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A Case Study on Waiting Line of a CNG Filling Station by Using Arena Simulation Software

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Abstract

Simulation modelling is the act of developing and evaluating a digital prototype of a physical model to forecast how well it will function in real life. Using simulation modelling, engineers and designers can better understand whether a part could fail, under what circumstances, how it could fail, and what loads it can handle. The purposes of this research are to create a simulation model of a CNG filling station, examine and assess the model, and note and draw conclusions from the model's output. For this project, literature searching took place after primary investigation and idea generation. The next procedure, data collection, was initiated with a justified idea and discussion with some recommendations to terminate the whole activity after extensive data analysis. This study aims to analyze a queuing system of a CNG filling station to develop a simulation model and later analyse the model and interpret the results obtained from this model with the help of 'Arena' software. During this simulation study on 6 h, the incoming Number of CNG automobiles in Line 1 is 94 and Line 2 is 88. The average waiting time in station 1 is 0.6457 h, and in station 2, it is 0.5912 h. The average waiting number in station 1 is almost 23, and station 2 is a maximum 1. By decreasing queuing length and average waiting time of station, customer satisfaction will be increased and can be decreased waste of time. Customers will enjoy a happy journey without any disturbance.

Keywords: Simulation; Waiting time; Modeling; Arena; Queueing System.

1. Introduction

Simulation modelling involves creating and evaluating a digital prototype to predict the performance of a physical system. Engineers and designers can better understand whether a part could fail, under what circumstances, how it could fail, and what loads it can handle using simulation modelling. Forecasting patterns of heat transfer and fluid flow can be aided by simulation modelling. Through the use of simulation software, it analyses the rough working circumstances ("Simulation Modelling," 2022). A simulation is an environment where a real-world process is recreated under supervision. It uses a process known as modelling to determine the simulation's outcome. When a phenomenon cannot be directly experienced, a model representative of the item or process describes and explains the phenomenon. In science, we develop many laws and regulations to characterize the world, and when we combine these models, we may produce a simulation (Morris et al., 2019). For instance, we could build a model to explain the motion of air molecules in a heat source by studying its behavior. After that, we could combine dozens of molecules and run a simulation. For realistic simulations on a computer, you will usually have to input all kinds of complex physics equations.

Computers can do calculations using those equations far faster than humans and have allowed us to take simulations to a new level in recent (Law, 2015).The gathering of reliable source data regarding the pertinent selection of important traits and behaviors, the use of simplifying approximations and assumptions within the simulation, and the accuracy

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and validity of the simulation results are important challenges. An ongoing area of academic study, improvement, research, and development in simulations technology or practice, notably in the work of computer simulation, is procedures and protocols for model verification and validation (Okuyelu et al., 2024).

In the CNG Filling station, if the queue length is increased, the waiting time increases too. Customers can switch services from a filling station. This will be lost in business. If problems can be identified with these issues by increasing the service capacity of the filling station, the customer will be satisfied. A simulation model was developed using Arena simulation software from the collected data. Through this process, it can be understood what the main problems are. In Sylhet, there are many CNG Filling stations. They are providing service regularly, but sometimes the queuing length of the station increases, and customers suffer some irritating time, even sometimes customers switch the service station. To identify the problems, authorities of CNG Filling stations can increase their capacity. The objectives of this research are,

- To create a CNG filling station simulation model.
- To investigate and evaluate the simulation model.
- To examine and assess the outcomes derived from the model.

2. Literature Review

2.1. Queueing Theory

A queue arises when there is a mismatch between the customer arrival rate and the service rate in any system. Customers have to wait for a short or long time for the desired service. But solving this problem is not that easy. Some questions are to be asked, such as “Why is this happening? How many people are there in the queue? How long do the customers have to wait to get the service?” and so on. To answer these questions, queueing theory attempts to use some mathematical analysis.(Shortle et al., 2018) In general, a queueing system has two main components: customers and servers. The former is seeking a service that can be provided immediately or otherwise by the server, depending on the kind of service and the number of customers. The queueing process can be characterized basically by the arrival patterns of customers, the service patterns of servers, queue discipline, system capacity, number of service channels, and number of service stages. (Bittencourt et al., 2018)

A basic queueing system has some elements such as input sources, customers, a queue, a service mechanism, and served customers, as shown in figure 1. Customers’ arrivals are referred to as the calling population. The time between customers' arrival is called inter-arrival time, and the duration a customer takes service is referred to as service time.

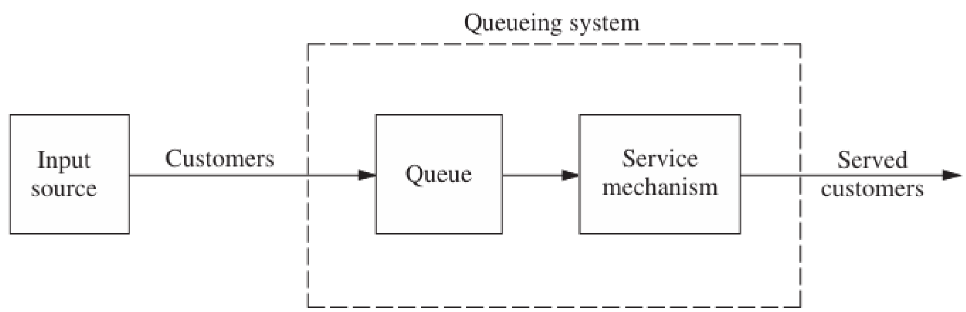


Figure 1. The Basic Queueing Process(Hillier & Lieberman, 2010)

Many organizations apply queueing theory to ensure proper services. A study (Hu et al., 2018) of applying queuing theory to the emergency operations showed that queueing models are invaluable tools for emergency department design and management. With minimal data requirements and efficient computation costs, queueing models offer theoretical insights to an emergency department system and provide directions and predictions to the large-scale operational process.

Researchers (Peter & Sivasamy, 2021) applied queueing theory techniques to the healthcare system. The result of this research highlighted the potential usefulness of queueing theory in the healthcare sector. In addition, they concluded that queueing theory can be used to develop and identify other opportunities for service improvement.

Queueing theory was also applied to the healthcare sector during the COVID-19 pandemic. When the number of COVID-19 infected patients was increasing gradually, the hospital management had to analyze the pattern of this and issue emergency beds (Meares & Jones, 2020).

2.2. Simulation

Simulation is the process of statistically modelling a physical or real-world system on a computer to predict its behavior and/or outcomes (Samad et al., 2024). Simulations are now widely used for the mathematical modelling of many natural systems in physics, astrophysics, climatology, chemistry, biology, and manufacturing, as well as human systems in economics, psychology, social science, health care, and engineering (Brailsford et al., 2019; Law, 2022). This is because they make it possible to verify the accuracy of selected mathematical models. To optimize decision-making and the design and operation of intricate and intelligent production systems, simulation is an effective technique for creating planning and exploratory models (Gitinavard et al., 2025). Additionally, it could help businesses assess the risks, expenses, implementation challenges, operational performance impact, and Industry 4.0 roadmap. Despite some developments in this field, few studies thoroughly describe and assess the evolution of simulation-based research in Industry 4.0 (De Paula Ferreira et al., 2020). Some researchers (Currie et al., 2020) showed the effectiveness of simulations in COVID-19 situations to identify lethal viruses in the near future and take preventive actions against them. Simulation can also be implemented in the clothing sector to optimize the sewing and designing processes (Cho et al., 2023). Simulation can be used in logistics processes and AGV or Automated Guided Vehicle systems for optimized solutions (Fedorko et al., 2018). Hajian Heidary (2023) developed a scenario-based supply chain model for global procurement of substitute products that was solved using a simulation-optimization approach. He considered complexities of global supply chains such as exchange rate risk, long lead times, and regional risks and stresses on the requirement for risk assessment. He employed Monte Carlo simulation for risk assessment and applied it to a revised case study with sensitivity tests on risk attitude, substitutability of products, and exchange rate changes. The researcher gave insights on management of uncertainties in global supply chain using simulation model. A study was conducted on a traffic signal control scheme integrating vehicle and pedestrian information to enhance urban traffic control. Using the SUMO traffic simulation tool, the study simulated realistic intersection conditions to test the effectiveness of the integrated control strategy. It was found that incorporating pedestrian information reduces waiting times for pedestrians and optimizes flow of cars and pedestrians. By considering all road users, proposed dual-focus

system offers a more complete strategy for traffic management that enhances road safety and reduces congestion through better synchronization of traffic lights.(Ergün, 2025)

2.3. Simulation Modelling

A third pillar for ecological analysis has evolved with the development of computers: simulation models have replaced the more conventional statistical and mathematical models (Morris et al., 2019). A simulation model is an algorithm that propagates a system's states forward; this algorithm is usually implemented as a computer program. But unlike in a mathematical model, this propagation uses a set of rules or equations that specify the future state explicitly, instead of using calculus techniques (Law, 2015).

An algorithmic model specification like this is very useful for characterizing systems like the following that are challenging to represent or evaluate using differential equations:

- Systems that are extremely chaotic or nonlinear.
- Discrete systems include things like networks and collections of unique people.
- Systems that are too complex to handle effectively by classical calculus and stochastic systems.

Since these conditions frequently arise in ecology, simulation models are used extensively. They have played a key role in developing fresh perspectives on various traditional issues, including population dynamics, biogeography, community assembly, and species coexistence. To work practically with simulation models, ecologists must acquire new skills such as coding, sensitivity analysis, calibration, validation, and uncertainty forecasting. The approaches for this relatively new discipline are still being developed. Furthermore, studying complex systems in science has brought many minor adjustments to the philosophical and epistemological perspectives on reductionism, simplicity, and the connection between understanding and prediction. (Hartig, 2018) A molecular simulation process developed by Zhu (2021) is illustrated in Figure 1.

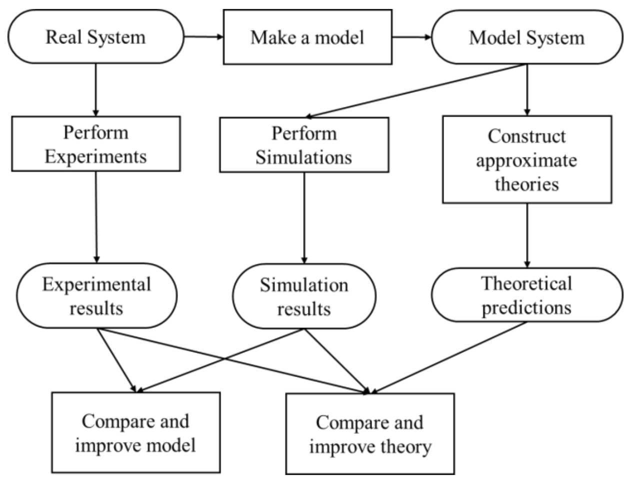


Figure 2. Molecular Simulation Process(Zhu, 2021)

Many sectors, particularly the automotive sector, heavily rely on modelling and simulation as part of system development to better understand system performance. The Department of Defense used modelling and simulation for multiple purposes, most notably to train users of new systems and to bolster arguments in analyzing alternatives to support moving forward with system development. Interest in using modelling and simulation in operational testing and evaluation has increased due to its success in comparable industrial applications and its advantages over operational testing considering cost, safety, and environmental factors. DoD authorities have vigorously supported the use of simulation to support operational test design and evaluation.(*Statistics, Testing, and Defense Acquisition*, 1998)

While many workshops have focused on using simulation to support operational testing and evaluation of defense systems, it is still unclear to what degree simulation can help with different tasks, like supporting operational test design or providing information for operational test evaluation. The information obtained from modelling and simulation must be carefully considered because if it is used carelessly, it could lead to the advancement of unreliable or ineffective systems to full-rate production or, on the other hand, cause the development of reliable systems to be delayed or abandoned.(Beason et al., 2024).

2.4. Application of Simulation & Modelling

An organized method for identifying important variable interactions inside a system is called simulation modelling. Systems are found in many fields, including zoology, aerospace and military, and agriculture. They are typically limited and function according to a predetermined set of business rules, which frequently forces decision-makers to make challenging trade-offs that may have a variety of advantageous or costly consequences.

Engineers and designers can examine designs for new or existing parts without building several physical prototypes with simulation modelling. Simulation can be useful to train and assess the skills of employees in the medical sector (So et al., 2019). Users can explore a variety of digital prototypes before producing the real prototype (Frick et al., 2007). Implementing the techniques, they could,

- Optimize the shape to balance strength and weight (Gafar et al., 2025).
- Choose materials that satisfy the specifications for strength, weight, and cost(Ramu, 2023).
- Evaluate and determine the loading conditions that lead to part failures by simulating them.
- Evaluate harsh environmental circumstances or loads that are difficult to test on tangible prototypes, like the seismic shock load.(Arslan Bin Riaz & Güden, 2025)
- Check manual computations for accuracy and confirm the likelihood of a physical prototype's survival before (German Aerospace Center (DLR) et al., 2024).
- Allocations for various manufacturing operations(Li & Qi, 2024).
- Variety and component estimation(Ramu, 2023).
- Queue system analysis(Murugan & W., 2025).
- Optimization of complex processes within hand reach (Gafar et al. 2025)

2.5. Optimization

Optimization is a technique where the best or optimum solution is identified considering multiple constraints. This could be a maximization or minimization problem (Gunantara, 2018). The classification of optimization problems can also be done by looking at the modality of the objective landscape, which can be divided into multimodal problems and unimodal problems, including convex optimization. In addition, classification can also be about the determinacy of the problem. If there is NO randomness in the formulation, the problem is called deterministic, and in fact, all the above are essentially deterministic. However, if there is uncertainty in the variables or function forms, then optimization involves probability distribution and expectation; such problems are often called stochastic optimization or robust optimization. (Yang, 2018)

2.6. ARENA

ARENA is a simulation software developed by Rockwell Automation in 2000 (“Arena (Software),” 2024). It has a user-friendly interface to develop models based on data sets and then simulate the model. ARENA has different modules to create and simulate a model. The modules of ARENA are,

Create module: The purpose of this module is to provide entities in a simulation model with their initial state. A timetable or the interval between arrivals is used to build entities. After exiting the module, entities start navigating the system for processing. This module contains the entity type specification.

Assign module: This module is used to set new values for other system variables, entity types, entity characteristics, entity photos, and variables. It is possible to create several assignments using a single "Assign module."

Process module: The primary processing mechanism for the simulation is meant to be this module. There are ways to capture and release resource limitations. Furthermore, a "sub-model" can be used to construct hierarchical user-defined logic. Process time is allotted to the entity and can be classified as transfer, wait, non-value added, or value added.

Decide module: The module facilitates system decision-making based on conditions or probabilities, including attribute values, variable values, entity type, or expressions, ensuring efficient and accurate operations.

Dispose module: The goal of this module is to serve as a simulation model's endpoint for entities. It is possible to capture entity statistics prior to the disposal of the entity.(Law, 2022)

There are some elements of ARENA available,

Entities: They are the frameworks that connect different modules. As soon as an event is initiated, every entity moves.

Resources: These are necessary components to complete a task.

Queues: These are the components where the entities hold off till resources become available.

Variables: These are global data structures that the entities have access to and control over.

Attributes: Local variables unique to each entity make up these components. A characteristic could be the gender or tone of skin. A variable could be the proportion of male and female pedestrians, for example.(Krisnawati et al., 2022)

Arena simulation software enables manufacturing organizations to increase throughput, identify process bottlenecks, improve logistics, and evaluate potential process changes. With Arena, you can model and analyze process flow, packaging systems, job routing, inventory control, warehousing, distribution, and staffing requirements. Successful plant operation requires that multiple process operations are coordinated to work at maximum efficiency. If your production line is unbalanced, the result can be increased WIP, higher off-grade material, and a reduction in plant throughput.(Rashidifar, 2021)

ARENA simulation software is widely used in industries such as manufacturing, service, healthcare, etc. A study (Zahraee et al., 2021) on concrete pouring analysis in a construction site integrated the lean tool value stream mapping and ARENA simulation software to find the best output. (Emmanuel Lorou et al., 2021) used the ARENA simulation model in a truck assembly line to improve performance. They acknowledged the potential power of this software. They managed to reduce the queue of the assembly line. A case study highlighted that by using ARENA simulation software, a manufacturing firm increased the utilization by 25% (Rashidifar, 2021).

The performance of the inventory management system was measured by using ARENA simulation software. That research proposed a model with limited variables to support this idea, which can be enhanced by adding more variables, machines, and stations. The result of the simulation showed that the availability of stock will cause less damage, while having lower stock than demand is always giving loss to the organization.(Alsolami, 2020)

3. Methodology

The steps we have followed in this research for simulation modelling have been illustrated in Figure 2.

- It started with problem formulation and then led to setting objectives and plans. We visited a CNG station and observed the queue system.
- Following these, model conceptualization and data collection were considered, and we collected data for two servers at the station for model conceptualization.
- After that, the model was translated to check if the model conceptualization meets requirements.
- We verified the model. Whenever the model showed any problem, we sent it back to the translation step.
- The model was validated after verification. Any problem in the validation step was considered seriously and returned to the model conceptualization and data collection step.
- When verification and validation were performed, an experimental design was made in the ARENA simulation software.

- After an experimental design was done, service providing processes along with analysis started to take place.
- Based on the requirements, multiple runs were performed. Following that, the documentation and reporting started.
- Finally, based on the outcome of the simulation model, we suggested the CNG filling stations management to improve on the defined scope.

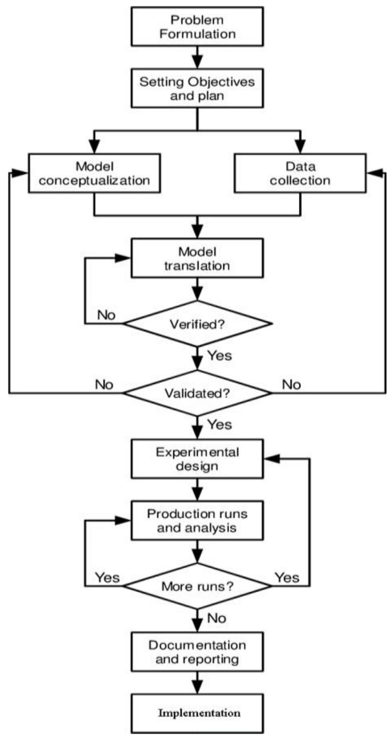


Figure 3. Steps of Simulation Modelling (Law, 2015)

4. Data Analysis, Findings, and Results

4.1. Data Analysis

The system on which the experiment was conducted is the CNG Filling Station located in Sylhet Sadar, Sylhet. Table 1 shows the selected system and resource data.

Table 1. System and Resource Data

The System	A CNG Filling Station	Resource	Service provider
Entity	CNG Automobiles	Measure of Performance	1. Average Service time
Attribute	3-Wheeler		2. Average waiting time
Variable	Number of customers in the queue		3. Average queue length
Event	1. Customer Arrival		4. Server Utilization
	2. Customer Departure		
Server	2 Filling Stations		

The inter-arrival time for CNGs of Line 1 is shown in Table 2,

Table 2. Inter-Arrival Time for CNGs of Line-1

Serial Number	Interarrival Time (sec)	Serial Number	Interarrival Time (sec)
1	0	26	167
2	198	27	154
3	230	28	277
4	361	29	241
5	268	30	299
6	401	31	129
7	311	32	212
8	278	33	221
9	288	34	278
10	299	35	303
11	341	36	156
12	100	37	178
13	120	38	197
14	241	39	234
15	232	40	288
16	312	41	303
17	254	42	122
18	289	43	304
19	231	44	211
20	351	45	233
21	420	46	163
22	311	47	201
23	300	48	209
24	60	49	166
25	201	50	181

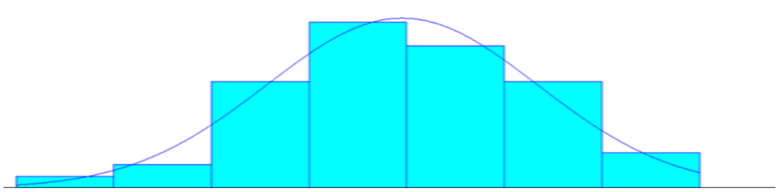


Figure 4. Distribution of CNGs of Line-1 (Interarrival time)

From Figure 4,

Distribution Summary

- Distribution: Normal Minimum
- Expression: NORM (236, 83.5)
- Square Error: 0.001492

Data Summary

- Number of Data Points= 50
- Minimum Data Value= 0
- Maximum Data Value= 420
- Sample Mean= 236
- Sample Std. Dev= 84.4

The inter-arrival time for CNGs of Line 2 is shown in Table 3,

Table 3. Inter-Arrival Time for CNGs of Line-2

Serial Number	Interarrival Time (sec)	Serial Number	Interarrival Time (sec)
1	0	16	167
2	120	17	234
3	233	18	256
4	351	19	345
5	234	20	321
6	313	21	167
7	342	22	156
8	288	23	199
9	259	24	241
10	433	25	234
11	182	26	267
12	356	27	322
13	68	28	181
14	301	29	267
15	289	30	101

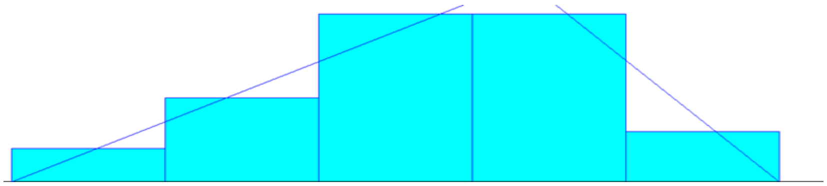


Figure 5. Distribution of CNGs of Line-2 (Inter-arrival time)

From Figure 5,

Distribution Summary

- Distribution: Triangular
- Expression: TRIA (-0.001, 290, 443)
- Square Error: 0.001887

Data Summary

- Number of Data Points=30
- Minimum Data Value=0
- Maximum Data Value=443
- Sample Mean=241
- Sample Std. Dev=94.8

Service Time for line 1 is shown in Table 4,

Table 4. Service Time for CNGs of Line-1

Serial Number	Service Time(sec)	Serial Number	Service Time(sec)
1	289	26	321
2	356	27	343
3	345	28	320
4	291	29	299
5	245	30	401
6	378	31	242
7	341	32	247
8	401	33	256
9	256	34	261
10	412	35	287
11	291	36	312
12	290	37	344
13	331	38	350
14	356	39	272

Serial Number	Service Time(sec)	Serial Number	Service Time(sec)
15	388	40	411
16	320	41	389
17	321	42	311
18	389	43	276
19	359	44	280
20	352	45	233
21	356	46	238
22	288	47	322
23	400	48	301
24	295	49	240
25	267	50	250

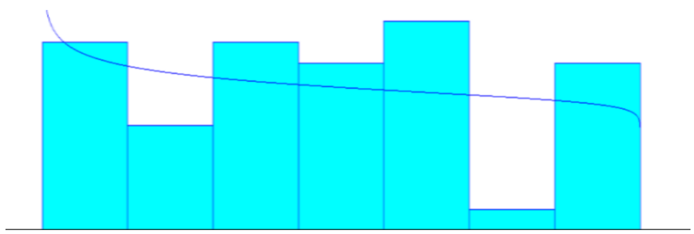


Figure 6. Distribution of Service Time of Filling Station-1

Figure 6 shows,

Distribution Summary

- Distribution: Beta
- Expression: 233 + 179 * BETA (0.904, 1.03)
- Square Error:0.022329

Data Summary

- Number of Data Points = 50
- Minimum Data Value= 233
- Maximum Data Value= 412
- Sample Mean= 316
- Sample Std. Dev= 52.1

Service time for line 2 is presented in Table 5

Table 5. Service Time for CNGs of Line-2

Serial Number	Service Time(sec)	Serial Number	Service Time(sec)
1	245	16	303
2	279	17	288
3	301	18	256
4	312	19	289
5	288	20	287
6	289	21	303
7	287	22	311
8	299	23	239
9	350	24	248
10	267	25	289
11	256	26	303
12	291	27	261
13	312	28	293
14	302	29	299
15	307	30	288

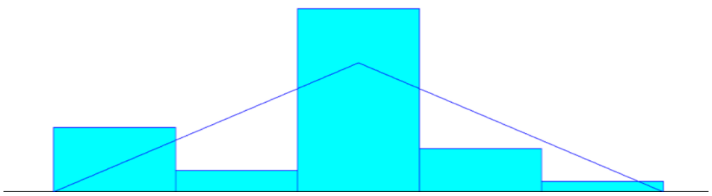


Figure 7. Distribution of Service Time of Filling Station-2

Figure 7 shows that,

Distribution Summary

- Distribution: Triangular
- Expression: TRIA (239, 295, 350)
- Square Error: 0.100711

Data Summary

- Number of Data Points=30
- Minimum Data Value=239
- Maximum Data Value=350
- Sample Mean=288
- Sample Std. Dev=23

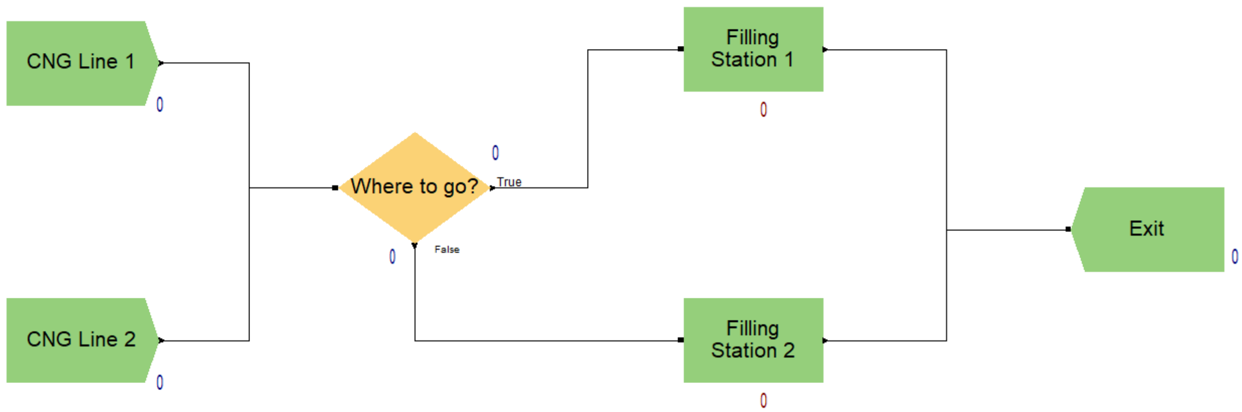


Figure 8. Developed Model in Arena

The simulation model is illustrated in Figure 8. This model illustrates that whenever a vehicle arrives at the station, it chooses the line to take CNG as fuel. After entering the station, the vehicle driver must decide observing the queue length available at the station. The vehicle driver observes which station has the shortest queue and waits in that line to take CNG. After the service is taken, the driver leaves the station immediately after paying the bill.

4.2. Results

5:37:29PM **Category Overview** June 4, 2021

Unnamed Project

Replications: 1 Time Units : Hours

Entity

Time

VA Time	Average	Half Width	Minimum Value	Maximum Value
CNG1	0.08464088	(Insufficient)	0.06723516	0.1144
CNG2	0.08416628	(Insufficient)	0.06480508	0.1122

NVA Time	Average	Half Width	Minimum Value	Maximum Value
CNG1	0.00	(Insufficient)	0.00	0.00
CNG2	0.00	(Insufficient)	0.00	0.00

Wait Time	Average	Half Width	Minimum Value	Maximum Value
CNG1	0.6457	(Insufficient)	0.00	2.1656
CNG2	0.5912	(Insufficient)	0.00	2.1251

Figure 9. Entity

Figure 9 shows the average waiting time of CNG1 is 0.6457 h and CNG2 is 0.5912 h. Maximum waiting times are 2.1656 h and 2.1251 h in CNG1 and CNG2, respectively. The minimum waiting times are 0 for both stations.

Transfer Time

	Average	Half Width	Minimum Value	Maximum Value
CNG1	0.00	(Insufficient)	0.00	0.00
CNG2	0.00	(Insufficient)	0.00	0.00

Other Time

	Average	Half Width	Minimum Value	Maximum Value
CNG1	0.00	(Insufficient)	0.00	0.00
CNG2	0.00	(Insufficient)	0.00	0.00

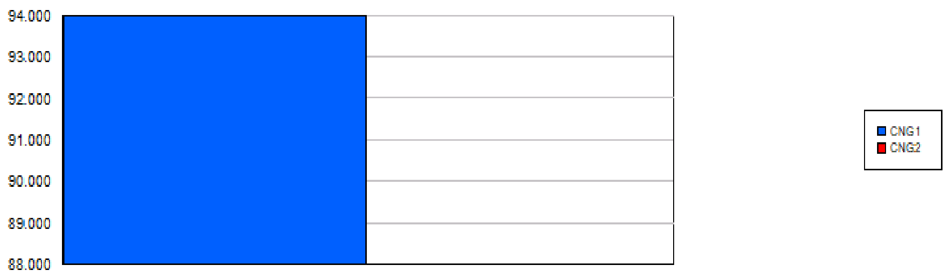
Total Time

	Average	Half Width	Minimum Value	Maximum Value
CNG1	0.7303	(Insufficient)	0.06760751	2.2469
CNG2	0.6753	(Insufficient)	0.07375697	2.2021

Other

Number In

	Value
CNG1	94.0000
CNG2	88.0000



Number Out

	Value
CNG1	63.0000
CNG2	66.0000

WIP

	Average	Half Width	Minimum Value	Maximum Value
CNG1	13.7292	(Insufficient)	0.00	32.0000
CNG2	11.1420	(Insufficient)	0.00	22.0000

Figure 10. Different Times

Figure 10 shows the times involved in the model. Average total times are 0.7303 h and 0.6753 h in CNG1 and CNG2 stations, respectively. This figure also illustrates that the number of in and out were 94, 88 and 63,66 in CNG1 and CNG2 stations respectively.

Queue

Time

Waiting Time	Average	Half Width	Minimum Value	Maximum Value
Filling Station1.Queue	1.1322	(Insufficient)	0.00	2.2229
Filling Station2.Queue	0.06311479	(Insufficient)	0.00	0.2396

Other

Number Waiting	Average	Half Width	Minimum Value	Maximum Value
Filling Station1.Queue	22.3498	(Insufficient)	0.00	50.0000
Filling Station2.Queue	0.6823	(Insufficient)	0.00	4.0000

Figure 11. Queue

The number of queues in Filling Station 1 is almost 23. On the other hand, in Filling Station 2, there is almost 1, as found in Figure 11.

Usage

Instantaneous Utilization	Average	Half Width	Minimum Value	Maximum Value
Gas 1	1.0000	(Insufficient)	0.00	1.0000
Gas 2	0.8391	(Insufficient)	0.00	1.0000

Number Busy	Average	Half Width	Minimum Value	Maximum Value
Gas 1	1.0000	(Insufficient)	0.00	1.0000
Gas 2	0.8391	(Insufficient)	0.00	1.0000

Number Scheduled	Average	Half Width	Minimum Value	Maximum Value
Gas 1	1.0000	(Insufficient)	1.0000	1.0000
Gas 2	1.0000	(Insufficient)	1.0000	1.0000

Figure 12. Resource Utilization

Resource utilization of the developed model is illustrated in Figure 12. It shows that utilization is higher in station 1 than in station 2.

Scheduled Utilization

	Value
Gas 1	1.0000
Gas 2	0.8391

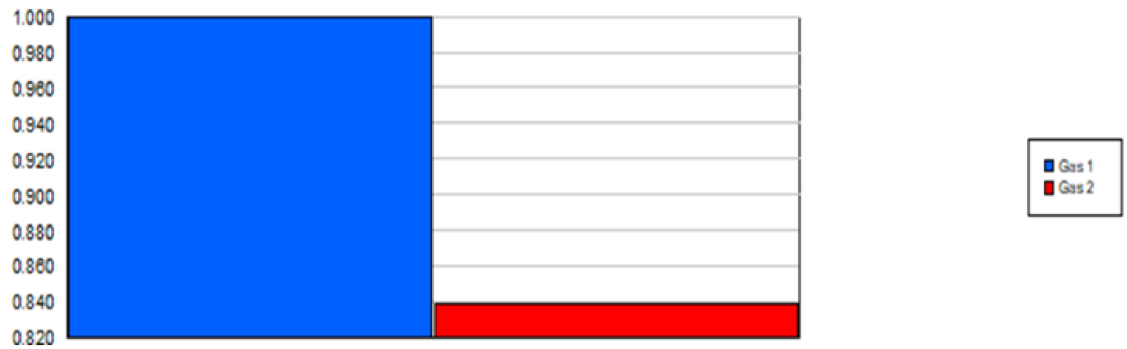


Figure 13. Scheduled Utilization

Figure 13 shows the scheduled utilization of stations. Station 1 has a utilization of 1, and station 2 has a utilization of 0.8391.

Resource

Usage

Total Number Seized

	Value
Gas 1	69.0000
Gas 2	62.0000

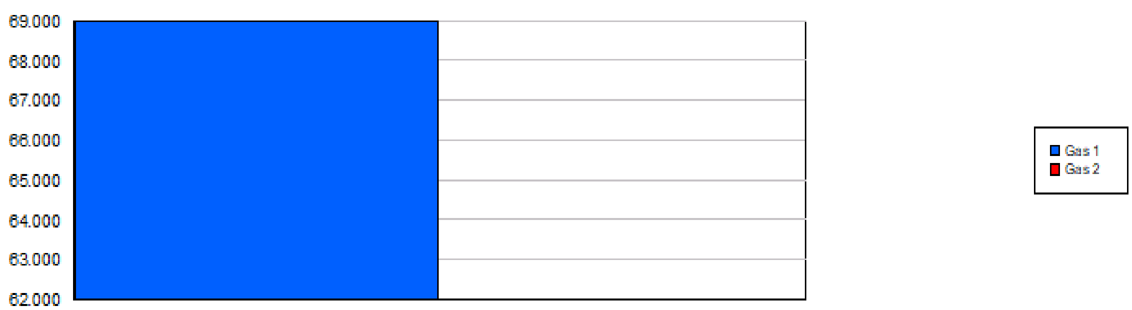


Figure 14. Resource Usage

This research has uncovered a general scenario in which the average waiting time of CNG Filling Station Line 1 is 0.6457 h, and Line 2 is 0.5912 h. Always work in process in Line 1 is almost 14 and Line 2 is almost 12. Figure 14 illustrates that resource utilization for Station 1 is 69% and for Line 2 is 62%.

5. Discussion

Tools and approaches for modelling and simulation are crucial in the modern world. Tools for displaying the outcomes aid in decision-making even though simulation performs the necessary labor. We conducted this research to visualize a real-life scenario in a CNG filling station. We collected data for about 4 to 5 h and in 7 days. While experimenting, we saw that station 2 was idle most of the time. So, the server utilization for that filling station dropped. We took about 80 sample data to simulate our model for about 5 h a day. We considered the value-added time as the resources were being consumed. But there were also some non-value-added times such as transaction time, queue moving time, and idle transportation time. We didn't consider those as a way of minimizing the complexity of the simulated model. There were also inefficient workers, and as a result, they hampered productivity.

If we took a large amount of data, the distributions would be more accurate and help us to visualize the system more closely and accurately. Server optimization, average queue length, and average waiting time are the key performance indicators for this queue system. We were able to measure them by observing the data and results obtained. The average waiting time of CNG Filling station Line 1 is 0.6457 h, and Line 2 is 0.5912 h. service taking or average work in process in Station 1 is almost 14, and Line 2 is 12. Resource utilization in Station 1 is 69%, and in Station 2, it is 62%.

6. Conclusion

The following conclusions were derived from the study,

The maximum average waiting time of CNG station 1 is 2.1656 h, which is higher than that of CNG station 2. The number of queues in Filling Station 1 is almost 23, and the number of queues in Filling Station 2 is 1, so we can say that the queuing length is very high in Filling Station 1, which may cause much suffering for customers, even customers can switch service from this station. That is unprofitable and lacks a reputation for the Filling station.

From the data analysis, we saw that Station 1 was busy most of the time, but sometimes, Station 2 was idle, so the authority can increase the service policy in station 2, which enhances their service quality and can decrease service time, which can minimize customers suffering and waste of time. The resource utilization of Station 1 is 69%, and that of Station 2 is 62%.

From the above data and other findings which were found from the simulation model, authority can visualize their service quality and can find out what are their basic problems. By identifying issues, they can emphasize service capacity and minimize service time. In Sylhet city, CNG automobiles are a common transport, every day many people suffer those kinds of difficulties in Filling Stations that kill valuable time of passengers. Proper planning and rearrangement of service lines can reduce those kinds of suffering, and the management of the Filling station will get much profit.

There are some real-life implications of this research. This research paper can act as a background for future work in the practical field of the service sector if researchers want to study any service organization's service quality, efficiency, and utilization.

7. Limitations

- More data can be taken, which was not possible during political unrest.
- Simulation can be run many times, and findings can be more precise.

Data Access Statement

Not Available: The data used in this study are confidential and cannot be shared.

Ethics Statement

All data were collected with the consent of the selected CNG Station's management.

Declaration

All authors have no conflict of interest to disclose.

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