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Monte Carlo Simulation of a Combined-Cycle Power Plant Considering Ambient Temperature Fluctuations

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Abstract

A combined-cycle power plant (CCPP) is broadly utilized in many countries to cover energy demand due to its higher efficiency than other conventional power plants. The performance of a CCPP is highly sensitive to ambient air temperature (AAT) and the generated power varies widely during the year with temperature fluctuations. To have an accurate estimation of power generation, it is necessary to develop a model to predict the average monthly power of a CCPP considering ambient temperature changes. In the present work, the Monte Carlo (MC) method was used to obtain the average generated power of a CCPP. The case study was a combined-cycle power plant in Tehran, Iran. The region's existing meteorological data shows significant fluctuations in the annual ambient temperature, which severely impact the performance of the mentioned plant, causing a stochastic behavior of the output power. To cope with this stochastic nature, the probability distribution of monthly outdoor temperature for 2020 was determined using the maximum likelihood estimation (MLE) method to specify the range of feasible inputs. Furthermore, the plant was accurately simulated in THERMOFLEX to capture the generated power at different temperatures. The MC method was used to couple the ambient temperature fluctuations to the output power of the plant, modeled by THERMOFLEX. Finally, the mean value of net power for each month and the average output power of the system were obtained. The results indicated that each unit of the system generates 436.3 MW in full load operation. The average deviation of the modeling results from the actual data provided by the power plant was an estimated 3.02%. Thus, it can be concluded that this method helps achieve an estimation of the monthly and annual power of a combined-cycle power plant, which are effective indexes in the economic analysis of the system.

Keywords

Combined-Cycle Power Plant, Monte Carlo Method, Ambient Air Temperature, Maximum Likelihood Estimation, Stochastic Behavior

1. Introduction

The construction of a combined-cycle power plant (CCPP) is one of the most efficient methods of generating electrical energy using fossil fuels, with a broad worldwide implementation record to satisfy the global energy demand [1]. Many environmental and non-environmental parameters influence the operation of CCPPs. Environmental parameters are related to location conditions, such as ambient air temperature (AAT), atmospheric pressure, and relative humidity [2]-[7], while non-environmental parameters involve component failure, fuel quality, and design challenges, such as compressor pressure ratio and pinch point temperatures [8].

Many studies report the impact of different parameters on the performance of combined cycles. Khaliq and Kaushik [9] evaluated the effects of steam pressure and pinch point on the exergetic and energetic efficiency of CCPPs. They concluded that the first and second-law efficiencies reduce by increasing the pinch point, while exergetic efficiency increases by increasing the steam pressure. Sanjay [10] studied the effect of fluctuations in the cycle process parameters on the efficiency of CCPP and reported that turbine inlet temperature (TIT) was the most effective parameter that directly depends on the gas turbine inlet temperature. Authors in [11] studied the influence of AAT, relative humidity, and site altitude on the output power of a dual pressure CCPP. The range of changes in AAT was between 24˚C - 35˚C, and the relative humidity fluctuated between 60% - 80%. The results showed that the generated power and thermal efficiency reached the maximum value of 205.52 MW and 47.46% at 24˚C. They concluded that by reducing the AAT at the optimum exhaust temperature and gas flow, the net power and efficiency of CCPP increase significantly. Matho and Pal [12] examined the different CCPP configurations, including single-pressure, double-pressure, and triple-pressure heat recovery steam generators (HRSGs), and calculated each arrangement's thermodynamic and economic factors. They showed that the SGTCC3PR (simple gas turbine combined-cycle using triple pressure HRSG with reheat) has the lowest operating cost per kWh of generated power.

In a CCPP the output power is highly sensitive to outdoor temperature changes [13]. Air temperature fluctuates widely during the year, directly influencing the power generation capacity of the system, thus leading to irreversible financial losses for operators and consumers [14]. Thus, AAT is a random and the most effective environmental factor with substantial impacts on the performance of a CCPP [15]. Several credible studies focus on the effect of AAT on the performance of a CCPP. Igoma, Alava, and Sodiki [16] designed an experiment to investigate the influence of ambient temperature on the performance of a gas turbine (GT) plant with a nominal capacity of 25 MW. They reported that a 1˚C increase in AAT led to a 0.12% decrease in net power and a 1.17% reduction in efficiency. Arrieta and Lora [17] studied the impact of AAT on the output power of a triple-pressure CCPP with supplementary firing in Brazil. The results showed that reduced ambient temperature could increase the output power of the plant by up to 75 MW for the specified case study. Rai *et al.* [18] employed practical data collected from a CCPP in full load to analyze the effect of AAT and temperature control on the output power. They concluded that the generated power falls significantly by increasing the gas turbine's inlet temperature. In [19], a 16.6 MW gas turbine was studied. The results indicated that as the temperature decreased from 34.2 to 15, the average output of the power plant increased by approximately 11.3%. Erdem and Sevilgen [20] investigated two simple gas turbine cycles with seven different climate conditions in Turkey to evaluate ambient temperature's influence on power generation. They compared the loss of annual capacity and fuel consumption increase with the standard state (sea level, 15˚C, 60% relative humidity). In [21], an experimental study was conducted on a CCPP with a capacity of 240 MW in Turkey to discuss the effect of ambient air fluctuations on the system's efficiency and net power. The output power for an ambient temperature range of 8˚C - 23˚C was registered. It was concluded that rising temperature could reduce the output power and efficiency of GT and steam turbine (ST). It has been recommended to install cooling systems in the inlet of GT to enhance the performance of the CCPP by reducing inlet air temperature [22] [23]. Cooling the inlet air of the GT is one of the best methods to increase the output power of CCPPs. By decreasing the inlet air temperature, the gas density will increase. As a result, a higher mass flow rate enters the compressor, thus generating more power [22]. De Sa and Al Zubaidi [24] proposed an experimental relation between the AAT and power generation in a CCPP. They concluded that raising the AAT by 1˚C above ISO condition leads to a 1.47 MW loss in output power and 0.1% loss in thermal efficiency.

Accurate modeling of a combined cycle and its components is the prerequisite for performing calculations. Almansoori and Dadach [25] simulated a natural gas combined-cycle (NGCC) with a capacity of 620 MW in ASPEN HYSYS. They used the Soave-Redlich-Kwong equation to obtain the plant's exergy efficiency. Estrada *et al.* [26] modeled a CCPP and calculated the output power using thermodynamic equations. Ersayin and Ozgener [27] conducted a parametric analysis to calculate the efficiency of CCPPs using the first law of thermodynamics and experimental data. The obtained energy efficiency was about 56%. Some articles present a methodology based on thermodynamic principles to obtain the efficiency of different sub-systems in a CCPP [28] [29] [30] [31]. Rovira *et al.* [32] present a method to predict the CCPP's behavior in different operation states (off-design and part loads).

The present study uses the Monte Carlo method to predict the stochastic behavior of the case study. It is one of the most useful probabilistic methods in investigating the effect of random input parameters on system behavior [33]. It has a wide application in renewable power plants, such as wind and solar plants. Solar and wind power plants do not have a constant output power and generate different power levels during the day due to solar radiation or wind velocity fluctuations [34] [35] [36]. Emami and Behbahaninia [37] determined the probability distribution of wind speed to obtain the average monthly and annually generated power to evaluate the potential of a wind power plant in Tehran, Iran. In [38], wind velocity in seventeen sites in Uzbekistan was recorded to analyze wind energy potential in this country. In [39], a combination of Monte Carlo and Marko methods was implemented on a waste-to-energy (WTE) power plant to obtain the plant's power factor considering fuel analysis variations.

Although the reviewed literature studied the effect of inlet air temperature on the performance of the CCPP either experimentally or numerically, and some of them have presented a relation between the ambient temperature and output power or efficiency, none of them can give us an accurate estimation of average generated power in a combined-cycle power plant considering the ambient temperature fluctuations. This study's novelty lies in that it is the first and only work implementing the Monte Carlo method on a simulated CCPP considering AAT as a random input to obtain average output power in full operation.

2. Power Plant Description

Figure 1 is a schematic of the studied power plant. A combined cycle consists of topping and bottoming cycles. Most of the heat is supplied to the topping cycle

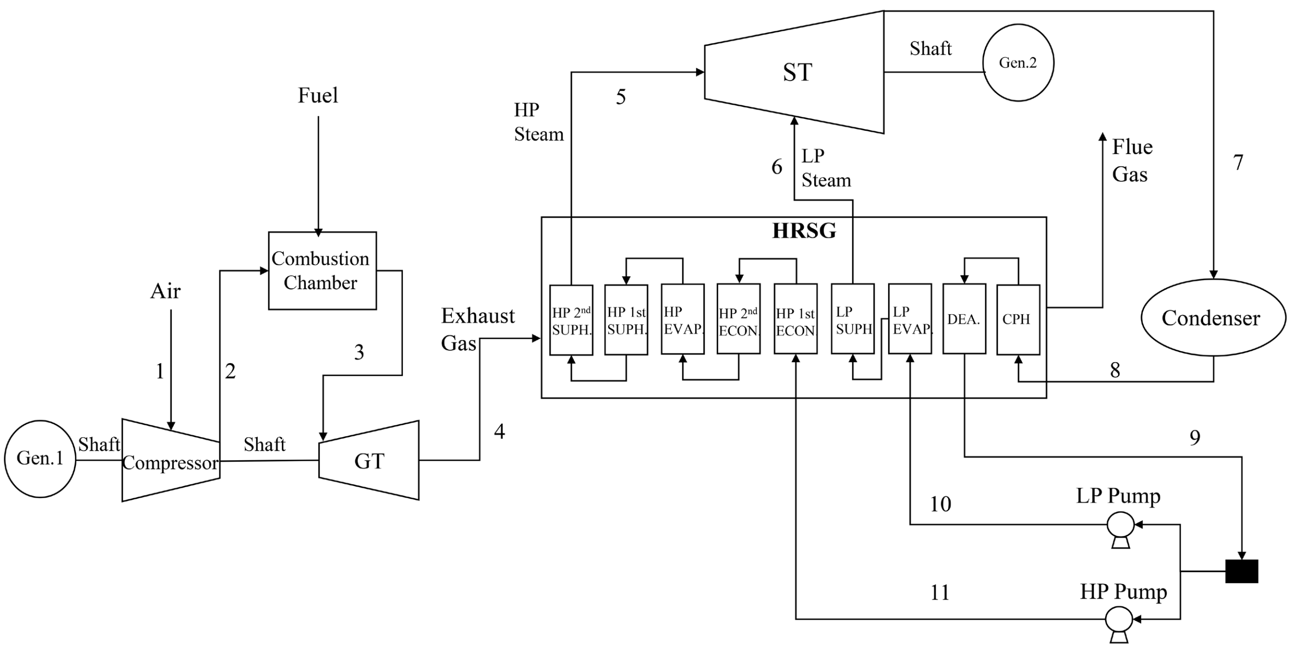

Figure 1. Flow diagram of the dual pressure combined cycle.

[15]. The waste heat it produces is then utilized in a second process operating at a lower temperature level and is, therefore, a "bottoming cycle" [15]. In this case study, the topping cycle is a Brayton cycle, and the bottoming cycle is a Rankine cycle. The Brayton cycle consists of four processes: First, air enters the compressor after passing through the filters. Meanwhile, the temperature and air pressure increase. The pressurized air enters the combustion chamber, where the combustion occurs at constant pressure after injecting liquid or gaseous fuel; thus, the temperature and, consequently, the gas's enthalpy increases significantly. After leaving the combustion chamber, the hot products of combustion enter the turbine, and passing through the blades, they expand and cause the rotation of the turbine shaft, thus causing the generator's shaft to rotate and generate power. The exhaust gases from the gas turbine enter the HRSG to exchange energy with water in the Rankine cycle. In this cycle, water passes through the evaporators, economizers, and superheaters. Therefore, superheated steam is produced in two pressure stages: low-pressure and high-pressure (LP and HP). Next, the HP and LP steam passes through the ST blades and causes the turbine's shaft and generator's shaft to rotate. Then, the expanded steam enters the condenser, condenses during an isobar process, and then is pre-heated by passing through the CPH (condensate pre-heater) and deaerator. Finally, the pre-heated water is divided into two low-pressure (LP) and high-pressure (HP) and is pumped by feed-water pumps (FWP) into the HRSG; thus, the cycle repeats continuously.

This CCPP consists of six units. Each unit includes two gas turbines (Ansaldo AE94.2) with a nominal capacity of 166.2 MW, coupled with a steam turbine with a capacity of 114 MW (Figure 2). All units of this power plant have similar properties and arrangements. Therefore, just one unit is simulated in this study,

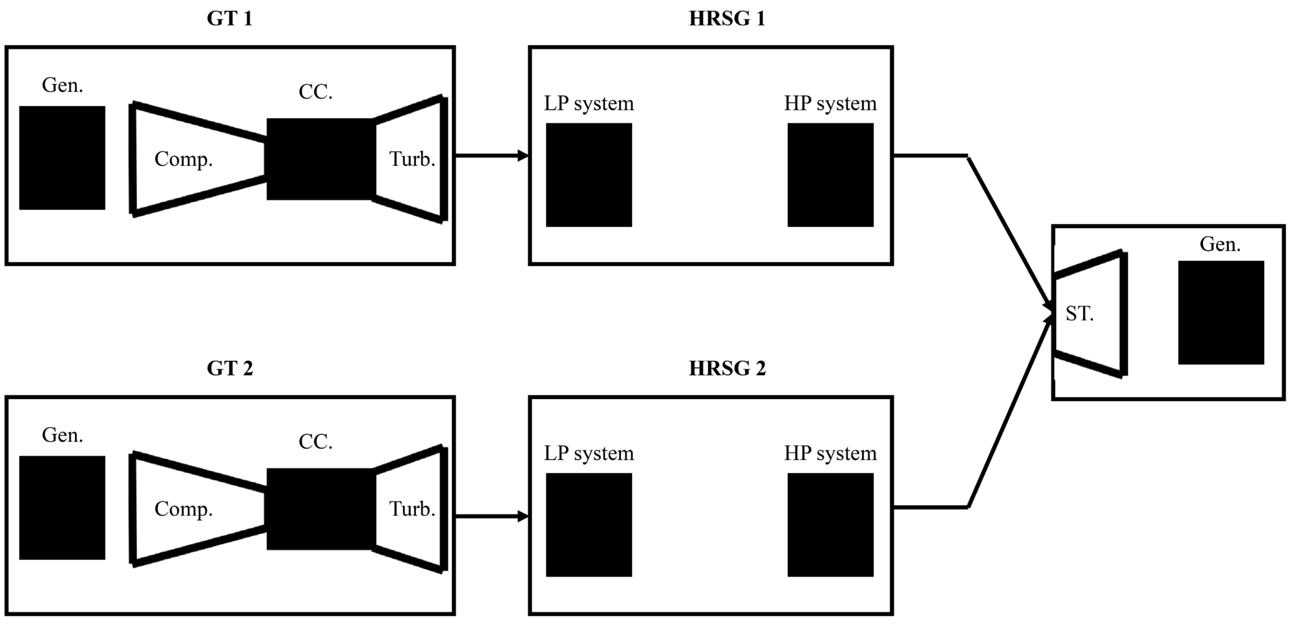

Figure 2. The sub-systems of a unit of the CCPP.

but the results can be extended to all six units. The CCPP is simulated in THERMOFLEX based on the power plant's piping and instrumentation diagram (P&ID). **Figure 3** shows the schematic of this simulation.

To verify and check the consistency of the model results with actual data, the actual values of monthly power (found in the power plant's annual reports) were compared with power calculated by the computer model. The comparison criterion was the error percentage between two values obtained by Equation (1).

$$\text{Error}(\%) = \frac{|\text{actual power} - \text{calculated power}|}{\text{actual power}} \times 100 \qquad (1)$$

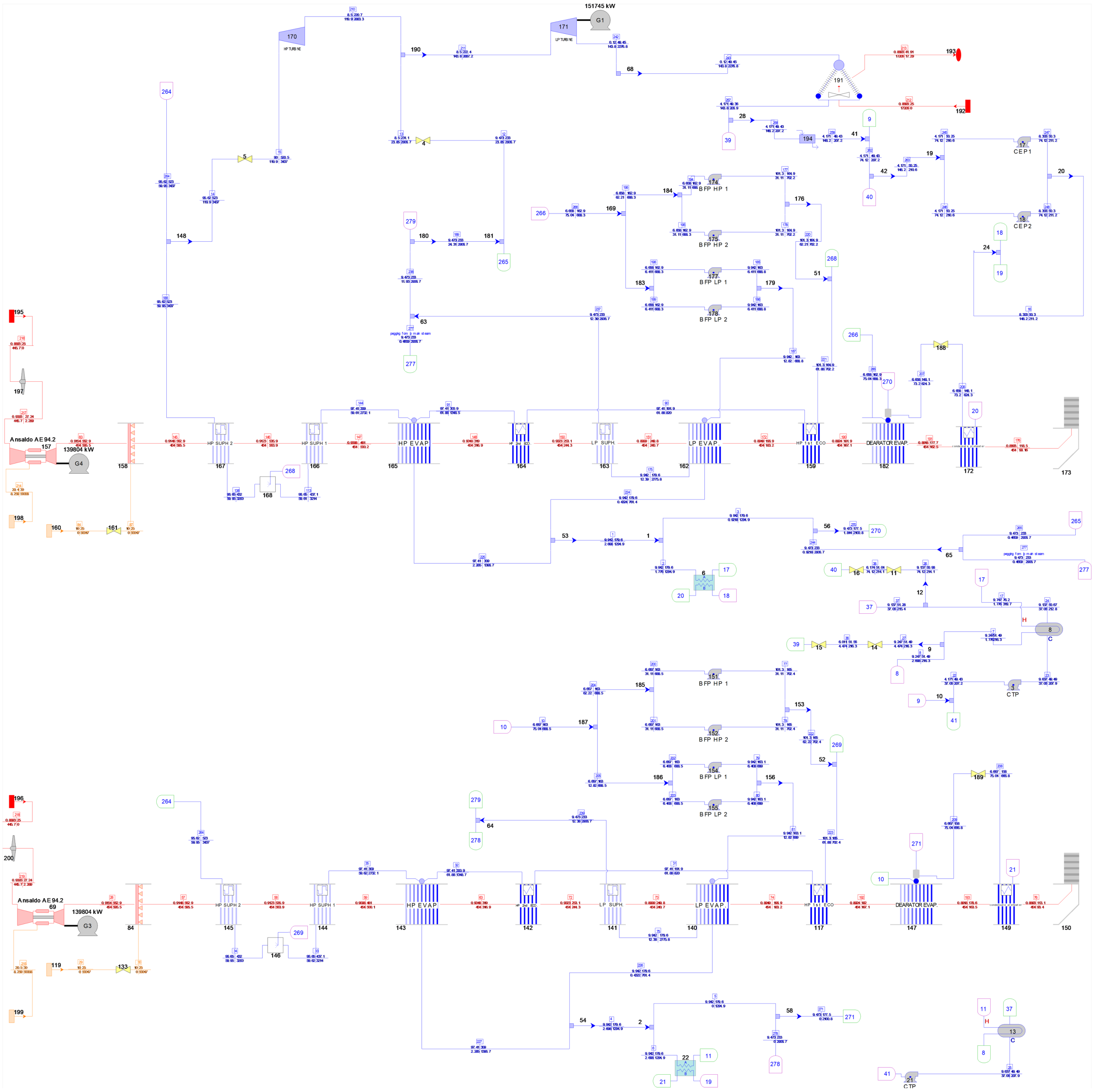

Figure 3. The combined cycle simulated in THERMOFLEX.

$$\text{Average error}(\%) = \frac{\text{Summation of errors for each month}(\%)}{12} \tag{2}$$

3. Methodology

The Monte Carlo method is a standard and efficient computational algorithm widely used in different fields, especially economics and system engineering [33]. Monte Carlo is an appropriate method for analyzing the behavior of systems with a determined uncertainty in input [33]. The Monte Carlo method is based on the concept of randomness and random sampling [40]. Applying this method requires seven main steps [41]:

1) Determining the main system and a parameter as uncertain input of the system.

2) Modeling the main system in computer software.

3) Determining the probability distribution of uncertain input parameter.

4) Generating random inputs from the specified distribution

5) Running the computer model with the generated random input.

6) Recording system results and behavior.

7) Making a probability distribution for output results.

Figure 4 is a flow chart of the mentioned steps (the Monte Carlo algorithm) implemented on the case study [39].

When studying and analyzing the behavior of a system with random inputs, the system should be modeled first to obtain the results of different inputs. Due to the randomness of input values, we should have a probability distribution of the input data to use the Monte Carlo method to know how likely each value will occur [33]. After obtaining the probability distributions, we have to select a random sample with a certain amount of data according to the required accuracy in the next step. Random selection from the data is the most important part of the Monte Carlo simulation because it is based on random selection [40]. After selecting a random sample, it is incorporated into the system so that the simulated model gives us one or more output values as a result.

Obviously, the greater the number of randomly selected samples, the closer the results will be to the system's actual behavior, thus more accurate calculations [40]. The number of randomly selected samples is a function of system complexity and the accuracy required in simulation [33].

In this research, the inlet air temperature of the plant, the same as the inlet air temperature of the compressor, was considered as input. After running the system with input values, the net power of the plant was considered as output.

3.1. Finding Probability Distribution

To obtain the probability distribution of ambient temperature, considering that the site construction is in Tehran, Iran, the air temperature of this city was recorded every thirty minutes from January 2020 to the end of December 2020 based on the meteorological organization reports [42]. Since the climate condition

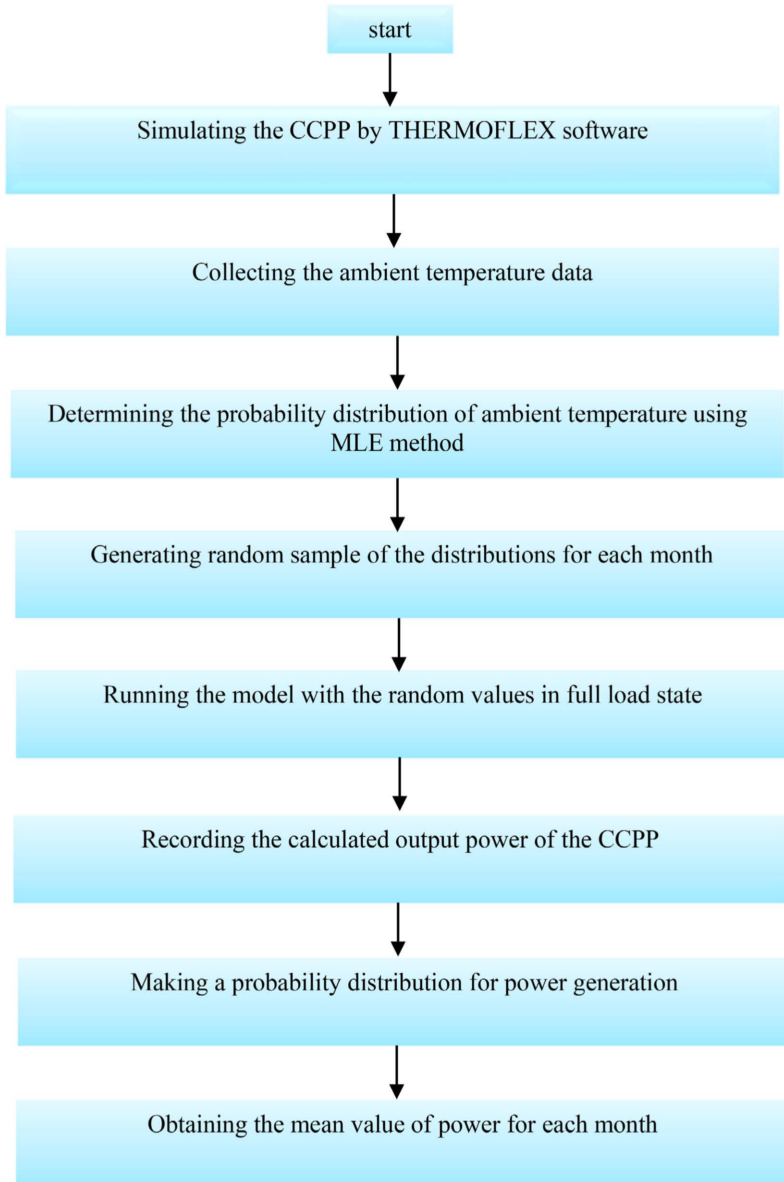

Figure 4. Monte Carlo algorithm flow chart.

of Tehran has been relatively stable in recent years [42], the use of temperature data for one year provides a good approximation of temperature. Furthermore, the results can be extended to the coming years.

Distributions were fitted to data using the maximum likelihood estimation (MLE) method. In statistics, MLE is a method for fitting typical statistical distributions to resulted data from modeling or observations [43]. In this method, to find the most appropriate statistical distribution for the available data, at first, all statistical distributions are fitted to the data, and a function called "likelihood function" is defined [43]. The value of this function is different for each fitted distribution. After calculating the values of this function, the distribution with the highest value of the likelihood function is considered the most appropriate statistical probability distribution for the data [43]. In this study, the MLE method was implemented on the input data (AAT) using the R language, and by comparing the values of the likelihood function for each month, the most suitable probability distribution for the temperatures was obtained.

3.2. Random Selection

After determining the probability distribution, a completely random sample of this distribution was selected by randomly generating 2000 temperature data for each month (a total of 24,000 random data) by Matlab codes that aimed to generate random numbers from a given probability distribution. After generating a random sample, the generated data was entered into the model, and the system was run in full load operation mode to determine the output results.

4. Results and Discussion

A real dual pressure CCPP (PARAND CCPP) in Tehran was simulated with all its details based on the P&ID of the power plant. The following tables (see Tables 1-4) summarize the critical and basic input data used in simulation of this plant. Data in these tables (see Tables 1-4) are extracted from the datasheets and information provided by the power plant.

Table 1. Plant's primary data.

Site Condition		Gas Turbine Specifications	
Ambient temperature	25˚C	Gas turbine type	Ansaldo AE 94.2
Altitude	1088 m	Shafts	1
Ambient pressure	0.8893 bar	RPM	3000
Ambient relative humidity	75%	PR	11.7
Ambient wet bulb temperature	21.55˚C	TIT (˚C)	1141
Line frequency	50 Hz	TET (˚C)	544
Makeup Water Condition		Air flow (kg/s)	521
Makeup water source pressure	3 bar	Gen. power (MW)	166.2
Makeup water source temperature	15˚C	LHV HR (kJ/kWh)	10365
Process condensate return pressure	3.447 bar	LHV eff. (%)	34.7
Process condensate return temperature	82.22˚C	Price (MM$)	42.5
Process condensate return percentage	98%	Manufacturer	Italy

Table 2. HRSG data.

Duct burner Fuel	Natural gas	Blowd'own percentage	3.8%	Pump types	Multistage centrifugal
Approach subcooling	5˚C	Gas flow direction	horizontal	Number of pumps per HRSG	2
LP and HP evaporator circulation	natural	LP and HP pinch	20˚C	mechanical efficiency	97%

Table 3. Input data for steam turbine.

Reference pressure ratio for steam turbine expansion step	1.35	LPT last stage rotation speed	3000 RPM
Condensation quality (Wilson line)	0.97	Exhaust loss correction factor	1
Steam turbine mechanical loss	0.25%	Moisture efficiency penalty (Baumann coefficient)	0.72
Steam turbine mechanical efficiency	99.75%	Exhaust loss	9.303 kJ/kg

Table 4. Generator specifications and transmission data.

Generator specifications		Transmission system data	
Generator rated power/nominal output	1.05	Transmission	500 kV
Single shaft GT/ST generator rated power/nominal output	1.15	GT/ST generator	11.5 kV
Generator power factor	0.9	ST generator	11.5 kV
Generator mechanical loss as a percent of generator total loss	12%	Medium (station service)	4160 kV

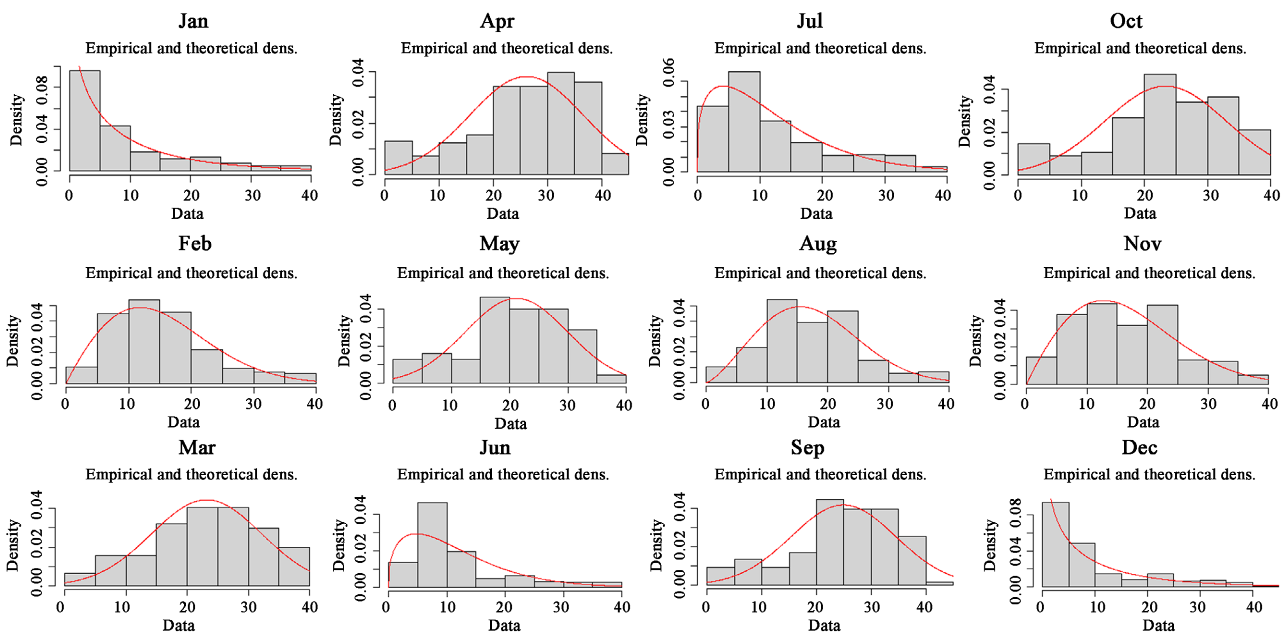

Figure 5. Monthly probability distribution of outdoor temperature (˚C) in Tehran.

After recording and categorizing outdoor temperature data, we arrive at a graph as shown in **Figure 5**, the probability distribution of ambient temperature in Tehran per month.

Table 5 presents the type of the fitted distributions per month and their parameters (mean value and standard deviation).

Finally, after running the model with input data in full load operation mode, the resulted values in different iterations are reported in **Table 6**. After converging these results to a fixed value, mean value and standard deviation (Std) of

Table 5. Type of monthly temperature probability distributions.

Month	Type of distribution	Mean	Std.
JAN	Gamma	8.926	0.118
FEB	Weibull	45.254	9.037
MAR	Weibull	55.389	7.538
APR	Weibull	59.218	9.183
MAY	Normal	75.705	10.463
JUN	Weibull	55.389	7.538
JUL	Normal	88.026	7.302
AUG	Normal	83.792	8.759
SEP	Normal	78.363	7.232
OCT	Lognormal	55.389	7.538
NOV	Lognormal	3.948	0.164
DEC	Gamma	3.826	0.102

Table 6. Monte Carlo results in different iterations.

Iterative number	JAN	FEB	MAR	APR	MAY	JUN
500	445.5	445.9	437.8	430.7	418.2	416.3
685	446.2	446.2	439.2	433.9	420.7	415.8
1000	456.1	446.7	439.5	434.8	422.6	417.5
1500	456.3	448.8	440.3	435.3	423.8	419.3
2000	456.3	448.8	440.3	435.3	423.9	419.4
Iterative number	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
500	415.3	427.4	428.4	435.2	450.4	441.3
685	416.9	425.7	428.1	437.6	449.6	439.5
1000	414.3	424.9	426.9	439.2	451.8	441.1
1500	415.8	423.1	427.8	438.6	450.3	440.6
2000	415.9	423.1	427.8	438.7	450.4	440.6

output power are compared with the actual data in Table 7.

Table 8 presents the deviation of the modeling results from the actual results for each month calculated using Equations (1) and (2).

Figure 6 shows the actual monthly average power and the resulted values from the Monte Carlo method. As shown in Figure 6 the mean value of output power has a downward trend until July and then takes an upward trend. Changes in the outdoor temperature can explain this behavior. From January to July, the temperature increases, thus decreasing the generated power, while from July to December, this trend is reversed.

Table 7. Mean value and Std. of power for upstate mode.

Month	Mean Value resulted from Monte Carlo method (MW)	Actual mean value (MW)	Month	Mean Value resulted from Monte Carlo method (MW)	Actual mean value (MW)
Jan.	456.303	443.666	Jul.	415.951	402.430
Feb.	448.859	435.658	Aug.	423.111	412.912
Mar.	440.385	428.224	Sep.	427.883	417.244
Apr.	435.305	423.654	Oct.	438.737	423.859
May.	423.968	410.345	Nov.	450.469	437.518
Jun.	419.408	405.264	Dec.	455.108	440.655
Average generated power from MC method = 436.3 MW			Actual average generated power = 423.4 MW		

Table 8. The monthly actual mean value of power.

Month	Error (%)	Month	Error (%)
Jan.	2.78	Jul.	3.36
Feb.	3.03	Aug.	2.47
Mar.	2.84	Sep.	2.55
Apr.	2.75	Oct.	3.51
May.	3.32	Nov.	2.96
Jun.	3.49	Dec.	3.28
Average error = 3.02%			

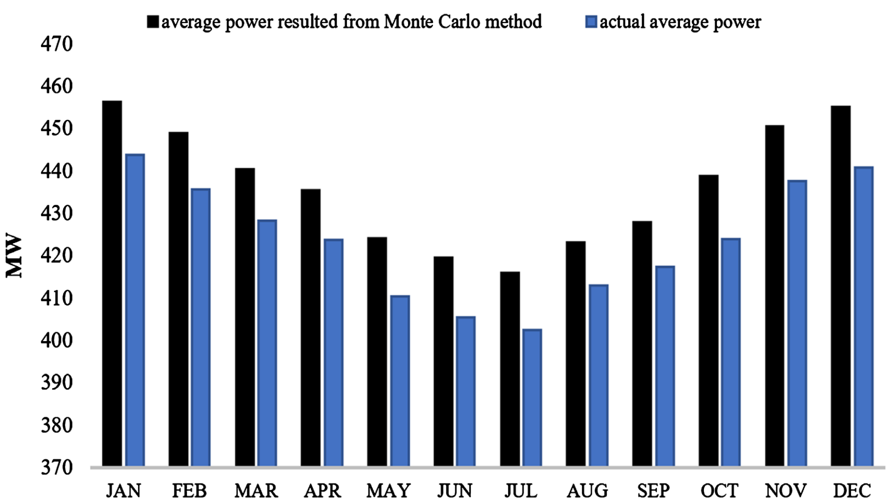

Figure 6. Actual and calculated average monthly power.

Some factors and parameters leading to differences among actual values and the modeling results are as follows:

- In modeling, equipment efficiency is assumed constant and equal to nominal efficiency, while some components operate with a certain percentage of nominal capacity depending on the situation.

- In the simulation, energy losses and pressure drop in the pipelines are assumed based on the design parameters, while over time, these losses increase.

5. Conclusion

A probabilistic method was implemented on a detailed model of a combined-cycle power plant to obtain the average generated power. Ambient temperature fluctuations during the year were introduced as the random factor influencing the power generation capacity. The average power was estimated at 436.3 MW, and the deviation in the simulation results from actual data was 3.02%. It can be concluded that this value can be a criterion for assessing the simulation's accuracy. This methodology can be implemented on different types of CCPPs or be combined with transient availability analysis methods to estimate a plant's power factor in the design process. The results can also be used in economic analysis.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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