DECISION SUPPORT SYSTEMS ANALYSIS WITH SIMULATION

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ABSTRACT

A decision support system (DSS) is developed for car registration in a Gulf Cooperation Council (GCC) country using simulation model. The car registration is managed by a government organization but a private corporation certifies the car fitness. High variation is noticed in registration and therefore a simulation model is developed to evaluate the registration operations and policies. The simulation model replicates the existing operational policies and evaluates feasible policies to maximize system performance. The suggested DSS model provides robust analysis in system time, service time and average queue lengths as an index to monitor the service quality.

Key Words: Decision Support System (DSS), Simulation, Car Registration, Service Operation, Systems Analysis, Information Maximization

INTRODUCTION

A visual SLAM [1] computer simulation model is developed to analyze car registration and inspection in a GCC country. Founded on 26 May 1981, the GCC countries consist of Bahrain, Qatar, Saudi Arabia, Kuwait, United Arab Emirates, and Oman. The aim of the GCC countries is to promote coordination between member states in all fields in order to achieve unity.

A series of interview are planned with the managers, engineers and workers at the car inspection stations to identify the steps a customer should follow to do the car registration, as shown in Figure 1. The pressing problem is the long waiting time for the customer at the car registration station. Figures 2 and 3 display the snapshot of the car arrival pattern. The car arrival is random. A variety of registration and renewal jobs exist depending on the status of the test, nationality of the person and time of the day. Customers demand high quality, customized services with fast response time [2]. The simulation model provides competitive strategy [1] and consequently improves organizational performance [3, 4]. A multivariate information maximization model is built from simulation results. The DSS model developed thus provides information about the system efficiency [5, 6]. The DSS model points to the critical factors for system improvements.

Data Collection
The necessary data is collected with a fact-finding technique [7]. In this approach, interviews, observations, sampling techniques and the existing documentation (including memos and data base) are used to collect information. The time between arrivals of cars is shown in Figures 2(b) and 3(b); which suggests that the service time and system time are stochastic in nature.
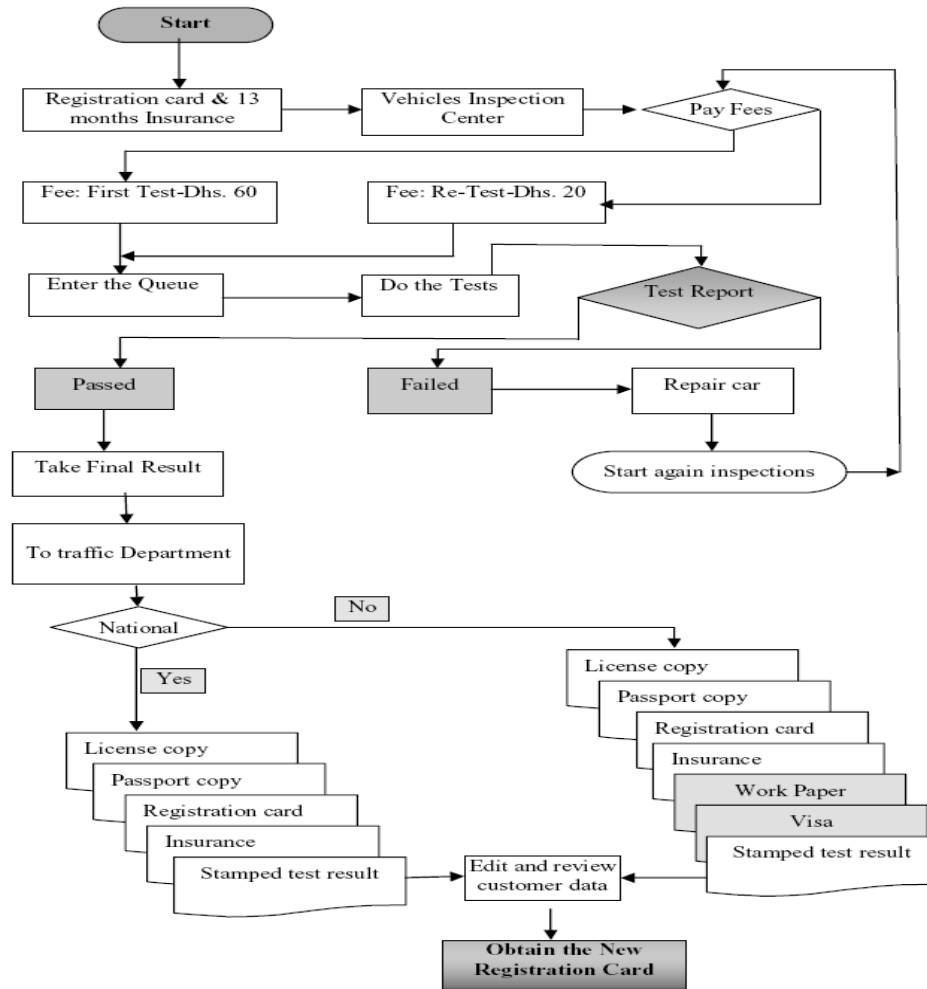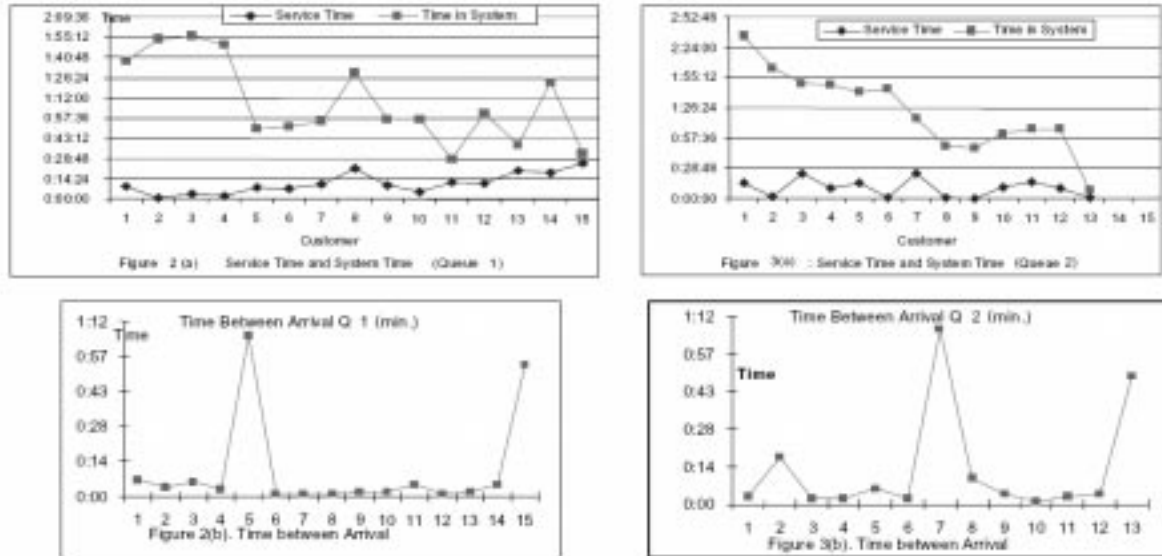
Figure 1: Flowchart Illustrating Renewal and Registration of Car

SIMULATION MODELING AND METHOD ANALYSIS

In a simulation model the cars move through a series of testing stations such as hydrocarbon, tires, rims, break system, shock absorber, visual, body and chassis in the inspection process. Figure 4 is the AweSim network simulation model. At the end of the inspection, the result is either pass or fail. If the final result is fault free, the car is routed to the traffic department to finish the renewal of the registration card. Otherwise, the result is fail if the car functions improperly. Hence, the car is routed to the repair center to fix the defects identified. After being repaired, the car is again sent back to the inspection center to obtain a pass certificate if it satisfies the test requirements. The car registration system is shown in Figure 1, while Figures 2(a) and 3(a) are the service and system time information.

The car arrives at the registration center and is routed to the inspection station according to Figure 1. The three independent lanes for testing in the inspection station are represented as servers [8]. If the three testing lanes are busy, three parallel queues of cars are formed. This process can be conveniently modeled in AweSim with three *QUEUE* nodes that precede the service activity as testing, which represents three independent *SERVERS*. The service activity is denoted by the inspectors and 80 percent of the cars passed the test and depart to the traffic

department. The remaining 20 percent of the cars inspected failed the inspection test. Hence, repair is recommended. The repair is modeled with a *QUEUE* node followed by a service activity with a capacity of 15 cars. Following the adjustment operation, the car is routed back to the inspection area of *QUEUE* with a first in first out (FIFO) criteria.

Figure 2 (a)   Service Time and System Time   (Queue 1)

Figure 3(a) : Service Time and System Time   (Queue 2)

Figure 2(b). Time between Arrival

Figure 3(b). Time between Arrival

The AweSim graphical model is shown in Figure 4. Entities representing cars are created by the *CREATE* node with the time between entities uniformly distributed between 10 and 25 minutes. Each car advances to one of the *QUEUE* nodes. The *QUEUE* node with the least number of cars proceeds directly to service for inspection. The inspection lane is represented by the three emanating *SERVICE* activities following the queue. The service time for all the servers is identified as uniform distribution in the range between 25 and 35 minutes.

After inspection the car arrives at a *GOON* node where it is probabilistically routed. One activity leads to the *COLECT* node, representing departure from the traffic department; the other activity leads to the *QUEUE* node, representing the waiting line for the repairing activity. Entities, which are routed to the *COLCT* node, have interval statistics collected based on the time of creation. The information is stored in *ATRIB* [1] that is *assigned* at the *CREATE* node. The total time a car spends in the inspection and repairing areas are recorded. The cars are then removed from the model with the *TERMINATE* node. The *CONTROL* statement runs the simulation model.

SIMULATION EXPERIMENT SETTING

The simulation summary report is collected in Table 2. The report contains interval statistics on the *TIME IN SYSTEM* acquired from the *COLCT* node. The length of simulation run is 6000 minutes and is controlled with the *INITIALIZE* statement. A high variability in system times for car registration is evident from the minimum and maximum times recorded in report. A high value of standard deviation in the system suggests that some of the cars can't be repaired on the spot in repair station. The second part of the report is the *FILE STATISTICS*. The *SERVICE ACTIVITY STATISTICS* show that the four service activities modeled as activities 31, 32, 33 and 34 (Figure 4) are highly utilized (e.g. more than 95% of the time) [6]. The inspection activities are 31, 32 and 33, while activity 34 is the repair phase when a vehicle fails the test.

Simulation Results

The model performance is evaluated according to the scenarios as shown in Table 1. The simulation model is run 14 times and the results are shown in Table 2(a). The average system time in registration and inspection center is approximately 83 minutes. The standard deviation is about 51, which suggests that some vehicles need longer times for repair. The number of observations in the simulation study is about 2530 cars for a period of 6000 minutes. The frequency distribution of the system time is an exponential distribution, with a mean of 83 minutes. The maximum and minimum system times are 519 and 31 minutes respectively. The average waiting time in Queues 3, 4, 5 and 6 are shown in Table 2(b). The average waiting time in Queue 3 is about 15 minutes, while in Queues 4 and 5, the waiting time is 5.4 and 1.55 minutes. The cars enter the *QUEUE* node based on *the smallest size in queue rule* with a *SELECT* node in a *BLOCK* mode and is used when the queues are in full capacity. The car is forced to enter the queue.

Evaluate the Performances in Category	Scenario A No. of servers	Scenario B No. of servers	Scenario C No. of servers
Average wait time for Queue 3, 4, 5 and 6	3	4	5
Average utilization for activity # 31, 32, 33 and 34	3	4	5
Maximum idle time for activity # 31, 32, 33 and 34	3	4	5
Maximum busy time for activity # 31, 32, 33 and 34	3	4	5

Table 1: Scenario Analysis

Run #	Man Value	Standard Deviation	Number of Observations	Minimum Value	Maximum Value
1	84.000	57.298	339	36.983	455.642
2	83.065	51.215	3374	26.198	527.652
3	83.158	51.748	3711	26.198	527.652
4	83.062	51.046	4045	26.198	527.652
5	82.996	51.442	4380	26.198	527.652
6	83.045	51.451	4723	26.198	620.678
7	79.498	46.792	673	36.384	455.642
8	80.913	46.914	1011	36.166	455.642
9	81.518	50.335	1344	34.28	527.652
10	81.112	48.141	1685	34.28	527.652
11	82.786	52.159	2025	34.28	527.652
12	82.887	52.161	2358	34.28	527.652
13	82.898	51.563	2704	34.28	527.652
14	83.119	51.464	3041	26.198	527.652
Average	82.4326	50.9806	2529.5	31.2944	518.866

Table 2 (a): System Time

| Run #	Queue3	Queue 4	Queue 5	Queue 6
1	21.09	5.355	2.058	0.189
2	14.212	5.556	1.502	0.209
3	14.987	5.64	1.581	0.29
4	14.355	5.63	1.567	0.269
5	15.002	5.6	1.553	0.263
6	15.085	5.554	1.588	0.269
7	13.856	4.457	1.399	0.102
8	12.335	5.514	1.608	0.22
9	13.48	5.41	1.486	0.238
10	11.973	5.349	1.489	0.23
11	16.041	5.424	1.475	0.197
12	15.667	5.364	1.39	0.168
13	15.287	5.449	1.421	0.172
14	14.681	5.632	1.498	0.218
Average	14.86	5.425	1.544	0.217

Table 2(b): Average waiting Time (Queue area)
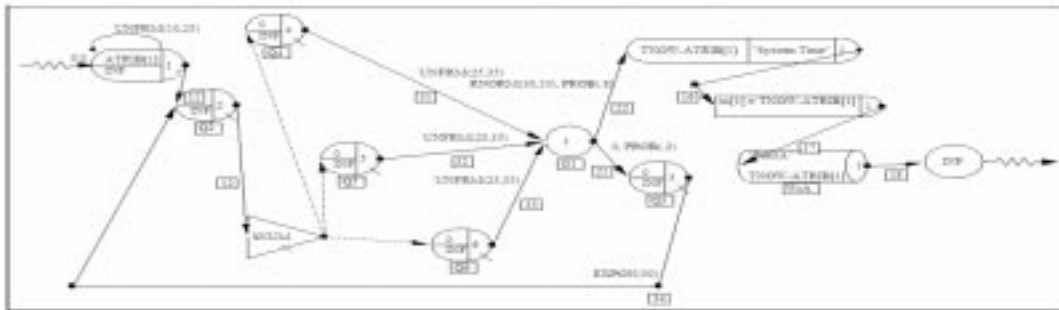
Figure 4: Visual SLAM network of car inspection

DECISION SUPPORT SYSTEM (DSS)

The simulation results show variability; hence, the decisions based on a single set of output is not reliable. To reduce variance in the simulation study, various replications of the study are generated. The DSS analysis with experimental design is a meta-model [9] and is convenient to

interpret the results [10, 11]. In DSS the factors of exogenous and endogenous variables are calibrated for sensitivity analysis [12, 13]. The DSS also optimizes the system response [14, 10]. For a small number of input variables, a 3k factorial design is preferred. In full factorial design, the number of design points is large for a large number of input. A response surface with a small design, the meta-model requires 2k fractional factorial design [15, 16 and 17]. The Plackett and Burmann [18] fractional factorial design investigates many factors simultaneously without having to investigate all the possible combinations of factors [19]. This design is not widely used in simulation. Multiple replications of simulation results constitute framework to design meta-model. The small designs require less number of simulation runs to model a DSS for performance evaluation [20]. The DSS model incorporates investigative and projection capabilities. The proposed DSS has the following steps:

a.) A design of experiment model with simulated data determines the model parameters
b.) Statistical analysis of the model and model parameters supports the DSS
c.) The simulation is validated with statistical analysis
d.) Cause effect analysis is provided for predictive purpose.

The statistical tests include R^2, Sum of Square Error, mean absolute error, Mean Percentage Error and probability test. The average waiting time, is an indication of the system response time. The system time is a system variable. It is the combination of the waiting time and service time. The service time is server related and is a technological factor. If service is considered constant with some parameter, then the system time is directly proportional to the waiting time. Hence, the waiting is an indication of the system time. The DSS model is expressed as

$$y = a_1 x_1 + a_2 x_2 + a_3 x_3 + \varepsilon$$

where

$$x_1 = \begin{cases} 1 & \text{,if it is } Scanerio\ A \\ 0 & Otherwise \end{cases} \quad ; \quad x_2 = \begin{cases} 1 & \text{,if it is } Scanerio\ B \\ 0 & Otherwise \end{cases}$$

$$x_3 = \begin{cases} 1 & \text{,if it is } Scanerio\ C \\ 0 & Otherwise \end{cases} \quad ; \quad and \quad \varepsilon = Error\ term$$

Next, the null hypothesis that the mean waiting times in the system are equal is tested
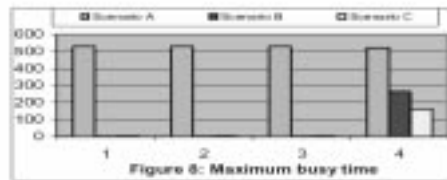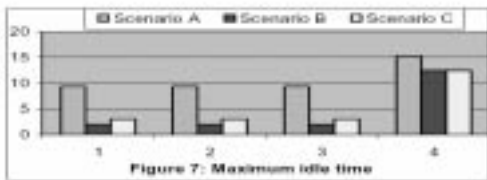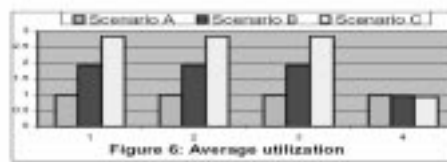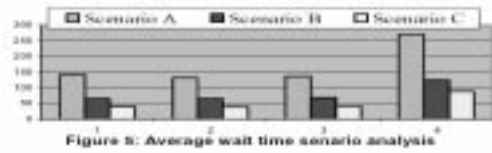$$H_0: a_1 = a_2 = a_3$$
against the hypothesis that at least one mean of the proposed scenario is different
$$H_0: a_1 \neq a_2 \neq a_3$$

In Tables 4 and 5, it is evident that the computed value of *F* exceeds the critical value; hence the null hypothesis $H_0: a_1 = a_2 = a_3$ is rejected and we conclude that the proposed scenarios have different mean waiting times. This implies that resources influence service factors. In order to test the validity of the DSS, we tested the flowing hypotheses: $H_{01}: a_1 = 0$; $H_{02}: a_2 = 0$; $H_{03}: a_3 = 0$ against $H_{11}: a_1 \neq 0$, $H_{12}: a_2 \neq 0$ and $H_{13}: a_3 \neq 0$. Since the p-values are almost negligible, we rejected $H_{01}: a_1 = 0$, $H_{02}: a_2 = 0$, and $H_{03}: a_3 = 0$ and concluded that the regressors in the proposed DSS contributed significantly. Hence some degree of delay in car registration is expected. Also, the correlation coefficient is significant and explains about the 85% of the variances, while the F value is also significant at 41.5. It is clear that the system time significantly reduced the waiting time from 51.33 minutes in scenario A to 12.67 minutes in scenario B, while with scenario C it

was 5.81 minutes. The results in Tables 3 and 4 show that the model is statistically significant. The ANOVA in Table 4 does not detect statistically significant lack-of-fit. Moreover, the overall F test is significant and leads to the acceptance of the proposed DSS meta-model.

The average waiting time for service, average utilization of the facilities, and maximum idle and busy time of the facilities are collected from the simulation summary report. The length of the waiting line and average waiting time are one of the indexes to measure the service performance. The sensitivity analysis provided relevant information for queue length in relation to the number of employees. Figures 5, 6, 7 and 8 display the scenarios information of the service system. From Figure 5, it is evident that by increasing the number of employees, the customer waiting time is improved for Queues 1, 2, 3 and 4. The utilization of the employees also improved, but for Queue 4, no significant improvement was recorded (Figure 6). Further, the idle time (Figure 7) was improved with the variations of employees. Figure 7 suggests that Scenario 2 is suitable, since the idle time is minimized compared to other alternatives.

Figure 5: Average wait time scenario analysis

Figure 6: Average utilization

Figure 7: Maximum idle time

Figure 8: Maximum busy time

Table 3: Associations between Factors

Table 4: ANOVA between Factors

CONCLUSIONS

From a simulation analysis a DSS model was developed for the car registration and renewal operation. The simulation analysis identified the inspection area as the bottleneck in the system. The DSS meta-model provides sensitivity analysis and evaluates the service industry performance. The model parameters help a manager to interpret decisions without the help of an expert. As the services of car registration and renewal are subcontracted to different agencies over the years, the analysis helps in proving reliable estimates of the costing and stuffing requirements. The simulation and DSS analysis measures the performance of the systems relative to the customer satisfaction. Also the analysis identifies the consequences of the resources as shown in the scenario analysis. The length of waiting time is high and hence such

circumstances indicate loss of productivity in the business. This scenario analysis illustrates how to improve the expected time required to finish the car registration and renewal.

REFERENCES

1. Pritsker, A.A. B., O'Reilly, J.J. (1999). Simulation with Visual SLAM. JW, NY, USA.

2. Valdivia M.T. R and Cowe T.J. (1997). Achieving Hospital Operating Objectives in the Light of Patient Performances, Int. Journal of health Care Quality Assurance, 10(5), 208-212.

3. Evans J. R. & Olson, D.L., (2002). Introduction to Simulation and Risk Analysis, 2nd Ed. PH,NJ, USA.

4. Lopez-Valcarcel, B.G & Perez, P. B. (1994). Evaluation of Alternative Functional Designs in an Emergency Department by Means of Simulation. Simulation, 63(1), 20-28.

5. Clark Jr. T.D., Hammond, D.H. & Cossick, K. L. (1992). Management Policies to Improve the Effectiveness of Multistation Service Organizations, Decision Science, 3, 1099-1022.

6. Harrell, C., Tumay. K. (1995). Simulation Made Easy A Manager's Guide, Engineering & Management Press, 25 Technology Park, Norcross, Georgia, USA.

7. Kelton W. D., Sadowski, R. P. & Sadowski D.A. (2002). Simulation with ARENA, McGraw Hill, NY, USA.

8. Fardane, T., Obaidly, M. (2002). Renewal & Registration in Traffic Department, Report, UAEU.

9. Friedman, L.W. (1996). The Simulation Metamodel, Kluwer Academic Pub., Norwell, MA.

10. Shang,J.S. & Tadikamalla, P.R., (1998). Multicriteria design and control of cellular manufacturing system through simulation & optimization, IJPR, 36(6),1515–1528.

11. Hurrion, R.D. & Birgul, S., (1999). A comparison of factorial & random experimental design methods for the development of regression & neural network simulation metamodels, J. of the Operational Research Society, 50(10), 1018–1033.

12. Kleijnen, J.P.C. (1977). Searching for important factors in simulation models with many factors: Sequential bifurcation, EJOR, 96 (1), 180–194.

13. Hunter, J.S., & Naylor, T. H. (1970). Experimental designs for computer simulation experiments, Management Science, 16(7), 422–434.

14. Madu, C.N. & Kuei, C.H. (1992). Group screening and taguchi design in the optimization of multi-echelon maintenance .oat simulation metamodels, Comp. & O.R, 19(2), 95–105.

15. Box, G.E.P., Hunter, J.S. (1961). The 2k_p factorial designs, Technometrics 3, 311–351.

16. Hood, S.J. and Welch, P. D. (1993). Response surface methodology and its applications in simulation, Proceedings of Winter Simulation Conference, 115–122.

17. Inci, B. & Semra, T. (2003). Small response surface designs for metamodel estimation, European Journal of Operational Research, 145, 455–470.

18. Plackett, R.L. & Burman, J.P (1946). The design of optimum multifactorial experiments. Biometrica, 33, 305-325.

19. Durig, T. & Fassihi, A. R. (1993). Identification of stabilizing and destabilizing effects of experiment-drug interactions in solid dosage from design. Int. J. of Pharmaceutics, 97, 161-170.

20. John, R.C. & Draper, N.R. (1975). D-optimality for regression designs: A review, Technometrics, 17, 5–23.