub request genome

- ***b.*** READING Supper-Market genome
- ***c.*** READING the next Request must be loaded on the scheduled M/c according to ODSI heuristic as a fitness rule for GA as will discuss in Step 1 of phase II.
- ***d.*** STAMP time when finishing the confirmation of the execution, T_{END_SCAN} **(request No.)**
- ***e.*** Derive information of the SM'sI assigned to transported the request with its arrival times at e-marketing path of the operation and e-marketing path of the operation's predecessor from its last trip's destination, e-marketing path where it processes its preemptive, e-marketing path processing the operation's predecessor and e-marketing path assigned to process the operation as well as the last operation scheduled on this e-marketing path.

5. WRITE a e-stock define the following
   - ***a.*** T_{Mfg} = e-marketing processing time = preemptive + non-preemptive = tact time for the specified request.
   - ***b.*** $T_{CCT} = T_{END\_SCAN}$ **(request No.)** $-$ T_{FIRST_SCAN} **(request No.)**
   - ***c.*** $T_i = T_{Mfg} + T_{CCT}$, where i, is the request No.
   - ***d.*** The Manipulation rate or booking-list SM's size
   - ***e.*** The manipulatable for each output= $\sum T_{i\,every.part} / (8hr)$.
   - ***f.*** Update information of (preemptive activities) tackled by the SM'sI with the time the preemptive activity is suspended and the up-to-date total processing time.
   - ***g.*** Schedule non-preemptive activity on its assigned e-marketing path based on the information from Step 4.e. Then check if the current gene is the last gene in the chromosome: If not, go back to Step1,a. Otherwise, check if all preemptive activities finished. If not, go to Step 6. If so, go to Step 7.
6. Update information of the unfinished preemptive activities with their completion times.
7. Evaluate the fitness of the chromosome that equals the maximum completion time of all non-preemptive and Preemptive operations (i.e., tact time).
8. READING EXIT genome CODE.
9. Perform Quality Control.

Figure. 2 illustrates the sequential tackling of booking activities to determine the optimal e-stock capacity (seats and paths) via SM'sI, the analysis of historical jerky requests as noted by Dai, T. et. al., 2011.

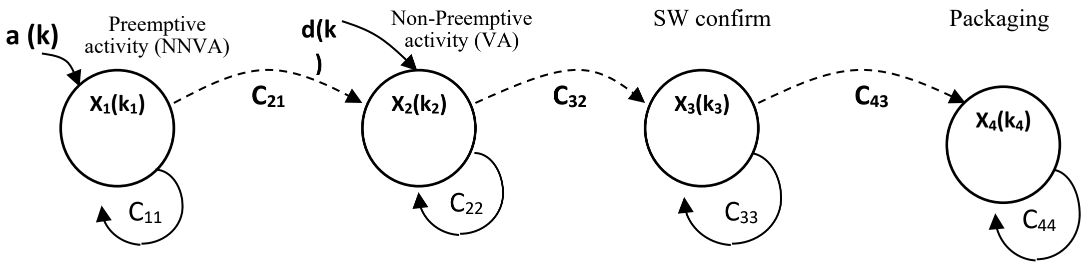

Figure 2: The e-stock operandi

Let $X_1(k_1)$ be the booking-list SM's size of specific request (k_1), where k_i= 1, 2, 3, … k, to (k_i+1) or the next schedule booking-list SM's is given by $X_1(k_1+1)$, and $X_1(k_1+1)$=***10*** ***(given requests)*** *percentage of* ***re-allocating*** **+** (jerky serviceable requests; ***42***).Therefore, the next interval must complete.

$$[0.1 * X_1(K_1) + 42],$$

Let $X_2(k_2)$ be the booking-list SM's size quantity that must be move to the next e-marketing path in time (k_2) only for items in SM'sI, it is found that there are **(15% of *Stage No.1 are leftover* due to cancelation)** where not moved and ***(10% of Stage No.1)*** repeated from (*Stage No.2*). IF there is ***(5% of Stage No.2)*** needs resale through backtrack path at its e-marketing path in time (k+1), the requests produced from (*Stage No.2*) is given by:

$$X_2(k_2+1) = 0.75 * X_1(k_1) + 0.05 * X_2(k_2) + 20,$$

Let $X_3(k_3)$ and $X_4(k_4)$ be request quantities that are produced from (*Stage No.3*) and (*Stage No.4*) respectively at time (k), ***(5% of Stage No.3 and Stage No.4)*** need re-allocate, thus ***(90% of Stage No.3 and Stage No.4)*** this can be represent as follows

$$X_3(k_3+1) = 0.9 * X_2 * (k_i) + 0.05 * X_3(k_3), \quad X_4(k_4+1) = 0.9 * X_3(k_3) + 0.05 * X_4(k_4)$$

These values differ from one e-marketing path to another; therefore, the general model defined as

$$\begin{bmatrix} X_1(k_1+1) \\ X_2(k_2+1) \\ X_3(k_3+1) \\ X_4(k_4+1) \end{bmatrix} = \begin{bmatrix} C_{11} & 0 & 0 & 0 \\ C_{21} & C_{22} & 0 & 0 \\ 0 & C_{32} & C_{33} & 0 \\ 0 & 0 & C_{43} & C_{44} \end{bmatrix} * \begin{bmatrix} X_1(k_1) \\ X_2(k_2) \\ X_3(k_3) \\ X_4(k_4) \end{bmatrix} + \begin{bmatrix} a(k)=1050 \\ d(k)=20 \\ 0 \\ 0 \end{bmatrix} \ldots\ldots \quad (1)$$

The above matrix presented as $X_i(k_i+1) = C_{XY}(k) + b(k)$ where ***i*** represents the number of repeated requests. If the initial manipulation rate 42 output, then 25 SM'sI path * 6 Output/interval = 150 output/interval move from stage to next.

$$a(k) = (Stage.1 + Stage.2) + 5 * k \ , \ d(k) = 1050 + 20 * k \ .$$

A Matlab model constructed to solve this matrix; Figure.3 and Figure.4 generated. Figure.3 illustrates the maximum handling via SM'sI, the stage No.4 illustrates the maximum handling ready to deal with e-stock without SM'sI, and the handling lay between 840 booking. Figure. 4 illustrates the case after using SM'sI, the handling increased to 1080 booking/sec, which represents 35%, which also discussed by Ahmed M. Abed, et al. (2020).

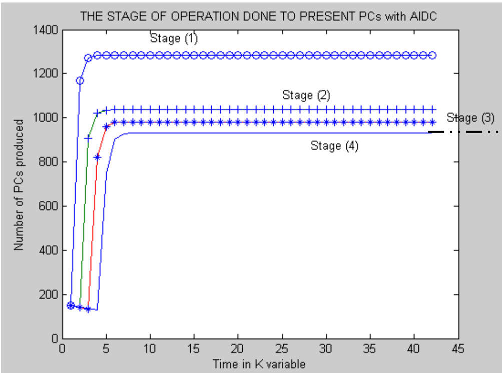

Figure.3: The productivity before activation of SM'sI.

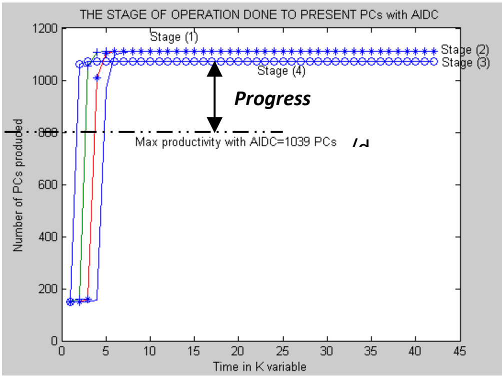

Figure.4: The productivity after activation of SM'sI.

Figure. 5 illustrates the difference between using the SM'sI and traditional e-marketing path, the standard scanning time [X] and the worst-case [Y], the x-axis presents the sequencing steps executed to assemble request #1, and y-axis presents the time consumed for the assembly. The optimum curve [X] is the required curve during assembly and transporting each request if the actual performance deviated upwards the optimal curve; this means that there is a delay in the assembly line or in transporting time, that needs immediate attendance. The size decreased from 1400 to 600 (i.e., 57%). Figure. 6 illustrates the MLT of requests capture to guidance the SM'sI, [The booking-list SM's size is 1050/Gantt tact time generated from step 1 of phase 2].

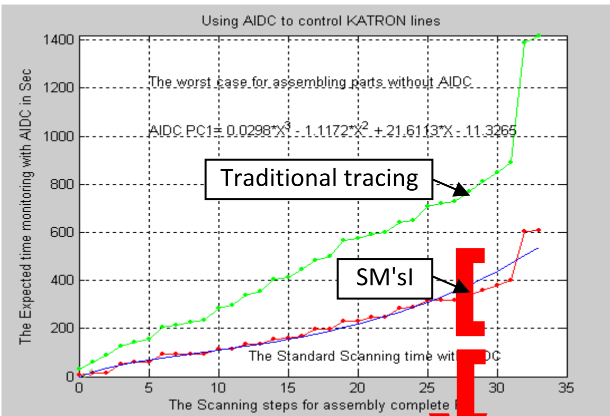

Figure.5: The best controlling time for the assembly steps to PC #1

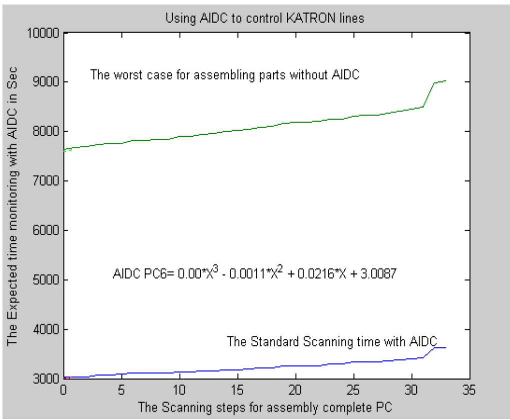

Figure. 6: The best controlling time for Order #6.

2.2. Phase I, Step-II, Schedule the completed requests

As aforementioned, this step works on completed requests done in the previous step of this phase. The collected completed requests are allocated in a one-dimensional selection and calculated via SM'sI icon to satisfy most customers in the shortest time span. Let there be n of requests (i.e., the population size to be MxO_j), to represent them, must create an initial Gantt tact time chart distributed from 0 to MLT. Earlier, define our chromosome to be permutations of the integers 1 to MxO_j. Suppose that $n=MxO_j$ listed in the request O_{ij} in a given chromosome. Since trying to minimize the total MLT, the fitness function will be the total MLT (MLT; manipulating lead time). $MLT = \sum_{k=1}^{n} d(J_{i,k,m}, J_{i,k,m+1})$. Where, *i* denote

to job number, k is a customer and m denote to occupied e-marketing path. Therefore, the fitness function will formulate and modified as discussed by Ahmed M. Abed, et al., (2020) to be as follow:
$MLT = \sum_{k=1}^{n} \sqrt{(M_{k+1} - M_k)^2 + (t_{k+1} - t_k)^2}$ and start replace the initial population with new offspring, to keep the fitter half of current population and generate the other half of the new generation through selection and crossover.

2.2.1. GA-based heuristic fitness rule

GA referred to a stochastic artificial intelligent technique providing a solution search process to mimic natural evolution phenomena as cited by Talaibek D. et al., (2018). In this section, GA enhanced via fitness heuristic rule ODSI, which allowed the optimal solution could be found near. The GA based heuristic is shown in Figure. 7 consists of the following main steps: representation and initialization; decoding operator and fitness evaluation through heuristic rule; genetic operators with crossover, mutation and selection and reparation operator.

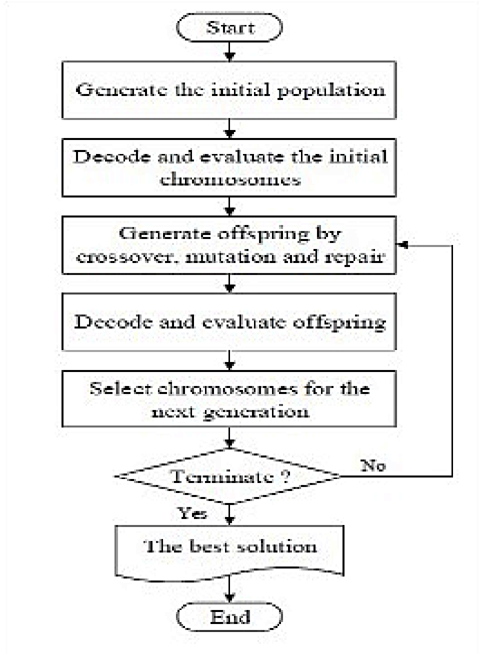

Fig.7: Procedure of GA-based heuristic.

2.2.1.1. Allocating

In the current system, numerous organizations are utilizing littler output sizes and attempting to lessen costs any place conceivable. Allocating is a great issue of finding the most effective format for transport outputs with the least waste utilization. Administrators choose the format from their experience, yet this, not a productive strategy since it is tedious and results don't effectively use the material. Allocating can decrease the ideal opportunity for e-marketing path and traveling costs. SM's I have an e-marketing path.

2.2.1.2. Types of Allocating via GA

- One-dimension allocating for requests to reduce the cycle time

The genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

Chromosome length	N
Selection	Binary selection method
Crossover	Mapped Crossover [PMX]
Mutation	Swap between 2 genes
Crossover Probability	75%
Mutation Probability	50%
Population size	20 chromosomes
Generation	25 population

- Selection rules select the individuals, called parents that contribute to the population at the next generation.
- Crossover rules combine two parents to form children for the next generation.
- Mutation rules apply random changes to individual parents to form children as illustrated in Figure. 8.

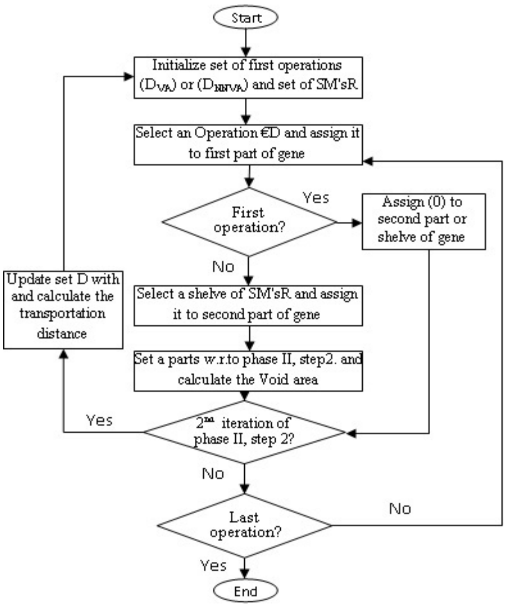

Figure.8: Procedure of the initialization

2.2.1.3. One-dimensional allocating heuristic steps

This phase aim at serving many requests at the same scheduling time and processing some of activities which are VA and NNVA (field indicators; Quantity of booking-list SM's, Dimension $_{(xi, yi)}$, Transportation time (In and Out), Dead-Time, Cycle time and Total lead-time).

1: Create the Network based schedule NWBS for requests' path and taking into account the suitable booking-list SM's, and build the VSM requests.

2: Analysis the scheduling time of preemptive + non- preemptive (NNVA + VA) time to create the prioritization matrix to calculate the relative weight of each e-marketing path.

3: Generate the one-dimensional allocating index $ODSI_{\ Index}$ for all requests as illustrated in Eq. 2, and create the first run of Gantt chart.

$$ODSI_{\ Index} = \frac{(ES_{final\ selected\ Order}+ET_{final\ selected\ Order})-ES_{first\ selected\ Order}}{(ES_{Predecessor\ selected\ Order}+ET_{Predecessor\ selected\ Order})+ET_{first\ selected\ Order}} \ldots\ldots \text{(Eq. 2)}$$

$ES_{finalRequest}$:Earliest start "NNVA" time of final selected request estimated for certain customer.
$ET_{finalRequest}$:Executing "VA" time of final selected request.
$ES_{firstRequest}$:Earliest start "NNVA" time to first selected request.
$ES_{predecessorRequest}$:Earliest start "NNVA" time of predecessor of first selected request.
$ET_{predecessorRequest}$:Executing "VA" time for selected predecessor request.
$ET_{firstRequest}$: Executing "VA" time for first selected request.

The equation's nominator indicates the NNVA time appeared between the request's execution. The denominator represents the total time required to finish the requests in time.

4: Schedule the one-dimensional allocating requests according to radar suggestion,
5: Fill any idle-time with the first request in the line appeared in (step-4) and removes from the next iteration.
6: Calculate the CCT for should-be situation and compared with as-is situation.
7: Distinguish among the stores via radar shape to guide us in creating the dynamic Gantt chart.
8: Continue till the difference between the $CCT_{\text{(should-be) } i+1} = CCT_{\text{(should-be) } i}$ for $\prod$ iteration i= **1, 2, …n.**
9: Maximum # of requests $N = \frac{\sum_i^n W_{i\emptyset} \times L_{\ i\emptyset}}{W \times L}\ \forall\ \boldsymbol{i = 1.2. \ldots .n. and}\ \emptyset = \boldsymbol{0 \ldots 90^o}$
10: Displacement without overlapping
11: $\boldsymbol{A_{in\ /out}} \ \leq \boldsymbol{W \times L}$
12: All requests that have same base area rotate with the same angle within cotangent
13: Requests reiterates allocating of selected requests booking-list SM's with respect to FIFO.
14: Problem findings and suggest improvement scope.

2.2.1.3.1. Implementation Results

The Implementation has done at SWVL e-marketing for Inland transport, Egypt. The requests collected via their mobile application shown in Table-2. The solution starts with creating the NWBS as illustrated in Figure. 9, and then calculate the ODSI for all requests with different specifications and jerky requested. In this phase, the intention to improve a previously published rule aims to reduce the total lead-time Ahmed M. Abed, et al., (2020). The requests in this context rely on feeding with different requests and the e-marketing analysis illustrated in Figure. 10 (a: f) and the final arrangement of the requests via e-marketing and ODSI illustrated in Figure. 11 and create Gantt as illustrated in Figure. 12, Figure. 13, and Figure. 14.

Table-2: Customer Registration time for different six ord

Order |	Carriage counter per customer					
1	3 (1)	1 (3)	2 (6)	4 (7)	6 (3)	5 (6)
2	2 (8)	3 (5)	5 (10)	6 (10)	1 (10)	4 (4)
3	3 (5)	4 (4)	6 (8)	1 (9)	2 (1)	5 (7)
4	2 (5)	1 (5)	3 (5)	4 (3)	5 (8)	6 (9)
5	3 (9)	2 (3)	5 (5)	6 (4)	1 (3)	4 (1)
6	2 (3)	4 (3)	6 (9)	1 (10)	5 (4)	3 (1)

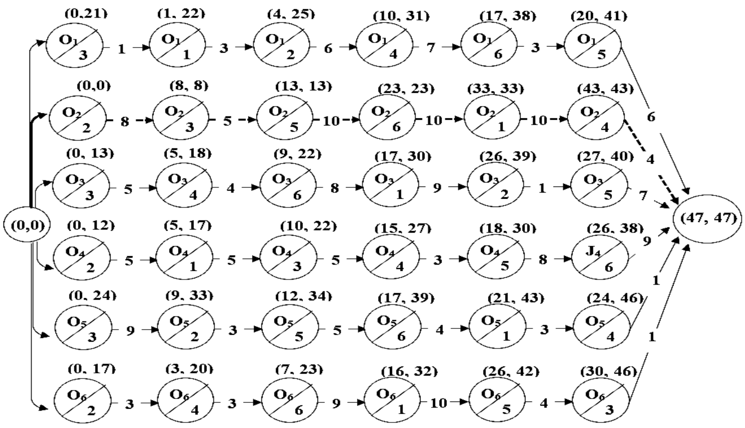

Figure. 9: The NWBS for data in Table-2

Priortization Matrix	Facilities#1	Facilities#2	Facilities#3	Facilities#4	Facilities#5	Facilities#6
Facility #1	1	1.538	1.379	1.818	1	0.9302
Facility #2	0.65	1	0.897	1.182	0.65	0.6047
Facility #3	0.725	1.115	1	1.318	0.725	0.6744
Facility #4	0.55	0.846	0.759	1	0.55	0.5116
Facility #5	1	1.538	1.379	1.818	1	0.9302
Facility #6	1.075	1.654	1.483	1.955	1.075	1
Diagonal Mac's weight	**5**	**7.692**	**6.897**	**9.091**	**5**	**4.6512**

Facility#1	Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
Order #1 O1	5	10.5	6.25	2.25	5.75	6.25
Order #2 O2	-0.674	5	-0.163	-0.535	-0.209	-0.163
Order #3 O3	-0.5	1	5	-0.269	0.27	0.3462
Order #4 O4	-0.1	3.8	2.1	5	1.9	2.1
Order #5 O5	-0.708	0.917	0.208	-0.458	5	0.2083
Order #6 O6	-0.462	1.038	0.038	-0.231	0.308	5
	2.556	22.26	13.43	5.757	13.02	13.742

Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
1.956	0.472	0.465	0.391	0.442	0.455
-0.264	0.225	-0.012	-0.093	-0.016	-0.012
-0.196	0.045	0.372	-0.047	0.021	0.025
-0.039	0.171	0.156	0.869	0.146	0.153
-0.277	0.041	0.016	-0.08	0.384	0.015
-0.181	0.047	0.003	-0.04	0.024	0.364
1.000	1.000	1.000	1.000	1.000	1.000

Facility#2	Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
Order #1 O1	7.692	0.4	2.3	0.1	0.8	-0.1
Order #2 O2	1.25	7.692	3.375	0.625	1.5	0.375
Order #3 O3	-0.593	-0.666	7.692	-0.778	-0.519	-0.852
Order #4 O4	0.6	1.6	5.4	7.692	2.4	0.6
Order #5 O5	0.083	-0.083	1.5	-0.333	7.692	-0.5
Order #6 O6	3.34	2.67	9	1.67	4	7.6923
	12.37	11.61	29.27	8.976	15.87	7.2155

Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
0.622	0.034	0.079	0.011	0.05	-0.014
0.101	0.662	0.115	0.07	0.094	0.052
-0.048	-0.057	0.263	-0.087	-0.033	-0.118
0.048	0.138	0.185	0.857	0.151	0.083
0.007	-0.007	0.051	-0.037	0.485	-0.069
0.27	0.23	0.308	0.186	0.252	1.066
1.000	1.000	1.000	1.000	1.000	1.000

Facility#3	Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
Order #1 O1	6.897	13	5	15	9	31
Order #2 O2	-0.054	6.897	-0.231	0.538	0.077	1.7692
Order #3 O3	0.2	2.6	6.897	3	1.8	6
Order #4 O4	-0.6	0.2	-0.333	6.897	-0.067	1.34
Order #5 O5	1	0.11	1	-0.111	6.897	3.4444
Order #6 O6	-0.936	-0.548	-0.806	-0.484	-0.677	6.8966
	6.507	22.26	11.53	24.84	17.03	50.45

Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
1.06	0.584	0.434	0.604	0.528	0.614
-0.008	0.31	-0.02	0.022	0.005	0.035
0.031	0.117	0.598	0.121	0.106	0.119
-0.092	0.009	-0.029	0.278	-0.004	0.027
0.154	0.005	0.087	-0.004	0.405	0.068
-0.144	-0.025	-0.07	-0.019	-0.04	0.137
1.000	1.000	1.000	1.000	1.000	1.000

Facility#4	Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
Order #1 O1	9.091	2.2	-0.112	0.47	0.88	-0.667
Order #2 O2	-0.553	9.091	-0.723	-0.532	-0.383	-0.787
Order #3 O3	1.34	4.7	9.091	1.45	2.3	0.112
Order #4 O4	0.112	0.78	-0.445	9.091	-0.5	-0.6
Order #5 O5	-0.28	-0.043	-0.6	-0.24	9.091	-0.72
Order #6 O6	2.34	7.34	1	2.5	3.67	9.0909
	12.05	24.07	8.211	12.74	15.06	6.429

Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
0.754	0.091	-0.014	0.037	0.058	-0.104
-0.046	0.378	-0.088	-0.042	-0.025	-0.122
0.111	0.195	1.107	0.114	0.153	0.017
0.009	0.032	-0.054	0.714	-0.033	-0.093
-0.023	-0.002	-0.073	-0.019	0.604	-0.112
0.194	0.305	0.122	0.196	0.244	1.414
1.000	1.000	1.000	1.000	1.000	1.000

Facility#5	Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
Order #1 O1	5	0.5	0.54	0.231	-0.176	0.35
Order #2 O2	0.57	5	0.9	0.567	0.174	0.5667
Order #3 O3	-0.036	-0.121	5	-0.03	-0.303	0.051
Order #4 O4	0.31	0.19	0.51	5	-0.038	0.42
Order #5 O5	0.82	0.62	1.3	0.82	5	1
Order #6 O6	0.03	-0.13	0.31	0.03	-0.3	5
	6.694	6.058	8.56	6.618	4.356	7.3877

Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
0.747	0.083	0.063	0.035	-0.041	0.047
0.085	0.825	0.105	0.086	0.04	0.077
-0.005	-0.02	0.584	-0.005	-0.07	0.007
0.046	0.031	0.06	0.756	-0.009	0.057
0.122	0.102	0.152	0.124	1.148	0.135
0.004	-0.022	0.036	0.005	-0.069	0.677
1.000	1.000	1.000	1.000	1.000	1.000

Facility#6	Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
Order #1 O1	4.651	0.8	0	0.9	0.2	-0.05
Order #2 O2	-0.091	4.651	-0.182	0.364	-0.061	-0.212
Order #3 O3	0.647	1.333	4.651	1.444	0.444	0.412
Order #4 O4	-0.171	0.286	-0.171	4.651	-0.143	-0.286
Order #5 O5	0.143	0.762	0	0.857	4.651	-0.048
Order #6 O6	0.722	1.444	0.555	1.555	0.777	4.6512
	5.901	9.276	4.853	9.771	5.869	4.4677

Order #1 O1	Order #2 O2	Order #3 O3	Order #4 O4	Order #5 O5	Order #6 O6
0.788	0.086	0	0.092	0.034	-0.011
-0.015	0.501	-0.037	0.037	-0.01	-0.047
0.11	0.144	0.958	0.148	0.076	0.092
-0.029	0.031	-0.035	0.476	-0.024	-0.064
0.024	0.082	0	0.088	0.793	-0.011
0.122	0.156	0.114	0.159	0.132	1.041
1.000	1.000	1.000	1.000	1.000	1.000

Figure. 10(a, f). SM'sI analysis to commence of schedule solution

Summary	Facility #1		Facility #2		Facility #3		Facility #4		Facility #5		Facility #6			Final Score of Priority Customer Serve
	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score	Weighting	Score		
Order #1 O1	0.075	0.697	0.150	0.130	0.025	0.637	0.175	0.137	0.150	0.156	0.075	0.165		0.148
Order #2 O2	0.385	-0.029	0.308	0.182	0.192	0.057	0.154	0.009	0.385	0.203	0.385	0.071		0.163
Order #3 O3	0.310	0.037	0.034	-0.013	0.172	0.182	0.138	0.283	0.241	0.082	0.276	0.255		0.171
Order #4 O4	0.227	0.243	0.227	0.244	0.227	0.031	0.136	0.096	0.364	0.157	0.409	0.059		0.212
Order #5 O5	0.075	0.017	0.075	0.071	0.225	0.119	0.025	0.062	0.125	0.297	0.100	0.163		0.088
Order #6 O6	0.233	0.036	0.115	0.385	0.034	-0.027	0.136	0.412	0.100	0.105	0.209	0.288		0.179

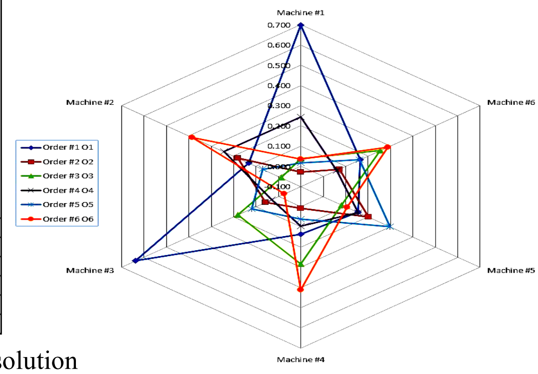

Figure. 11: The ODSI initial solution

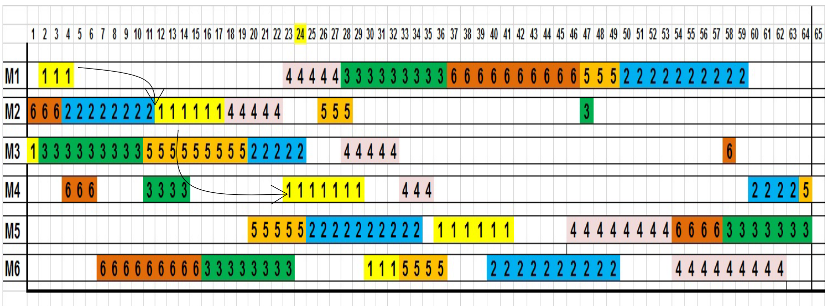

Figure. 12. The Gantt chart of registration orders

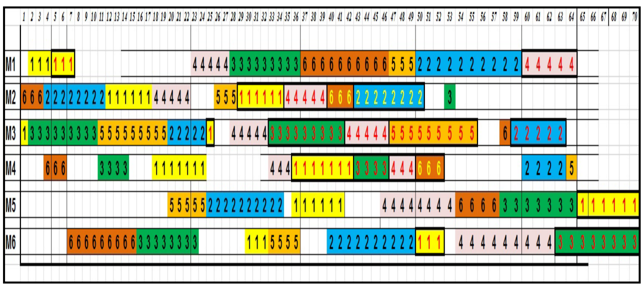

Figure. 13: Waiting time plan

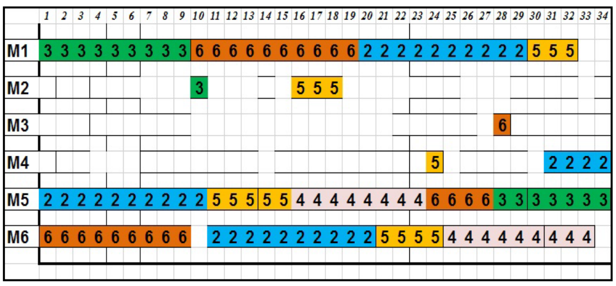

Figure. 14: Final iteration for schedule and MLT

The e-marketing's Requests retraces the arrangements as proposed after check the consistency ODSI index as discussed by Ahmed M. Abed, et al., (2020). The e-marketing's requests represent a closed loop to enhance continuity of results with time (i.e., Matureness situation). The GA begins its trails from e-marketing's analysis solution to enhance the result and creates the overlap Gantt chart taking into account the crossover and mutation as illustrated in **Table-2**.

3. Phase-II, Shortage Cost Analysis

This phase based on previous schedule output data, which aims to schedule the transit situation, if the customer needs to book many paths to go to specific point.

Decision variables

$\propto_{ij}$: Fraction of request that is allocated to specific booking source $\boldsymbol{j}$ (i.e., trip) from request customer $\boldsymbol{i}$, $i = 1, 2, \dots, n$, $j = 1, 2, \dots, m$,

μ_j: Capacity (# of seats) of service trip j; j = 1 ,…, m;

Given parameters

c_{ij}: Travel cost per unit time between facilities i and j, i = 1, 2, … , *n*, j = 1, 2, … , m,
k_j: servicing cost per seat at booking source j; j = 1 …. m,
m: Number of booking source,
n: Number of requested sources,
r_0: Required booking reliability, $0 \le r_0 \le 1$;
τ_{ij}: Average time between request source *i* and booking source *j*; i =1, 2, … , *n*; j = 1, 2, …,*m*;
T : Interval arrival time during which the customer should be satisfied,
λ_i: Requested rate at customer i; i = 1 … n;

Performance measures

$\bar{B}_j$: Average (back-request/cancelation) at service trip j; j = 1, …, *m*;
C: Total cost which includes the transportation cost and the capacity servicing cost,
$\overline{R}_{ij}$: Service reliability for the partial request $\propto_{ij} \lambda_i$ that is assigned to booking trip j from request source i; i = 1, 2, … , *n*; j = 1, 2, … , m;
$\bar{R}$ Aggregated service reliability for all the trips,$\rho_j = \sum_{i=1}^{n} \alpha_{ij}\lambda_i / \mu_j = \bar{\lambda}_j / \mu_j$, Traffic intensity at facility j; j = 1 … m;. There are *n* requested and *m* service facilities. Service facility j, which is allocated with capacity μ_j . Requested at source i follows Poisson distribution with rate λ_i. Each customer from any request source has the same unit request. Service facility j serves an M/M/1 queue, based on a first-in-first-serve (FIFS) scheduling policy. service reliability according to Wang et al. (2006), which is the probability of meeting request within interval T time, and the result of Sox et al. (1997), which shows the booking level within interval time T for a multi-paths, the booking obtains reliability within arrival interval time T for the partial request $\propto_{ij} \lambda_i$ that is assigned to specific trip j from request source I, where $\overline{R}_{ij} = 1 - e^{-\mu_j(T-\tau_{ij})(1-\rho_j)}$ Another indicator of system performance in proposed case is the average waiting time. In the setting of one seat-booking facility with service capacity μ, s_i as the base-stock level for seat i, request λ_i for seat-trip i, and total demand λ for all the seat-path as deduced and mimicked, Sox et al (1997) ideas .Show that the back request level for seat-path booking i that adopts a make-to-stock strategy can be expressed as: $\boldsymbol{B_I} = \eta_i^{s_i+1} / \boldsymbol{1 - \eta_i}$, Where $\eta_i = \lambda_i/(\mu - \lambda + \lambda_i)$ is the parameter for steady-state distribution booking in the e-marketing system for seat-path i, which follows geometric distribution. The proposed equations can derive the average "request\back requested" at booking j, where the concept of inventory is no longer applied: $\bar{B}_j = \rho_j / 1 - \rho_j$ As a result, the average waiting time per customer request can be calculated as the weighted sum of the delay caused by both \back request and traffic:

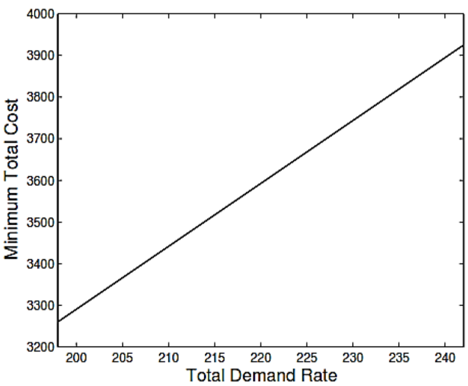

Figure. 15: Total cancelation requests cost

$$\bar{W} = \frac{\sum_{j=1}^{m} \bar{B}_j + \sum_{i=1}^{n} \sum_{j=1}^{m} \alpha_{ij} \lambda_i \tau_{ij}}{\sum_{i=1}^{n} \lambda_i} \dots\dots (3)$$

Figure.15. shows that the total cancelation cost increases as the total requested increases. The reason is to reduce available paths to meet the increased request, which brings up the total cost to shortage. Figure.16 shows the effect of the arrival time interval on the total cost and the average waiting time. The total cost decreases as the arrival time interval increases. The reason is that we have more time to fulfill the request, therefore, the booking must not be stopped after the trip start, thus require less seat at the service path. As a result, the total cost is reduced. Note that when the arrival time interval approaches infinity caused by rush-hour traffic. The average waiting time, on the other hand, increases with the arrival time interval due to reducing the remaining seats at the paths booking. Also, observe that the total cost increases as the required service reliability increases, while the average waiting time shows the opposite trend via implement eq. 4. The reason is that we need more capacity to meet the increased service reliability, which brings up the total cost and reduces the average waiting time. When the seats at each service trip are predetermined, we can calculate the maximum service reliability that the system can achieve by introducing an alternative model:

$$\text{Max } \bar{R} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} \alpha_{ij}\lambda_i[1-e^{-\mu_j(T-\tau_{ij})(1-\rho_j)}]}{\sum_{i=1}^{n}\lambda_i} \;\dots\dots (4)$$

$$\text{s.t. } \sum_{i=1}^{n} \alpha_{ij}\lambda_i \le \mu_j, \quad \text{j=1,2,…,m,}$$

$$\sum_{i=1}^{m} \alpha_{ij} = 1 \quad i = 1,2,\dots,n,$$

$$\alpha_{ij} \ge 0, \quad i = 1,2,\dots,n; \quad j = 1,2,\dots.,m,$$

These equations are similar to proposed model except that the values for μ_j are predetermined and its target is to maximize the service reliability. For example, with μ_j = {194.21; 54.9}, we obtain the maximum service reliability $\bar{R}$= 0.914, and the optimal request allocation strategy as shown below. The number of replication is set at 3. The average waiting times

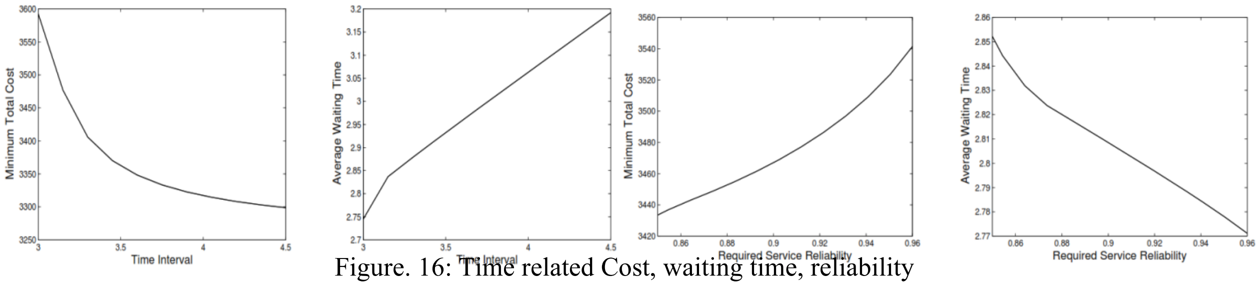

Figure. 16: Time related Cost, waiting time, reliability

$$\propto = \begin{Bmatrix} 0.762 & 0.945 & 0.99 & 1 & 0.164 & 0.959 \\ 0.238 & 0.055 & 0.01 & 0 & 0.836 & 0.041 \end{Bmatrix}$$

The optimum servicing level handling between different tasks facilities**,** the transportation cost will be large if stream produce too many seats without market form, if there is any seats not handled weather transportation system become in position will increase transportation cost and that is a worst case. Each replication contains 200 days, with 10 days of high warm-up. Each day contains 16 working hours. After the running of a total of 10344 simulations, the best solution is found at the 244th running. The following matrix shows the optimal request strategy. The row index represents the booking trip and the column index represents the requested source.

The simulated code to estimate the optimum quantity/commodity to be produced and transported to design a suitable super market:

```
        n=10344;
Min_servicing_capacity = MIP;
Max_ servicing_capacity = MXP;
Fixed_Cost = FC;
Variable_Cost = VC;
level=[MIP: MXP];
cost = FC + VC * level;
for k=1:1201
   cum_saves=0;
   for m=1:n
      request = floor(rand*( MXP - MIP)+ (MXP-MIP)+1);
      if request >= level(k)
         partial_saves = Unit_Price * level(k);
      else
Unit_Price = X;
Booking_cost= Y;
Capacity_shortage_cost= Z;
            partial_saves= X * request + ((X-Y-Z)) *(level(k)- request);
```

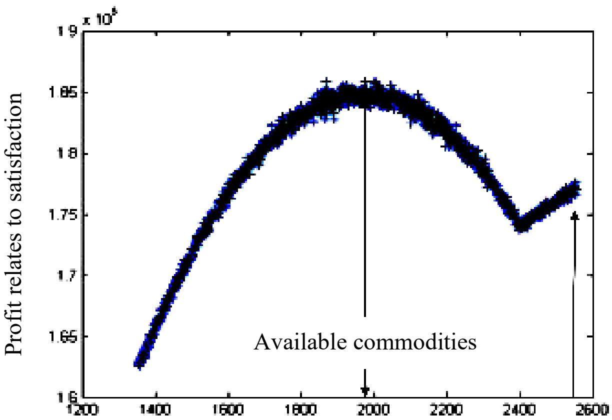

Figure. 17: Simulation results for optimal booking

```
        end
            saves = partial_saves-cost(k);
            cum_saves = cum_saves+saves;
        end
            expected_saves=cum_saves/n;
            p(k,1)=level(k);
            p(k,2)=expected_saves;
        end
plot(p(:,1),p(:,2),'+',p(:,1),p(:,2),'-'), xlabel ('NO. of bathtubs'), ylabel ('Transportation saves $')
```

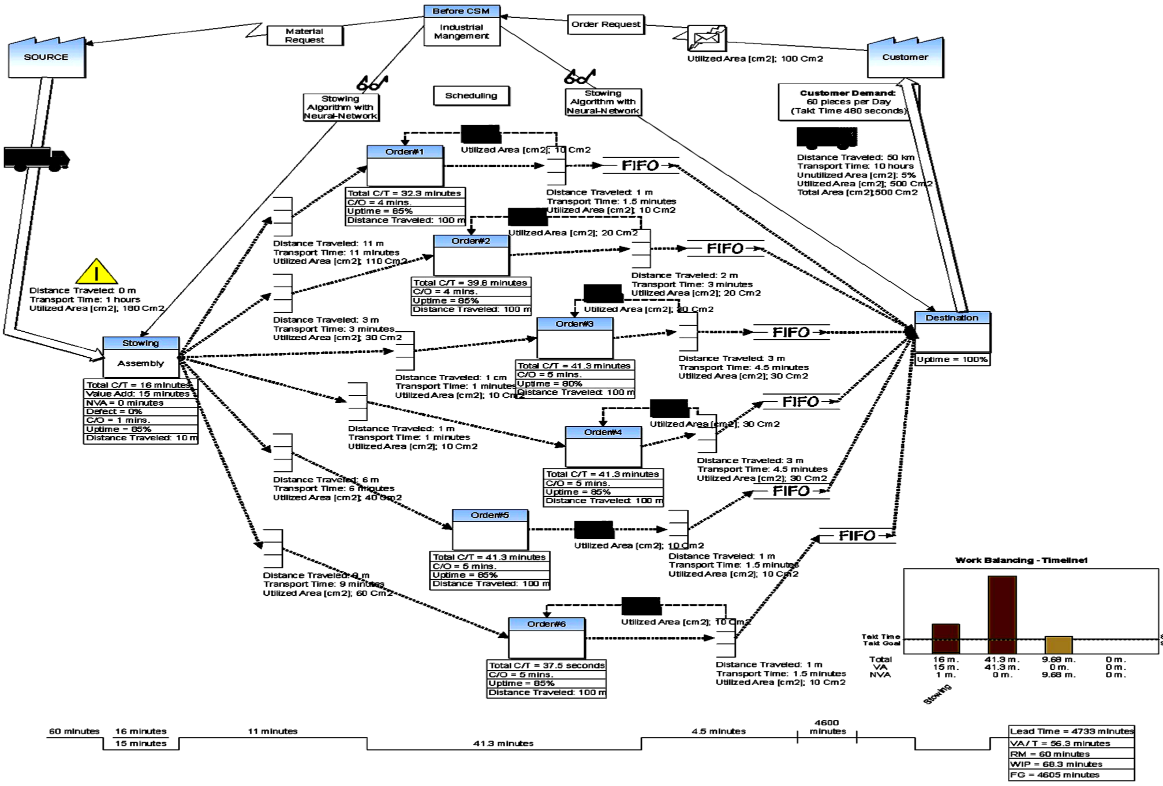

Figure. 18: VSM in To-be situation

Figure.17 illustrates the optimum booking that minimizes the shortage cost and increases their customer satisfaction, and increase profit at 1990 booking/day. Also Figure.18 illustrates the VSM that emerges the MLT and describes all e-marketing sequences till sale a commodity or rent the seat at specific trip and so on.

4. Conclusion

This work suggests making bookings available until reaching the trip to the final station and tabulates all waiting requests in SM'sI local dataset. The proposed algorithm tackles the uncertainty of booking/cancelation via two sequences phases. The first aims to schedule the waiting booking-list in minimum delivery time to increase the customers satisfaction by 21%, while the second phase makes an analysis for significant costs such as fixed, variable, shortage, and opportunity cost to satisfy the enterprise via increase their profit by 47%. the e-marketing has four variables that have impact relations such as time interval with minimum cost and service reliability with waiting time as illustrated in Figure. 16, the waiting time reduced by selecting the nearest suitable station for customers with respect to a minimum serviceable time and cost and increase utilization to achieve satisfaction to customers and enterprise via e-marketing processes.

Author Contributions: Conceptualization, A.A. Methodology, A.A and T.G.; Software, A.A and T.G.; Validation, A.A; Formal Analysis, A.A.; Investigation, A.A. and T.G.; Resources, A.A.; Data Curation, T.G.; Writing-Original Draft Preparation, A.A.; Writing-Review & Editing, A.A; Visualization, A.A.; Supervision, A.A.; Project Administration, A.A

Biography

Ahmed M. Abed received the Mechanical Engineering, B.Sc in Industrial and Production engineering, also M.Sc. degrees at (2002:2006) from Zagazig University, Egypt, and complete his Ph.D. at 2014. His researches interest is "Safety, Waste reduction, and TQM". He has published 23 papers. He is a Fellow member of Engineering syndicate and Industrial Consultant for Ideal Standard Egypt and BestBuy Co., He has a good reputation in this field in more than 12 Factories in Industrial 10th of Ramadan City as a consultant. He is an associate professor in IE department, He candidate to work at HTI (higher technology institute) and AIET (Alexandria Institute of Engineering and Technology), Alex.; I have my special public service work as a treasurer of engineering club syndicate in 10th of Ramadan City.

Reference

Weng Marc Lim,., Challenger marketing, *Industrial Marketing Management*. Vol. 84, pp. 342–345, 2020 www.elsevier.com/locate/indmarman

Ebers, M., & Oerlemans, L., The variety of governance structures beyond market and hierarchy. *Journal of Management*, vol. 42, no. 6, pp. 1491–1529, 2016.

Dean, T., Griffith, D. A., & Calantone, R. J.,. New product creativity: Understanding contract specificity in new product introductions. *Journal of Marketing*, vol. 80, no. 2, pp. 39–58, 2016.

Gould, A. N., Liu, A. H., & Yu, Y., Opportunities and opportunism with high-status B2B partners in emerging economies., *Journal of Business & Industrial Marketing*, vol. 31, no. 5, pp. 684–694, 2016.

Kang, H., Min, J., & Lee, J. K., The effects of uncertainties on network embeddedness and the mediating effect of information sharing. *Journal of Marketing Thought*, vol. 2, no. 4, pp. 1–14, 2015.

Xie, X., Fang, L., & Zeng, S., Collaborative innovation network and knowledge transfer performance, *A fsQCA approach. Journal of Business Research*, vol. 69, no. 11, pp. 5210–5215, 2016.

Maria E. N., Luca Giustiniano, and Luca Pirolo, Demand Forecasting in the Fashion Industry. *A Review, International Journal of Engineering Business Management*, Vol. 5, Received 1 June 2013; Accepted 15 July 2013. DOI: 10.5772/56840

Zhang, W. Y., Zhang, S., Cai, M., and Huang, J. X., A new manufacturing resource allocation method for supply chain optimization using extended genetic algorithm. *Int. J. Adv. Manuf. Technol.*, vol. 53, pp. 1247-1260, 2011.

Sox, C. R., Thomas, L. J., and McClain, J. O., Coordinating production and inventory to improve service. Management Sci., vol. 43, no. 9, pp.1189-1197, 1997.

Wang, N., Lu, J.-C., and Kvam, P., Reliability modeling in spatially distributed logistics systems. *IEEE Trans. Reliab.*, vol. 55, no. 3, pp. 525-534, 2006.

Talaibek D Osmonbekov, Brent Adamson, Matthew Dixon, Challenger sale: a dynamic method for customer engagement and value creation in business-to-business relationships, *journal of Business and Industrial Marketing*, Accepted/In press - Jan 1 2018

Askin-RG., Bidanda-B., Jagdale-S., Integration of just-in-time production and material handling for an assembly environment, *Proceedings of the 5th Industrial Engineering Research, Conference*. Inst. Ind. Eng, Norcross, GA, USA; pp. 281-286, 1996.

Ibrahim, M.S., Adel A. Elmoe'z and Ahmed M. Abed, Minimize make-span for machine sequencing of jobs with precedence constraints, *7th Conference on Theoretical and Applied Mechanics*, the academy of scientific research, Egypt, 2003.

Duan, F., Morioka, M., Tan, J. and Arai, T. Multi-modal assembly-support system for cell production, *International Journal of Automation Technology*, Kobe, Vol. 25, pp. 384-393, 2008.

Singer, S.M. and Akin, D.L. "Scheduling robot activity performance for a cooperative human and robotic team", *Acta Astronautica*, Vol. 66, no. 1/2, pp. 102-16, 2010.

Bannat, A., Bautze, T., Beetz, M., Blume, J., Diepold, K., Ertelt, C., Geiger, F., Gmeiner, T., Gyger, T., Knoll, A., Lau, C., Lenz, C., Ostgathe, M., Reinhart, G., Roesel, W., Ruehr, T., Schuboe, A.,Shea, K., Stork genannt Wersborg, I., Stork, S., Tekouo, W., Wallhoff, F., Wiesbeck, M. and Zaeh, M.F. Artificial cognition in production systems, *IEEE Transactions on Automation Science and Engineering*, Vol. 8, no. 1, pp. 148-174, 2011.

Dai, T., Sycara, K. and Lewis, M., A game theoretic queueing approach to self-assessment in human-robot interaction systems, *IEEE International Conference on Robotics and Automation*, Shanghai, pp. 58-63, 2011.

Ahmed M. Abed, Samia Elattar, Tamer Gaafar, Fadwa Alrowais, Artificial Poka-Yoke Increases Process Reliability Via A Hybrid Of The Neural Network With ARIMA Results, *International Journal of Mechanical and Production Engineering Research and Development,* Vol. 10, no. 2, Issue date Apr-30 2020, pp. 931–954, 2020**.** IJMPERDAPR202092**, DOI**: 10.24247/ijmperdapr202092**.**

Ahmed M. Abed, Samia Elattar, Minimize the Route Length using heuristic method aided with Simulated Annealing to reinforce Lean management sustainability, *international journal of Processes* (ISSN 2227-9717), *Processes*, Vol. 8, no. 4, pp. 495, 2020; https://doi.org/10.3390/pr8040495

Ahmed M. Abed, Samia Elattar, Tamer Gaafar, Fadwa Alrowais, The Neural Network revamping the process's reliability in deep Lean via internet of things, *International journal of Processes* (ISSN 2227-9717), *Processes* 2020, Vol. 8, no. 6, pp. 729; 2020. https://doi.org/10.3390/pr8060729