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Optimizing the Utilization Rate for Electric Power Generation Systems: A Discrete-Event Simulation Model

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ABSTRACT The problem of measuring the availability of generation units in electric power systems has been addressed in the literature by using a set of analytical equations and Monte Carlo Simulation (MCS). MCS, as a powerful simulation tool, is much easier to use than analytical approaches in measuring the availability of large applications. However, the simulated process using MCS entails deducing the operating state sequences for each component along the simulated time followed by combining all sequences for all components in order to deduce system availability. This simulated process is both lengthy and time-consuming. This paper introduces a new method to measure the availability of generation units and optimize their utilization using Discrete Event Simulation (DES) model. The experimental result of a real case study illustrates the efficiency of using DES.

INDEX TERMS Discrete-event simulation; power generation system availability; SIMUL8.

I. INTRODUCTION

Electricity is undoubtedly considered a lifeline and an indispensable basis of modern life. The journey that is typically taken by electricity until it reaches the end user may undergo different stages; understanding the technical and economic challenges associated with each stage is considerably important to assure maintaining as high as possible power continuity level. These stages of the journey may be represented as separate but interconnected systems referred to as generation, transmission, and distribution which together comprise the power system. Thus, electricity is primarily generated by generation units, transmitted through transmission cables, and then distributed among the end users. Similar to any physical system, the electric power system may encounter unavoidable power interruptions due to the natural phenomenon associated with its components' outages. Component outage models can be generally categorized by their nature into independent and dependent. Independent outage of a component may occur as a result of a cause that only influences the respective component and has no effect on other components in the system. On the other hand, dependent outage may occur when a component fails due to an initiating simultaneous outage of another component(s). Examples of independent outage include planned outage to perform scheduled maintenance or forced outage due to inherent aging. In contrast, dependent outage may take several forms including, for example, common-cause outage, component group outage, cascading outage, and weather-based outage [1]–[12]. All outage models share the attribute of being random and uncertain in terms of nature, outage time, and recovery time; nonetheless, planned outage can also be modelled as a certain activity performed at a scheduled time during a specific time interval such as preventive maintenance or scheduled replacement.

Studying the component outage model is essential in most reliability assessment studies. When a component is in an outage state, it is considered unavailable; hence, it is not expected to perform any function. Indeed, this state may, in turn, influence the overall system availability and thus the system reliability. Therefore, the measuring of system availability has vital important and is considered the basic aspect of most reliability-related studies [13].

For instance, the availability of a generation system is significant in studying the potential risk associated with taking some generation units out of service for scheduled

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maintenance [14]. Due to the intermittent nature associated with most renewable energy sources, measuring the availability of these sources is of paramount importance. For solar energy, the availability is used as a core index in the assessment of designing utility-scale photovoltaic (PV) power plants, as described in [15], and in the estimation of PV power and energy generated over different seasons during a year, as described in [16]. The availability of wind power, on the other hand, is investigated and analyzed for multiple wind farms in [17]–[19]. The availability of hydroelectric power plants is also considered in some research studies for systems in different regions including, for instance, Brazil [20], [21]; Iraq [22]; Pakistan [23]; and Spain [24]. In addition, measuring the availability of transmission and distribution systems is a key indicator to assess the overall reliability performance of their assets, as discussed in [25]–[27]. Due to the importance of evaluating system availability in most reliability-related studies, different methods have been introduced in the literature to measure power system availability including generation system. The main methods are discussed in the subsequent section.

The remainder of this paper is comprised of four sections. Section II reviews work that is related to the proposed method. Section III describes the proposed method in detail. The proposed method is numerically illustrated in Section IV. Section V concludes the paper and presents the potential future work.

II. RELATED WORK

Essentially, there are two main variables to consider when studying the outage model of any system: time-to-failure (TTF) and time-to-repair (TTR). TTF represents the time when a component is available and able to function until it experiences an outage. TTR, however, is the time required to repair a failed component. Since there is often uncertainty associated with the components of TTF and TTR, these variables must be represented as random variates modelled using appropriate probability distribution(s) over the total operating time. In fact, uncertainty in component outage should be taken into account with regards to system operation and planning, as emphasized in [1]. An electric power system has numerous components, including generation units, all of which are susceptible to different kinds of outages. Although a generation unit could experience an outage because of non-repairable forced failure due to end of life or unexpected fatal failures, the focus of this paper is on repairable forced failure during a component's normal operating lifetime. The lifetime of any repairable generation unit can be modelled using a chronological up-down-up operating cycle [28], [29] as shown in Fig. 1.

When a generation unit is installed in a system, it is expected to operate for time-to-failure (TTF_1) time units before it fails, be repaired for time-to-repair (TTR_1) time units, be returned to operate for (TTF_2) time units, and so on. Likewise, the operating cycles of a system composed of a set of generation units can be modelled, as illustrated in Fig. 2, for a two-generation unit system.

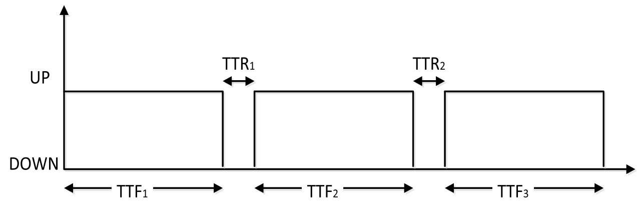

FIGURE 1. Up-Down-Up process of a repairable generation unit.

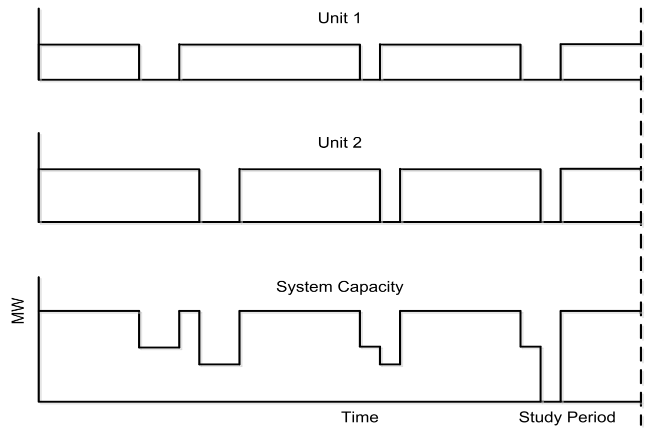

FIGURE 2. Available capacity model of a two-generation unit system.

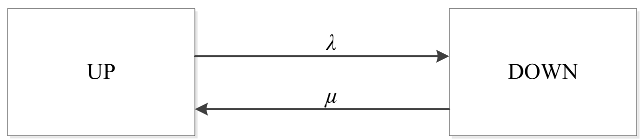

FIGURE 3. State space diagram of a two-state generation unit.

The availability, A, of a generation unit can be defined as the probability of the unit being energized (operated) during a defined period. The availability can be computed as follows [28]–[30]:

$$A = \frac{Operating\ time}{Operating\ time + time\ on\ outage} \tag{1}$$

In most reliability studies of power systems, however, the availability and corresponding unavailability of any generation unit are typically computed by identifying the failure and repair rates from historical data. The concept of state space diagram is often used to model the operating state of the unit [28]. Fig. 3 shows a state space diagram for a generation unit with two operating states — available (up) and unavailable (down) — where λ and μ are the failure and repair rates respectively.

The failure rate, λ, of a generation unit represents the transition rate of the unit from the state of being available to the state of being unavailable, and it can be found using (2),

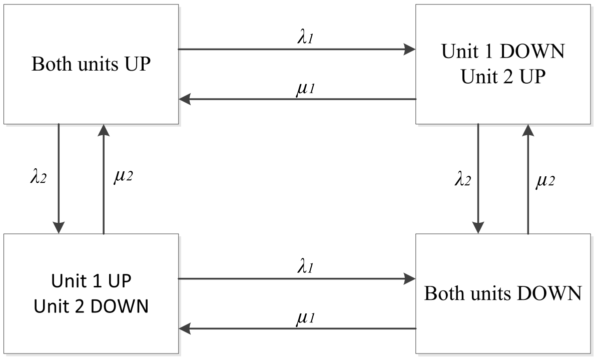

FIGURE 4. State space diagram of two generation units.

as introduced in [28]–[30]:

$$\lambda = \frac{Number\ of\ failures\ in\ a\ given\ period\ of\ time}{Total\ operating\ time} \quad (2)$$

For most reliability studies, the failure rate is usually expressed by the number of failures per year. On the other hand, the repair rate, μ, is the transition rate from the unavailability state to the availability state, and it is usually expressed by the number of repairs per year. The repair rate, μ, of a generation unit can be given by (3), as introduced in [28]–[30]:

$$\mu = \frac{Number\ of\ repairs\ in\ a\ given\ period\ of\ time}{Total\ repairing\ time} \quad (3)$$

The state space diagram can involve more generation units, as shown in Fig. 4, for a two-unit system in which each unit has two operating states. In fact, the diagram could also be modified to include more units and more operating states and transitions.

According to the literature, the availability of generation units has been measured by using a set of analytical equations and Monte Carlo Simulation (MCS) technique [29], [31]. Accurately formulating the state space diagram is the first and most important step in the analytical approach. The size of the state space diagram is dependent upon the number of components as well as the number of operating states for each component. The analytical approach is thus only applicable for simple and small systems, as this approach would be unmanageable for large and multi-state systems [1], [28]. On the other hand, MCS is a powerful simulation tool which is much easier to use than analytical approaches in measuring the availability of large applications. Measuring the availability of a generation system using MCS typically involves the following steps [29], [31]:

1. Determine the number of generation units in the system.
2. Generate a random number.
3. Convert this random number into a TTF value using the appropriate distribution function.
4. Generate a new random number.
5. Convert this new random number into a TTR value using the appropriate distribution function.
6. Repeat steps 2–5 for a period equal to or greater than the mission time in order to form the chronological up-down-up operating cycles, such as the process shown in Fig. 1.
7. Repeat steps 2–6 for each component in the system.
8. Combine the chronological up-down-up operating cycles of all components to obtain the chronological up-down-up operating cycles of the whole generation system, such as the process shown in Fig. 2. If the system's components have overlapping TTR at any point, then the system is considered unavailable; otherwise, the system is considered to be in the available state.
9. Repeat steps 2–8 for the desired number of simulations.

As observed from the above steps, the simulated process using MCS entails deducing the operating state sequences for each component along the simulated time followed by combining all sequences for all components in order to deduce system availability. This simulated process is both lengthy and time-consuming. Therefore, this paper proposes a new method to measure the availability of a generation system using the concept of Discrete Event Simulation (DES). In the proposed method, there is no need to construct the state space diagram of the generation system, nor is there a need to track the operating sequences of each component. The objective of this paper is to discover the availability of a generation system by using the DES concept to overcome the limitations and drawbacks of analytical and MCS approaches. DES, which models the changing states occurring in a system using a discrete set of points in time, often uses a queuing model to study the overall performance of the system. For this purpose, many performance indicators are measured including the utilization rate [32] which in turn can be standardized to represent the availability as both terms signify the percentage of time that the system is operating (busy). In the proposed method, generation units refer to servers that provide the loads (customers) with the required power (service). The generation units are considered busy when they are in the operating state. Thus, the utilization rate of all generation units is assumed to represent the availability of the generation system in which all units are working in parallel. SIMUL8 Simulation Software is used for the purpose of simulation modelling. The proposed method will be applied to a generation system using N number of generation units with different generation capacities. The proposed technique has four main phases which are addressed in detail in Section III.

III. PROPOSED TECHNIQUE

The proposed technique has four phases:

Phase 1: Important Parameters
Phase 2: Building and Running the Model
Phase 3: Simulation Steps
Phase 4: Absolute Performance Estimation

A. PHASE 1: IMPORTANT PARAMETERS

The goal of this phase is to identify the required data, assign the appropriate probability distribution(s), and compute the necessary parameters for each generation unit. These parameters include:

- Operating Time (OT);
- Time-To-Failure (TTF);

- Time-To-Repair (TTR); and
- Time-Between-Failures (TBF).

As each unit is expected to continuously operate as long as it is in service, the OT for each generation unit is set to be equal to the simulation study period with distribution type: Average. The TBF is the summation of both TTF and TTR. The TTF and TTR represent the lifetime of the generation unit; therefore, they can be modelled using the exponential distribution [28], [29], [31]. Exponential distribution has only one parameter which is the mean value. Therefore, the mean values of TTF, TTR, and TBF are mean-time-to-failure (MTTF), mean-time-to-repair (MTTR), and mean-time-between-failures (MTBF) respectively.

These parameters can be analytically calculated using (4), (5), and (6) [28]–[30].

$$MTTF_{calc} = \frac{8760}{\lambda} \tag{4}$$

$$MTTR_{calc} = \frac{8760}{\mu} \tag{5}$$

$$MTBF_{calc} = MTTF_{calc} + MTTR_{calc} \tag{6}$$

where,

λ	Component failure rate (failure/year);
μ	Component repair rate (repair/year);
$MTTF_{calc}$	Calculated mean-time-to-failure (h);
$MTTR_{calc}$	Calculated mean-time-to-repair (h); and
$MTBF_{calc}$	Calculated mean-time-between-failures (h).

B. PHASE 2: BUILDING AND RUNNING THE MODEL

In this phase, the operating lifetime of a generation system is simulated using SIMUL8. The process starts with building the model by placing the appropriate building blocks and setting the properties of blocks and simulation. In addition, certain important notes should be indicated upon building the simulation model using SIMUL8. These are summarized as follows:

- In practice, generation units in a power system usually operate for 24 hours per day unless they encounter forced outage. Therefore, in order to mimic the operation of real systems, the Running Time of the simulation is set to 24 hours, as shown in Fig. 5.
- Each generation unit is represented individually by three blocks comprised of one Queue and two Work Centres (Activities) as depicted in Fig. 6.
- Block *A* is the Queue which acts as a Work Entry Point with Start-Up content of one Work Item. The Work Item represents the MW capacity that the unit should produce, and it is routed out from the Queue at time $t = 0$ to block *B*. Block *B* is the Work Centre which represents the operating activity of the generation unit. Two important properties are set for block *B*: Operating Time (OT) and Efficiency. The OT is the simulation period of time as previously discussed. For efficiency, MTBF and MTTR calculations from Phase 1 are provided. The last Work Centre is a dummy activity (Timing = 0) which has been placed in order to immediately return the Work Item to the operating activity if the Work Item has left the operating activity before the end of the simulation time. Work Exit Point is unnecessary in this simulated system.

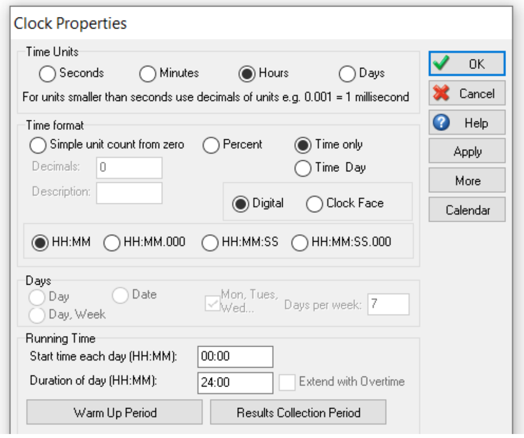

FIGURE 5. Setting of running time for generation units in SIMUL8.

- As in all simulation studies which depend upon generating random variates, there is always a variation in obtained simulated results. Therefore, to avoid the results being vastly varied, the simulation must be run for a sufficient number of replications. Nonetheless, there is no unique rule to follow in order to determine the sufficient number of replications. However, more replications of the simulation lead to the obtaining of more accurate results.
- Based on the historical data provided from Phase 1, SIMUL8 will simulate the operation of the system by generating random variates for TTF and TTR for each generation unit as follows:

$$TTF_{sim} = -MTTF_{calc} \ln (U_1) \tag{7}$$

$$TTR_{sim} = -MTTR_{calc} \ln (U_2) \tag{8}$$

$$TBF_{sim} = TTF_{sim} + TTR_{sim} \tag{9}$$

where,

TTF_{sim}	Simulated time-to-failure (h);
U_1	Uniformly distributed random number between [0,1];
TTR_{sim}	Simulated time-to-repair (h);
U_2	Uniformly distributed random number between [0,1]; and
TBF_{sim}	Simulated time-between-failures (h).

- The simulated utilization (availability) of each generation unit is given by:

$$Utilization = \frac{Total\ busy\ time}{Total\ simulated\ time} = \frac{\sum TTF_{sim}}{\sum TTF_{sim} + \sum TTR_{sim}} \tag{10}$$

C. PHASE 3: SIMULATION STEPS

As pointed out previously, the objective of the proposed method is to identify the availability of the generation system which represents the utilization of all generation units. The following steps explain the procedure of finding the availability of the generation system using DES via SIMUL8:

1. Run simulation for n number of replications.
2. Record the utilization, availability, (A_{ij}) of each unit for each replication. A_{ij} denotes the availability of unit i for replication j where $i = 1, \ldots, N$ and $j = 1, \ldots, n$.
3. Compute the expected available capacity (EAC_{ij}) of each generation unit for each replication.

$$EAC_{ij} = A_{ij} \times US_i \tag{11}$$

The term US_i denotes the unit size of generation unit i.

4. Compute the total expected available capacity ($TEAC_j$) for each replication.

$$TEAC_j = \sum_{i=1}^{N} EAC_{ij} \tag{12}$$

5. Compute the simulated total expected available capacity ($TEAC_{sim}$) of the generation system, which is the sample mean (Y) of the simulated total expected available capacity over n number of replications.

$$Y = TEAC_{sim} = \frac{1}{n}\sum_{j=1}^{n} TEAC_j \tag{13}$$

6. Compute the simulated availability of the generation system (A_{sim}). The term TIC is the total installed capacity of all generation units.

$$A_sim = \frac{TEAC_{sim}}{TIC} \tag{14}$$

Additional terms can be evaluated such as the simulated unavailability of the generation system (U_{sim}), which represents the forced outage rate (FOR) of the whole generation system. This can be found by using (15):

$$U_{sim} = 1 - A_{sim} \tag{15}$$

D. PHASE 4: ABSOLUTE PERFORMANCE ESTIMATION

This phase aims to investigate the accuracy of the results (performance indicators) obtained from the simulation model. The users or the builders need to estimate their level of confidence with the obtained results. The error can be estimated in any of the simulated results through different statistical estimation methods. In this paper, a Confidence-Interval Estimation is conducted to estimate the error around the sample mean of the total expected available capacity [32], [33].

$$Y \pm Error \tag{16}$$

The error can be estimated as follows [32]:

$$Error = t_{\alpha/2,n-1}\sqrt{\frac{1}{n-1}\sum_{n}^{j=1}(TEAC_j - Y)^2} \tag{17}$$

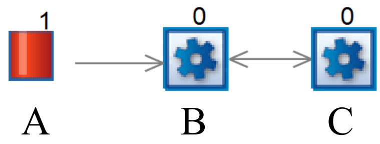

FIGURE 6. Conceptual model of a generation unit in SIMUL8.

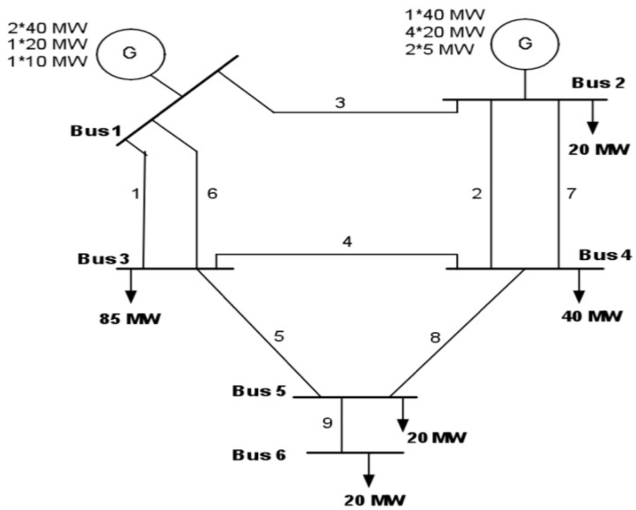

FIGURE 7. Single line diagram of IEEE RBTS.

where $t_{\alpha/2,n-1}$ is the quantile of the student's t distribution with n–1 degrees of freedom that cuts off $\alpha/2$ of the area of each tail.

IV. CASE STUDY

The generation system of the IEEE Roy Billinton Test System (RBTS) [34], [35] is used to numerically illustrate the proposed method. The generation system of IEEE RBTS has two generator buses with eleven generation units. The total installed generation capacity (TIC) of the units is 240 MW. The configuration of the system allows either generation bus to feed any load bus, as depicted in Fig. 7.

All units are assumed to have two operating states: up and down. The operation will be simulated for 1000 replications over a study period of one year (8760 hours). The OT of the units is set to 8760 hours. The rating and reliability data of the IEEE RBTS generation units in addition to their parameters are tabulated in Table 1.

To illustrate the setting of properties for the generation units, Fig. 8 and Fig. 9 show the MTBF and MTTR for one of the two 5-MW hydro generation units respectively.

The computations of the parameters are explained in Section III. The simulated total expected available capacity of the generation system $Y = TEAC_{sim}$ is found to be 234.791738 MW. Table 2 presents a sample of the results obtained from the simulation. Consequently, the simulated availability of the generation system (A_{sim}) can be computed using (14) and is equal to 0.9783. In other words, the probability of encountering a forced outage in the generation system

TABLE 1. Generation unit rating, reliability data, and parameters.

Group	Unit size (MW)	Type	Number of units	λ (1/yr)	μ (1/yr)	MTTF (h)	MTTR (h)	MTBF (h)
1	5	Hydro	2	2.0	198.0	4380	44.24	4424.24
2	10	Thermal	1	4.0	196.0	2190	44.69	2234.69
3	20	Hydro	4	2.4	157.6	3650	55.58	3705.58
4	20	Thermal	1	5.0	195.0	1752	44.92	1796.92
5	40	Hydro	1	3.0	147.0	2920	59.59	2979.59
6	40	Thermal	2	6.0	194.0	1460	45.15	1505.15

TABLE 2. Simulated results.

Group	Generation Unit	Availability			*EAC* (MW)		
		$j = 1$	$j = 2$	$j = 1000$	$j = 1$	$j = 2$	$j = 1000$
1	Hydro 1	0.9899167	0.9982812	0.9982385	4.9495835	4.991406	4.991193
	Hydro 2	0.9872506	1	1	4.936253	5	5
2	Thermal 1	0.9970316	0.9792857	0.9828582	9.970316	9.792857	9.828582
3	Hydro 3	1	0.976548	0.984868	20	19.53096	19.69736
	Hydro 4	1	0.976548	0.984868	20	19.53096	19.69736
	Hydro 5	1	0.976548	0.984868	20	19.53096	19.69736
	Hydro 6	1	0.976548	0.984868	20	19.53096	19.69736
4	Thermal 2	0.98362	0.9791794	0.9827703	19.6724	19.58359	19.65541
5	Hydro 7	0.9960421	0.9748569	0.9837768	39.841684	38.99428	39.35107
6	Thermal 3	0.9827167	0.9742398	0.9806117	39.308668	38.96959	39.22447
	Thermal 4	0.9827167	0.9855736	0.9392019	39.308668	39.42294	37.56808
$TEAC_j$					237.9875725	234.878503	234.4082365

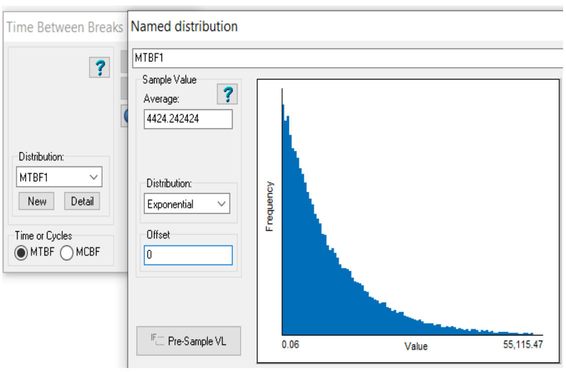

FIGURE 8. MTBF properties for Hydro 1 in SIMUL8.

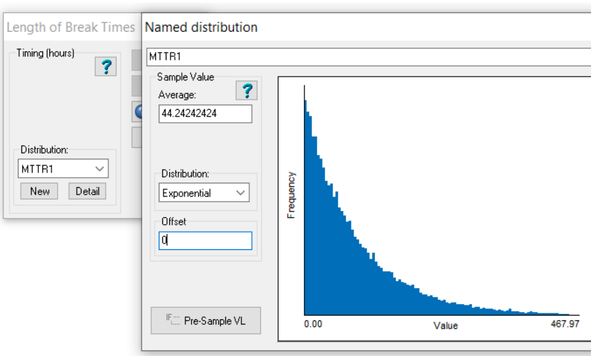

FIGURE 9. MTTR properties for Hydro 1 in SIMUL8.

of IEEE RBTS is 0.0217. Since the number of replications considered in this study is large, the degrees of freedom can be assumed to reach infinity. The error in the simulation results is estimated by using the Confidence-Interval Estimation as pointed out in Phase 4. At a significance level of $\alpha = 0.05$, the estimated error is found to be approximately 0.18 MW, which indicates a 95% confidence level that the *TEAC* of the generation system lies between 234.6116 and 234.9718 MW (234.791738 $\pm$0.18004).

V. CONCLUSION

This paper proposed a new efficient method to evaluate the availability of a generation system using the concept of discrete event simulation. The new method is proven to be superior in evaluating the availability of a generation system to both analytical and MCS techniques in terms of computational simplicity. The proposed method was presented through four main phases. The operation of the IEEE RBTS generation system was under study to illustrate the proposed method. A complete analysis of the simulation model was carried out through four main phases. The required parameters of the generation units were calculated in Phase 1. Phase 2 discussed the framework of building and setting the simulation model. Phase 3 outlined how the availability of the generation system can be mathematically obtained. A statistical estimation to the error in the simulated results was conducted in Phase 4. The observation indicated a negligible error. In future research, the load model may be incorporated in the analysis to comprise the computing of generation-load reliability indices using DES model.

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